Exploring the mechanism-based explanation of complex social phenomena: A social simulation study of the diffusion of college students drinking behavior in friendship networks

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Exploring the Mechanism-Based Explanation of Complex Social Phenomena: A Social Simulation Study of the Diffusion of College Students Drinking Behavior in Friendship Networks

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Declaration

I declare that this is my own work and has not been submitted for the award of a higher degree anywhere else.

Statement of Copyright

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Abstract

Research Topic

This study aims to develop and apply research paradigm based on a generative approach to address the methodological challenges current social complexity theory-based methods face in explaining the emergent properties of complex social phenomena. We situate this study within the context of a substantive social phenomenon, focusing on the diffusion of college drinking behavior within friendship networks as the target social phenomenon (Explanandum), analyzing and explaining how social capital and the cultural significance of college drinking (Explanans) contribute to the emergence of the target complex social phenomenon.

Methodology

We developed a Reinforcement Learning (RL) based Pattern-oriented Agent-Based Modeling (ABM) model to test mechanism-based explanations (MBE) that bridge Explanans and Explanandum through social simulation studies within artificial social systems.

Main Findings

The ABM-based social simulation research illustrates non-linear interaction processes among individuals, suggesting that the target complex social phenomenon can emerge through a co-evolution process between college students' drinking behavior and friendship networks. The results of the social simulation indicate that the social capital-driven drinking motives of college students and the mechanisms of social exclusion within college students' social drinking context are indispensable explanatory factors in accounting for the emergence of the diffusion of college drinking behavior within friendship networks.

Significance of Study

This study explores and implements an ABM social simulation approach to test MBE hypotheses on the emergence of complex social phenomena under the principle of abductive reasoning, offering a replicable and feasible generative methodological paradigm. This research paradigm is grounded on a clear and robust epistemological foundation, namely

structural individualism. It clarifies the ontological status and causal effect of social structures in MBE and the direct causal power of the interaction processes among individuals. Additionally, employing an enhanced "Coleman's boat" diagram, this research paradigm provides a coherent multi-level (micro-macro) analytical framework, which facilitates the tracking and analysis of interactive processes among individuals embedded within social structures. The advancement of this research paradigm signifies an optimization of the existing "generative methodology" analytical toolbox proposed by analytical sociologists (Bearman and Hedström, 2009:16; Manzo, 2021: 3) and represents an exploratory attempt to address existing methodological challenges within the social complexity framework.

Figures and Tables

Chapter 1: Introduction

The introduction chapter serves to introduce the research background of this study, the research topic and objectives, and significance of this study, concluding with the organizational structure of this dissertation.

Research Background

Theoretical Background: Development and Challenges of Social Complexity Theory

The academic discourse on social complexity has witnessed a remarkable growth in recent decades, garnering significant attention within the social sciences. Research in this field typically conceives human society as a complex dynamic system, comprised of multiple, highly interrelated yet autonomously active components and the nonlinear interactions among them. Social complexity emphasizes the nonlinear interactions between components, rather than solely focusing on the intrinsic attributes of the components themselves, which are believed to contribute to the emergence of complex social phenomena.

The study of social complexity is posited to hold significant potential in overcoming the limitations of traditional reductionist approaches in social science, particularly in explaining the emergent properties of social systems. However, practical explanatory research grounded in social complexity faces epistemological, methodological, and technical challenges, which impede the progression of this field.

In the subsequent sections, we provide a brief introduction to the theoretical concept of social complexity, the principal tenets of the social complexity, and the main challenges in its current development, thereby delineating the theoretical background of this study.

The Concept of Social Complexity and Its Evolution

Castellani and Gerrits (2024:20) have noted that the study of social complexity has evolved over the last eight decades into a broad, interdisciplinary field of inquiry. The core of these studies has been identified as a theoretical framework commonly referred to as complex systems theory, systems theory, social systems theory, complexity theory, or simply 'complexity' (within this study, these terms are used interchangeably without distinction) (Castellani and Gerrits, 2024:20).

Sawyer (2005:10-26) has provided a historical review of the evolution of the complex systems theory. He identifies three distinct waves of social systems theory within the social sciences:

- "Parsonian systems theory" is identified as the first wave of complexity theory, which emphasized social systems as structured entities, assumed to be hierarchical, decomposable, and with functional localizability. Parsons posited the analytic independence of distinct levels within social systems (Sawyer, 2005:13).
- "General systems theory and chaos theory" are identified as the second wave of complexity theory, which highlighted the nonlinearity of dynamical systems, leading to their extreme sensitivity to initial conditions and resulting in the properties of unpredictability and non-reducibility of the systems. General systems theory also assumed the independence of higher-level systems (Sawyer, 2005:22).
- Complex adaptive systems theory" is identified as the third wave of complexity theory, fundamentally concerned with emergence, component interactions, and the relations between levels of analysis (Sawyer, 2005:23).

In the most recent developments of social complexity, although it is still identified as a framework rather than a 'one' or 'singular' unified theory (Byrne and Callaghan, 2022: 9; Castellani and Gerrits, 2024:20), to the extent that social complexity theory can claim a unified focus, it is found precisely in its approach to systems thinking, which is inherently different from that of traditional reductivism social science (Heylighen et al., 2006). From a system thinking perspective, human society can be conceptualized as a complex dynamic system composed of multiple, highly interrelated yet autonomously active components and non-linear interactions among these components (Greve, 2012). In this framework, non-linearity suggests the existence of closed feedback loops within the interaction process of components, while complexity refers to the system-level irreducible emergent properties resulting from these nonlinear interactions. Within the paradigm of systems thinking, the notion that 'the whole is more than the sum of the parts and their interactions' holds valid, as emergent properties define the systemic entity as a whole, endowed with emergent causal powers that cannot be reduced to a mere aggregation or subtraction of its constituent components (Byrne and Callaghan, 2022:1; Elder-Vass, 2010:22; Alaimo, 2022). This discourse, rooted in system thinking, has profoundly influenced the methodologies and frameworks that social scientists utilize to interpret and explain social phenomena within various social systems.

Explaining Complex Social Phenomena Based on Systemic Approach

Developing empirically grounded theories and explanations regarding why and how specific social phenomena occur is one of the principal objectives of social science research (Elster, 2015:3; Sorrell, 2018). From the perspective of social complexity, traditional reductionistic methods are inadequate in addressing the complexity of social phenomena, even though reductionism has often been considered as one of the cornerstones of classical social science (Alaimo, 2022:7; Törnberg, 2017:18). Reductionism posits that social systems are optimally understood by synthesizing information derived from the independent analysis of their constituent components (El-Sayed et al., 2012). A prime example of reductionist approach is "variable sociology", which reduces sociological explanation to showing the extent to which dependent variables can be statistically "accounted for" by independent variables (e.g. by analyzing and estimating causal dependence effect under potential outcome model), without considering the underlying social processes from a realist ontological perspective (i.e., the interactions among entities within social systems) that inform the results obtained (Goldthorpe, 2016:103; Anderson and Sharrock, 2013).

Turner and Baker (2019) argue that employing a reductionistic framework entails dissecting an entity into its constituent elements, with the epistemological basis being that a comprehensive understanding of the whole can be achieved by grasping the attributes of its parts (Turner and Baker, 2019; deMattos et al., 2012). However, system thinking posits that complex social systems are characterized by nonlinear dynamic interactions among components, and the emergent properties at the societal system level are irreducible and cannot be reduced to a mere summation or difference of the components (Byrne and

Callaghan, 2022:1). This irreducibility renders reductionistic and natural language approaches to analysis impracticable and inadequate for delineating complex causal relationships (Edmonds and Meyer, 2013:4). System thinking thus motivates the objection to traditional reductionistic analytical methods in the study of complex social phenomena.

For instance, researchers employing systemic thinking have widely critiqued 'variable sociology': Coleman (1986: 1314–1315) highlights a paradox that sociologists engaged in “empirical, statistical survey research” primarily analyze individual-level data without explicitly referencing the individual actions and interactions from which these data derive. Similarly, Boudon (1987: 61–62) has criticized that in such research, variables rather than entities are often taken as the units of analysis, and that demonstrations of the statistical effect of one variable on another are considered as “final results” without any attempt being made to show how these statistical relations derive from their “real causes”, which can lie only in the actions of individuals (Goldthorpe, 2016:103). Castellani and Gerrits (2024:365) further note that “Variables are often nothing but remote proxies and black boxes that hide considerable social action (as variables themselves do not “do” things)”. Jörg (2011: 13) has emphasized that human beings should not be examined in isolation, devoid of their 'social' attribute, but rather as entities that are deeply embedded within their social environment, interacting with other individuals within that social context. Törnberg (2017: 18-19) points out that although variable sociology has indeed proven powerful and highly useful in many cases, conventional statistical analysis shifts the focus away from the interactions between actors and towards labels that we treat as properties of individuals, and thus the social part of behavior is neglected, regarding the ways people interact and influence each other.

In summary, the specific relationships among structured components, along with their ongoing interactions, give rise to a particular kind of whole that is typically characterized by irreducible emergent properties (Elder-Vass, 2010: 20). These emergent properties bestow upon a social entity an emergent causal power (powers of the whole and not of the parts) enabling the entity to exert a particular diachronic causal impact on the world that is not simply the sum of the impacts its parts would have if they were not organized into this kind of whole (Elder-Vass, 2010: 5, 23).[1] Therefore, from a system perspective, aggregating information obtained through the independent study of components and their attributes is inadequate for a comprehensive understanding of irreducible emergent properties (El-Sayed et al., 2012). Alaimo (2022: 15, 17) elaborates that in a complex social system, the interconnections between the components can sometimes be more significant than the components themselves. In recent decades, approaches grounded in social complexity theory attempts to augment the reductionistic approach by not only demanding a comprehension of the individual components and their attributes, but also by discerning how these components interact with all others in social dynamic processes, leading to the emergent properties of the social system (Turner and Baker, 2019). This paradigm shift - from analyzing the dependence causality between the attributes of components and system properties to emphasizing the nonlinear interactive processes among componential entities within a social context - distinguishes methods based on social complexity theory from reductionist approaches in social science.

Moreover, this research paradigms shift also illustrates the differing interpretations of complexity and complication between the complex social theory approach and the reductionist approach. The complex social theory framework emphasizes a clear differentiation between these two concepts, while reductionist methodologies often use these terms interchangeably:

In reductionist approaches, the term 'complex' is misleadingly used to describe systems simply because they consist of many parts, leading to an inaccurate attribution of complexity when the systems are, in fact, merely complicated (Garnsey and McGlade, 2006:4-5). A complicated system can be explained by detailing its component parts; it is understandable through the process of disassembly and reassembly, allowing for a comprehensive understanding of the system by examining its individual elements (Garnsey and McGlade, 2006:4-5).

[1] The concepts of emergent properties and causal powers will be further explored in the “Epistemological Foundations” section of Chapter 3.

In contrast, within the complex social theory framework, 'complicated' is more precisely defined as either a simple hierarchical structure, which could be considered 'weakly complicated,' or a hierarchical structure with interconnected circuits of influence, termed 'strongly complicated.' The term 'complex,' on the other hand, is reserved for configurations marked by numerous closed feedback loops among interacting components (Garnsey and McGlade, 2006:4-5; Sun et al., 2012).

Based on these conceptual disparities, the research pathways for explicating complicated and complex social phenomena diverge. Alaimo (2022:2) likens complicated social phenomena to a linear plicum, whereas complex social phenomena are akin to an interwoven plexum. Addressing complicated issues can be done using a traditional reductionistic analytic approach: one identifies the correct solution by unfolding the problem, decomposing it into fundamental components, and analyzing each part individually. Despite the challenges, a solution is invariably attainable. In contrast, grappling with complexity requires a synthetic or systemic approach. The plexum cannot be understood by scrutinizing individual components alone, as this would result in losing sight of the entire system. "If you dissect the fabric of the weave into its threads or basic components, you end up with a set of threads whose analysis does not assist in recreating the original system, the original fabric" (Comello and De Toni, 2010). The resolution to complex issues must be sought by striving to understand it as an integrated whole, which implies that in understanding complexity, the components within the system are interdependent and interactive, embedded within a social context.

To summarize this section, the transition from analysis to synthesis marks one of the most significant advancements in 20th-century social science: "The properties of the parts can only be understood within the context of the larger whole. ... Systems thinking is contextual, which is the antithesis of analytical thinking” (Bertalanffy, 1968:30; Alaimo, 2022:3). Consequently, mainstream complexity science has come to be understood as a discipline that examines the emergence of novel social patterns/structures arising from the interaction of micro-entities (Törnberg, 2017: 30).

This necessitates the development of non-reductionistic, synthetic, or systemic research frameworks by social scientists to explain complex social phenomena within the purview of system thinking. However, in research practice, understanding and explicating the emergent properties of complex social phenomena from a systems thinking perspective is an exceedingly challenging endeavor.

The Challenges of the Social Complexity Approach

To develop systemic methods for addressing complex social phenomena within the social complexity framework, researchers confront several pivotal challenges that must be addressed in practical research endeavors:

- Castellani and Gerrits (2024:38) emphasize a glaring absence of well-established, enduring philosophies of complexity that have garnered widespread acceptance within the academic community. This dearth, particularly the scarcity of attempts to formulate a social ontology and epistemology tailored to social complexity, constitutes one of the major impediments to the progression of social complexity theory.

- Secondly, there is a lack of mature, operable non-reductionist multi-level systemic analytical frameworks. System thinking emphasizes that the emergent properties of social systems arise from the nonlinear interactions among interdependent and structured components. Therefore, a comprehensive explanation of complex social phenomena requires researchers to illustrate the dynamic interaction processes at the micro-level (components), the characteristics of emergent properties at the macro-level (social), and most critically, the micro to macro transition issue. At present, there is still a lack of such non-reductionist systemic analytical frameworks to help researchers analyze the causal structure between multiple layers of social systems (micro-, macro-, micro to macro) and provide a clear research path to test potential theoretical hypotheses.

- Lastly, there are challenges in empirical data collection and analysis. Given the focus of complexity theory on the non-linear interaction process among components, the systemic approach within the complex systems framework for explaining the emergent properties of complex social phenomena requires a high quantity, quality, and dimensionality of empirical data. Skopek (2023:146) highlights that, despite the vast quantities of data generated to track various human activities in contemporary society, much of this data (particularly unstructured data) is often produced and collected in ways that are not directly applicable to the study and explanation of complex social phenomena. This is because the study of complex social phenomenon often requires data that describes how components relate to one another, as well as how these components and their relationships change over time. Consequently, researchers often need to collect a large amount of attribute data at the component level of the system, interaction data between components, and attribute data at the social level. More importantly, to grasp the interaction process between components, this data often needs to be structured in a network and temporal manner. The cost of collecting such empirical data is high, and the difficulty of collection is great. In addition, Castellani and Hafferty (2009:25) emphasize the limitations of conventional statistical and qualitative methods, particularly those grounded in structured data, in addressing increasingly complex and high-dimensional databases, underscoring the pressing need for advanced analytical techniques.

Social Complexity, Analytical Sociology and Generative Approach

Analytical sociology is one of the most important sociological methodological movements within the social complexity framework (Elster, 1989, 2007; Hedström, 2005; Hedström and Bearman, 2009; Hedström and Ylikoski, 2010; Pérez-González, 2020). This movement promotes and contributes to the research focus shifts advocated by the social complexity framework in social science research and further emphasizes the need for causal mechanism-based explanations (MBEs)[2] of social phenomena to bridge the gap from producing causes to resulting effects, unfolding the "the linked chain of causes" in between (Conte, 2009).

[2] The concept of causal mechanism-based explanations advanced by analytical sociologists is grounded in the production accounts of causality. This perspective contrasts with the causal dependence explanations found in variable sociology, which are based on the dependence accounts of causality. Chapter 3 will further elucidate the distinctions between these two different positions on causality within the context of this study.

Specifically, analytical sociologist, such as Hedström (2009:332) advocate for “explaining complex social processes by carefully dissecting them, bringing into focus their most important constituent components, and then to construct appropriate models which help us to understand why we observe what we observe”. Wan (2012) notes that, for analytical sociologists, providing rigorous microfoundations is paramount in sociological explanation, which entails detailed accounts of “the pathways by which macro-level social patterns come about” (Little, 1998: 4), or of “how efforts on the ground…may prompt macrolevel changes and responses’’ (Powell and Colyvas 2008: 295).

Furthermore, it is important to recognize that analytical sociology is primarily a research methodological movement that offers a set of guidelines for constructing causal explanations of social phenomena, often referred as "a 'syntax' of explanation" (Manzo 2010: 140; León-Medina, 2017b) or "some general ideas about what good social science is all about" (Hedström and Ylikoski 2010: 58; Wan, 2012). It does not constitute a mature and explicit research framework or paradigm for analyzing, proposing, and testing MBEs of complex social phenomena.

Anderson and Sharrock (2013) noted that one of the critical challenges for the analytical sociology methodological movement is to delineate the concatenations of individual lines of activity to demonstrate how the macro emerges from the micro. Without this capability, analytical sociology explanations risk being as opaque as other sociological approaches, with accounts amounting to little more than causal narratives. Such traceability is a central requirement of MBE.

To address the challenges of opening the so-called 'black box', researchers have developed various analytical tools suitable for exploring the emergent properties of complex social phenomena, including agent-based modeling (ABM), evolutionary game theory, system dynamics methods, process tracking and qualitative comparative analysis (Castellani and Gerrits, 2024:20). Among these, the generative approach to social science, particularly the ABM approach to social simulation, has emerged as a popular and potent computational method within the social complexity framework in recent years due to its modeling precision, traceability, and theoretical flexibility, and has been particularly welcomed by analytical sociologists (Manzo, 2022: 25; Flache and Matos Fernandes, 2021). ABM generative approach is mainly employed to model and reproduce known social phenomena (Salgado and Gilbert, 2013; Vu et al., 2020).

The generative approach posits that explaining a social phenomenon involves identifying its underlying generative social mechanisms– a configuration of real entities and activities that recurrently produce specific outcomes under study (Hedström, 2005; Hedström & Bearman, 2011; Vu et al., 2020).[3] However, this process often entails examining the interactions among numerous entities and their ongoing interrelations, which can be cognitively challenging as the chain of causation is typically too lengthy and complicated to trace effectively (Törnberg, 2017: 30). Consequently, generative social simulation approaches offer a powerful quasi-experimental method for investigating the process of micro-interaction, thereby bridge this cognitive gap.

Employing generative modeling approach, researchers construct an artificial society where mechanisms are translated into the model's micro-specifications, i.e., the set of rules defining agent behavior and reactions to their environment, including other agents. Since agents' actions are interdependent, feedback enters the system, leading to a continuous interplay between emergent structures and agents' actions, altering the system's dynamics and potentially moving it toward unpredictable states. When a simulation can generate the type of outcome to be explained, the researcher has provided a computational demonstration that a given micro-specification is indeed sufficient to generate the macrostructure of interest (Epstein, 1999). This demonstration, known as generative sufficiency, offers a candidate causal mechanism-based explanation for the macro-social phenomenon (Salgado and Gilbert, 2013; Vu et al., 2020).

[3] This assertion is based on the premise that analytical sociologists embrace the ontological realism inherent in critical realism, which implies a transcendental stance. This stance assumes the existence of stable, real mechanisms underlying changing empirical social phenomena, independent of researchers' abilities to detect them (Miller, 2015; Bhaskar, 2008).

However, despite its promising potential, applying the ABM generative approach to explain social phenomena within the social complexity framework also confronts a variety of epistemological, methodological, and technical challenges (Salgado and Gilbert, 2013).

- Philosophical Disputes: there are philosophical challenges within the social simulation method, with ongoing social ontological and epistemological debates, such as the division between "individualist" and "collectivist" emergentists (Salgado and Gilbert, 2013), as well as divergences within methodological individualism.
- Technical Hurdles on Modeling Human Behavior: from a modeling perspective, difficulties arise from modeling complex human behavior in society, which depends on the interplay between adaptive autonomous individuals, a multitude of non-linear interactions, the dynamically evolving social structure (Squazzoni et al., 2014; Zhang, 2013). Constructing, calibrating and validating a competent simulation model requires overcoming numerous technical challenges
- Real-world Applicability: There are ongoing debates focused on the epistemological status of the social simulation approach (Manzo, 2020). For instance, the question of "the extent to which conclusions drawn from social simulation studies can be applied to real empirical studies remains a contentious issue" (Manzo, 2020). According to Manzo (2022:3), the disagreement among researchers centers on whether and under what conditions ABM generative social simulation methods can contribute to causal inference in the real world.[4]

Summary on Theoretical Background

In this section, we provide a brief overview of the concept of social complexity, outlining its principal tenets, and the primary challenges encountered by social science research practices grounded in social complexity. Based upon this theoretical background, this study is dedicated to the development of the existing social generative research paradigm to explore and test

[4] Further elucidation concerning the limitations of the real-world applicability of the ABM approach will be discussed in the chapter 6.

causal mechanism explanations of the emergent properties of social phenomena. It also aims to offer exploratory responses to the epistemological, methodological, and technical challenges mentioned above regarding the generative approach.

Specifically, over the last few decades, the claimed link between ABMs and methodological individualism (MI) has been systematically investigated, leading to opposing conclusions (Manzo, 2020; Marchionni and Ylikoski,2013; Bulle and Phan, 2017). Although proponents of MI universally support the notion that social macro-phenomena must be elucidated in terms of interactions among individuals, with individuals being the primary entities and their actions being the principal activities that engender social macro-phenomena (Pérez-González, 2020), different researchers may adhere to varying interpretations of MI, which could also encompass elements such as an individual's nonrelational properties, the physical environment of actions, social relations, and the social environment of actions (Kincaid and Zahle, 2022). The conceptual ambiguity surrounding MI complicates the ability of researchers employing generative methods to clearly define what constitutes a causal mechanism explanation for complex social phenomena.

In this study, we posit that structural individualism, as a broad form of MI, provides an appropriate epistemological foundation for applying the ABM generative approach to explain the emergent properties of social phenomena within the social complexity framework. However, there is currently a lack of mature research pathways for constructing and utilizing ABM social simulation methods to explore and test MBEs regarding the emergent properties of complex social phenomena under the epistemological basis of structural individualism. This study aims to address these gaps by exploring and refining existing generative research paradigm for social simulation under the epistemological foundation of structural individualism.

In doing so, we situate this study within the context of an interpretive study of a substantive social phenomenon: the spread of college students' drinking behavior within friendship networks, which is considered a quintessential complex social phenomenon within a social network environment.

Substantive Topic Background: The Current Status and Consequences of College Student Drinking Behavior in Friendship Networks

The selection of the diffusion phenomenon of college student drinking behavior within friendship networks as the substantive target of our research is primarily based on the following considerations:

1. The widespread use of alcohol within college students' social networks remains a significant public health issue in industrialized societies. This social phenomenon has real-world implications and is of practical significance for exploration.
2. The diffusion of college drinking behavior within friendship networks is a typical complex social phenomenon that emerges from the nonlinear interactions of a large number of autonomous college students embedded in social relational and cultural structures. This complex social phenomenon is well-suited for research under the social complexity framework using generative social simulation, analyzing the co-evolution of drinking behavior and friendship relationships resulting from interactions among college students.
3. There is a research gap in existing literature, as studies based on the social complexity perspective are lacking, hindering the construction and testing of mechanism-based explanations for this social phenomenon.

In this section, we will introduce the current status of college drinking in various industrialized societies and the consequences of widespread college drinking. This introduction aims to clarify the aforementioned point 1, that is, to demonstrate why this substantive topic remains an important and worthy social phenomenon to explore. Points 2 and 3 will be subsequently reviewed in Chapter 2.

Current Status of College Student Drinking

The purpose of this section is to introduce the current status of alcohol use among university campuses, as well as the prevalence of alcohol consumption spreading through the social networks of college students[5]. Despite extensive attention and research on this issue over a long period, the widespread use of alcohol among college students continues to represent a major public health concern in most industrialized societies (Ham and Hope, 2003; Durkin et al., 2005).

In the United States, college students consistently report higher rates of alcohol use, binge drinking, and alcohol dependence than their non-college peers (Substance Abuse and Mental Health Services Administration, 2010; Ham et al., 2013) and are at increased risk for alcohol problems (Foster et al., 2014). According to Johnston et al. (2015), alcohol (76.1%, with binge drinking accounting for 35%) remains the most prevalent substance among college students, followed by marijuana (34.4%), tobacco (22.6%), and amphetamines (10.1%). Alcohol use is still considered one of the greatest public health hazards on college campuses (Ansari et al., 2013). Binge drinking, defined as consuming 5 or more American standard drinks on a single occasion for men or 4 or more for women (Ham et al., 2023), is also prevalent among college students in the U.S. Data from a nationally representative sample indicate that 43.5% of college students are current binge drinkers (Substance Abuse and Mental Health Services Administration, 2010). Similarly, National Survey on Drug Use and Health (NSDUH) data show that 60.1% of college students report monthly alcohol use, with 39% reporting regular binge-drinking (Lipari and Jean-Francois, 2016). Differences in binge drinking exist between male and female college students, but both genders face concerning issues with widespread excessive alcohol use. For instance, data from the American College Health Association (2016) show that 29.4% of female students and 40.2% of male students reported engaging in binge drinking within the past two weeks.

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[5] For the purposes of this text, "college" and "university" students are used interchangeably, referring to individuals aged approximately 18-23, enrolled full-time in either two-, three- or four-year academic programs post-high school (Skidmore et al., 2016).

In Canada, a large survey of 6,282 students at 40 universities indicates that 32.0% of students reported hazardous or harmful drinking during the previous 12 months, and almost one-third reported binge drinking (Tremblay et al., 2010). A Belgian university's web questionnaire in 2010, with 7,015 student participants, showed widespread and concerning alcohol use issues, with an average of 1.7 drinks per day and 2.8 episodes of abusive drinking per month (Lorant et al., 2013). University environments in the UK maintain their reputation as "intoxigenic" (McCreanor et al. 2008; Fenton et al., 2023), where excessive alcohol consumption is considered relatively typical and acceptable (Conroy et al., 2021). A recent survey by the National Union of Students found that approximately 25% of respondents reported drinking alcohol with the intention of getting drunk at least once a week (National Union of Students, 2018). Ansari et al., (2013) note that alcohol use among UK university students remains a significant public health problem, posing challenges for higher education institutions. A recent study in England found that 21% of a sample of 770 undergraduate students from seven universities displayed a likelihood of having a diagnosable alcohol use disorder. Similarly, heavy alcohol use is prevalent on university campuses in Australia, with empirical data indicating that Australian university students are at risk of excessive consumption, particularly those living on-campus (Leontini et al., 2015; Supski et al., 2017). These findings underscore the urgency and importance of addressing widespread alcohol use among college students as a critical public health issue in industrialized societies.

Consequences of Widespread College Drinking

Some studies suggest that the drinking behavior of college students can, to a certain extent, facilitate their social integration and alleviate emotional stress. For example, Nyström (1992) documented that Finnish university students experienced several social advantages from drinking, including diminished shyness, improved interpersonal relationships, greater optimism, and enhanced problem-solving capabilities. In a similar vein, Park's (2004) research highlighted that positive experiences related to drinking, such as enjoyment, social interaction, networking, and self-expression, were more commonly reported by U.S. college students compared to adverse outcomes. Nezlek et al. (1994) indicates that moderate drinkers tended to exhibit higher levels of intimacy and self-disclosure in their relationships compared to both those who abstained and those who drank heavily. Additionally, Murphy et al. (2006) observed that undergraduate students in the U.S. who curtailed their drinking following a brief intervention experienced reduced social involvement and enjoyment, further implicating the potential social benefits associated with alcohol use for college students. Buettner et al. (2012) indicate that a substantial proportion of those who engage in drinking, including episodic heavy drinking, perceive both social and coping advantages from alcohol consumption.

However, most research on college student drinking behavior reports concerning negative consequences of excessive college drinking for both drinking and non-drinking students (Merrill and Carey, 2016). Widespread drinking behavior among college students is generally recognized as having significant negative impacts on students themselves and others, posing severe academic, health, and safety consequences.

Extensive empirical research evidence(Capece and Lanza-Kaduce2013; Werch et al., 2000; Esteban and Schafer, 2005; Beck et al, 2013; Jackson et al., 2005) indicates that risky drinking behavior may serve as a causal or contributory factor to a spectrum of adverse outcomes experienced by college students, including academic impairment (Wechsler et al., 2002; Lorant et al., 2013), emotional issues(Read et al., 2006; Orford et al., 2004), property damage and theft(Wechsler et al., 1995; Orford et al., 2004), physical injury(Hingson et al., 2002; Wechsler et al., 2002; Hingson et al . 2009; Read et al., 2013), unplanned and unsafe sexual activities (Hingson et al., 2002; Orford et al., 2004) and legal issues (Wechsler et al., 2002; Hingson et al., 2002) experienced by college students. Particularly,

- Academic Impairment

  Alcohol consumption has been empirically associated with diminished academic performance among college students. A study conducted by Engs, Diebold, & Hanson (1996) surveyed 12,081 students across 168 U.S. institutions, indicating that approximately 11% of low-risk drinkers reported missing classes due to hangovers, and 3% indicated that their grades were lower because of drinking. National Institute on Alcohol Abuse and Alcoholism (NIAAA) reported that 25% of U.S. college students attribute their missed classes or reduced academic performance to alcohol use, highlighting the pervasive impact of alcohol on academic success (NIAAA, 2014; Fitzpatrick et al., 2015).

- Health Damage

Widespread college drinking is associated with both short-term and long-term health consequences for college students. The immediate effects of heavy drinking include hangovers, nausea, and vomiting, which are commonly reported by students. For instance, Presley et al. (1996) noted that 47% of all students and 56% of those who drank had episodes of nausea or vomiting due to alcohol or drug use within the year. Campus health centers and emergency rooms frequently deal with cases of alcohol poisoning, with occasional fatalities due to dangerously high blood alcohol levels (Perkins, 2002).

Moreover, students who frequently engage in drinking are at a significantly higher risk of becoming victims of assault, highlighting the health risks associated with alcohol-related violence and hazardous behaviors (Hensley, 2001; Mustaine and Tewksbury, 2000; Durkin et al., 2005). Research indicates that widespread college drinking is implicated in an annual average of 1,825 deaths, 599,000 unintentional injuries, 696,000 physical assaults, and 97,000 sexual assaults among college students (Hingson et al., 2009; Johnston et al., 2011; Reid et al., 2015).

- Unintended and Unprotected Sexual Activity

Empirical data consistently demonstrates a significant link between excessive alcohol consumption and the propensity to engage in risky sexual behaviors. The 1997 College Alcohol Survey by Wechsler et al. (1998) indicated that 18% of the surveyed sample (23% of drinkers) engaged in unplanned sexual activity during the academic year, and 9% (11% of drinkers) reported not using protection due to alcohol consumption. Recent data show that around 690,000 US students are assaulted by a student who had been drinking, with over 97,000 sexual assaults involving alcohol (NIAAA, 2014; Fitzpatrick et al., 2015).

Substantive Research Questions

Given the inherent multi-determinant nature of explanations for complex social phenomena (Vu et al., 2020), this study maintains a concentrated scope by focusing on two specific potential social structural explanatory factors related to the target social phenomenon:

- Social Capital: Most campus drinking behaviors are embedded within social contexts. Empirical evidence suggests that a significant number of college students partake in drinking activities to assimilate into social groups, to forge broader and more robust friendships, or to avoid the adverse outcomes of exclusion or isolation while seeking sufficient social support from their friendship networks. The causal relationship between social capital and the emergence of the target social phenomenon is one of the substantive research interests of this study.

- Cultural Significance of College Drinking Behavior: Drinking behaviors on college campuses are imbued with potent cultural implications. Empirical research has demonstrated that alcohol consumption is often viewed as ritualized behavior and a form of social expression that fulfills instrumental social roles and meanings, reinforcing the identities of college students. For instance, "Drunkenness is portrayed as a highly desirable social performance representing risk-taking, entertainment, physical exploration, sexual encounters, and situational behavior within the college subculture," and "Cultural norms endorse heavy drinking as a rite of passage during the undergraduate years" (Tan, 2012; Workman, 2001).The connection between the emergence of the target social phenomenon and the cultural significance of college drinking behavior is another focal point and research interest of this study.[6]

In summary, this study explores how the cultural significance of college drinking behavior and

[6] A detailed review and introduction of the concepts of social capital and the cultural significance of college drinking behavior, along with their potential relationships to the target social phenomenon, will be presented in the Literature Review chapter (Chapter 2).

social capital influence the diffusion of college drinking behavior within college student friendship networks. We will apply a generative approach to explore mechanism-based explanations (MBEs) for the target social phenomenon, thereby bridging the gap between the explanatory factors (Explanans) and the phenomenon to be explained (Explanandum). Essentially, the research will propose causal MBEs for the following two main substantive research questions:

- **Research Question 1**: How does the cultural significance of drinking behavior contribute to the emergence of the spread of drinking behavior within the friendship networks of college students?
- **Research Question 2**: How does social capital contribute to the emergence and spread of drinking behavior within the friendship networks of college students?

The Significance of the Study: Advancing Knowledge in Methodology and Substantive Domains

This research holds significance in both methodological innovation and the advancement of substantive knowledge:

- **Advancing the ABM-based Generative Research Paradigm**: Under the structural individualism epistemological foundation, this study explores the application of abductive reasoning principle in the ABM social simulation approach to test causal MBE hypotheses on the emergence of complex social phenomena, offering a clear, replicable, and feasible generative methodological paradigm. The advancement of this research paradigm signifies an optimization of the existing "generative methodology" analytical toolbox proposed by analytical sociologists (Bearman and Hedström, 2009:16; Manzo, 2021: 3)[7]and is an exploratory attempt to address the existing methodological challenges within the social complexity framework.
- **Addressing Technical Challenges in Establishing ABM within Social Network Environment**: Recognizing the prevalent issue of limited adaptability in agents within current multi-agent interaction models in social networks, this study offers a viable

[7] The "generative methodology" research paradigm constructed by Bearman and Hedström (2009:16) is referenced in the conclusion chapter of this study.

potential solution. We design and implement a multi-agent reinforcement learning (MARL)-based ABM social simulation model to enhance the adaptability of agents within the model. This enhancement enables dynamic decision-making and learning from past experiences. Drawing on suggestions from Gupta et al. (2017) regarding model control, we have employed a shared experience data pool to train controllers for distributed control of agents. This approach offers a solution to the control issues of multi-agent interactions within social network structures and represents a potential technical contribution.

- **Substantive Insights on Social Capital**: In the realm of substantive knowledge, our research illuminates the extent to which and the mechanisms by which the pursuit of social capital influences the diffusion of college drinking behavior within friendship networks.
- **Cultural Significance of College Drinking and Identity Dynamics**: This study elucidates the heterogeneity of identity caused by the cultural significance of college drinking behavior and the extent to which and how social inclusion and exclusion affect the diffusion of college drinking behavior within friendship networks.

Dissertation Structure

The dissertation is structured as follows:

- Chapter 2: This chapter reviews the existing literature related to the substantive research topic. It delineates the key concepts within the Explanandum and Explanans alongside relevant theories and empirical studies. The review identifies limitations and gaps in the current research, particularly in explaining the target complex social phenomenon using reductionist approaches, which fail to capture the full breadth of nonlinear interaction processes among college students. Finally, the chapter clarifies how this study aims to bridge these gaps and make original contributions to this substantive domain of knowledge.
- Chapter 3: This chapter provides a comprehensive introduction and discussion of the research methodology utilized in this study. It covers the ontological and epistemological foundations predicated on structural individualism, the pursuit of causal mechanism-

based explanations for the emergent properties of complex social phenomena, and the application and refinement of Coleman's boat diagram as an analytical framework. Furthermore, the chapter details the construction of causal MBE hypotheses regarding the target social phenomenon and outlines the methodology for testing and exploring these MBE hypotheses using the ABM social simulation approach under the principle of abductive reasoning.

- Chapter 4: This chapter focuses on the first step of the abductive reasoning process: “Redescription”. The MBE hypothesis will be transformed and formalized into a carefully designed Reinforcement Learning (RL)-based ABM model. The RL-ABM model is then used to conduct generative sufficient tests on the MBE hypotheses, aiming to demonstrate the generative sufficiency of the MBE in reproducing the target social phenomenon.
- Chapter 5: This chapter addresses the second step of the abductive reasoning process: “Retroduction”. It involves a rigorous process of scrutinizing the indispensable explanatory components of the Mechanism-Based Explanations (MBEs) that have passed the generative sufficient test in the “Redescription” stage. The chapter assesses the inherent indispensability of the candidate MBE hypotheses' explanatory components (i.e., social capital and the cultural significance of college drinking behavior) in reproducing the target social phenomenon. It also discusses the refinement of the original candidate MBE hypotheses based on the findings from the simulation research to ensure alignment with the "best explanation" standard under abductive reasoning principles.
- Chapter 6: This chapter clarifies the extent to which social simulation research can contribute to making causal statements about real-world social phenomena. We also discuss the real-world applicability of this simulation research and explore the potential policy implications.
- Chapter 7: The concluding chapter discusses the potential original contributions of the study to both methodological advancements and substantive knowledge. It also summarizes the main limitations of the research and offers recommendations for future research endeavors.

Chapter 2: Literature Review

The literature review chapter is devoted to systematically summarizing and evaluating extant empirical and theoretical research pertinent to our substantive research topic. Its purpose is to furnish essential background knowledge on the substantive research topic, critically analyze the primary discourses and findings in existing studies regarding the research topics, discuss the principal limitations of existing research, and elucidate how our study can contribute to filling the research gaps in this substantive domain of knowledge.

Part 1: Key Concepts Constituting the Explanandum

Part 1 of the literature review chapter contains three sections that respectively review existing research on three key concepts constituting the Explanandum target phenomenon: college student, college students' drinking behavior and college students' friendship networks.

College Student Characteristics

College students are participants in drinking activities on college campuses. Although college students are often recognized as a highly heterogeneous group, extant empirical evidence suggests that college students share certain typical social-psychological characteristics that distinguish them from individuals in other life stages or professions. These characteristics include their "emerging adulthood" life stage, changes in social connections and social support systems, and identity exploration and formation. The emphasis of this section lies in reviewing extant research on the socio-psychological facets of the stage of life that college students are currently experiencing, referred to as "emerging adulthood." We elucidate the two major pivotal shifts faced by college students in this life stage: social connections and identity formation.

“Emerging Adulthood”

College students exist within a distinct age period (typically ranging from 18 to 25 years old): While no longer considered adolescents, these individuals are only partially considered adults, as they are in the process of transitioning into adulthood but have not yet fully attained the characteristics associated with adulthood (Arnett, 2003; Macek et al., 2007; Mayseless &

Scharf, 2003).

Over the past two decades, researchers have referred to this stage of life, between adolescence and early adulthood, as "Emerging Adulthood" (American Psychological Association, 2015), which is known for heightened experimentation, a significant degree of personal freedom, engagement in risky behaviors, and the development of one's identity (Hoffman et al., 2006). Arnett (2004) agree that it is appropriate and necessary to use the new term “emerging adulthood” to define the stage of life between age 18-25. He contends that previously existing terms cannot accurately capture the distinct features of emerging adulthood, despite their common use in the literature to describe the college students. Commonly used terms that are not suitable for accurately describing the 18-25 age period include “late adolescence”, “young (early) adulthood”, “youth”, and “the transition to adulthood” (Arnett, 2004).

Firstly, Arnett asserts that unlike adolescents (roughly ages 10-17), the 18 to 25 age group is not going through puberty, and they are not legally defined as children or juveniles. They have left secondary school and entered college and often have moved out of their parents’ household. Secondly, terms such as "young (early) adulthood" and "youth" encompass such broad age ranges that they cannot accurately describe the specific issues faced during the 18-25 period. "Young adulthood" is commonly used to describe ages from preteens to age 40, and “youth” has been used to refer to a wide range of ages, from middle childhood through the 30s. Finally, using the term "the transition to adulthood" to describe the 18-age group can mislead people about the nature of this stage of life, as Arnett (2004) pointed out that it spans 7 years, which is longer than infancy and as long as adolescence, necessitating a more precise and independent definition. Additionally, referring to it as a mere "transition" focuses attention primarily on the events that occur at the beginning or end of this age range, disregarding the multitude of developmental features that define this stage.

Arnett (2005) contends that "emerging adulthood" more accurately captures the socio-psychological characteristics of the college students, which is a distinct developmental period characterized by heightened exploration and profound change. The exploration and transformation during the "Emerging adulthood" period are primarily reflected in two aspects: (1) Changes in social connections and the development of social support systems based on new social connections. (2) Exploration and formation of identity.

Shifts on Social Connections and Social Support

The transformation of social connections and the construction of new social support systems are pivotal characteristics of university students and serve as one of the fundamental challenges they encounter during the stage of "emerging adulthood."

Social Connections Transformation

The transformation of social connections during Emerging Adulthood typically consists of two key components: the weakening of parental monitoring and the increased importance of friendship relationships. Initially, before reaching Emerging Adulthood, family relationships play a significant role in adolescents' social connections. The existing research indicate that the peers, kin, and non-related adults are three important categories of network members during adolescence, with peers and kin making up the largest portion of social connections (Buysse, 1997). Parents, especially in early adolescence, often serve as the main influencer on adolescence's attitudes and behaviors (Gayman et al., 2010; Borsari and Carey, 2001). According to Dolan (2006), nuclear and extended family members are the most likely source of natural support, representing a durable and reliable source (Dolan, 2006).

As emerging adults transition to college campuses, they usually move out of their parents' household and their original communities, resulting in less frequent contact with their family. This social change is particularly significant for students who leave home to pursue higher education, as their previous community, friendships, and family networks are no longer in proximity (Buettner & Debies-Carl, 2012). The shift in social connections often weakens the influence of family social connections on emerging adults, granting them greater autonomy and independence from their parents (Berkowitz & Perkins, 1986). As Villar et al. (2022) pointed out, during the Emerging Adulthood stage, the number and diversity of social relationships typically increase, while the time spent and frequency of interactions with family diminish, and time spent with peers increases (Villar et al., 2022). Peer influences thus become more dominant in emerging adulthood, and are relatively independent of parental oversight or control, outweighing the effects of family and environment. In this context, the development of new social connections within the college environment becomes crucial for facilitating social integration, particularly for incoming freshmen in new college campuses (Pesola et al., 2015; Borsari, 2007; Borsari and Carey, 2001). Paul and Kelleher (1995) indicate that matriculating students seek to establish a peer network that can be a source of support and intimacy and assist the transition to college by providing role models and social opportunities (Hays & Oxley, 1986; Borsari and Carey, 2001).

Social Support Systems Transformation

When college students relocate to attend university, they must leave behind their existing social networks and establish new social connections within the university environment (Taylor et al., 2002). As a result, their social support systems undergo a transformation. This reconfiguration of social support systems is considered a significant consequence of the aforementioned change in social connections. The development of new social support systems is a critical task and a key challenge for college students.

Definition and categories: Social support is defined as the social resources that individuals perceive to be available or that are actually offered to them by helping relationships in their social networks, and it is widely recognized as one of the main components of individual social capital (Villar et al., 2022; Friedlander et al., 2007). Social support typically encompasses four categories: (I) **Instrumental support**, which involves providing tangible assistance in the form of materials or services, such as financial aid, specific goods, or helpful services (Taylor et al., 2004). (II) **Emotional support**, which involves conveying empathy, care, concern, encouragement, and other positive sentiments to individuals (Arifuddin et al., 2022). For instance, providing warmth and nurturance to another individual and reassure them that they are valued and cared for (Sica et al., 2015). (III) **Informational support**, which involves offering guidance, suggestions, or feedback regarding individuals' attitudes and behaviors. (IV) **Companionship support**, which involves the presence of other individuals to engage in shared interests and social activities, fostering a sense of belongingness (Arifuddin et al., 2022).

Furthermore, based on the activation status of social support, some researchers classify social support into two categories: **perceived (subjective)** and **received (objective)** support (Wang et al., 2022). Perceived social support refers to an individual's perception of the availability of support from others, such as friends and family, and has been the most commonly assessed aspect of social support (Friedlander et al., 2007; Wang et al., 2022). Although perceived social support represents an un-activated form of social support, relevant research indicates that, under certain circumstances, the unutilized perception of social support can be more beneficial than the mobilized support (received support) (Taylor et al., 2004).

<u>**Source of social support**</u>: Empirical studies indicate a close association between social support and social networks (Arifuddin et al., 2022). Sources of social support emanate from interpersonal relationships within an individual's social network, encompassing family, friends, partners, and social communities, which collectively constitute potential support channels and form integral connections to the broader societal context (Arifuddin et al., 2022). Relational networks provide individuals with a sense of belonging and intimate relationships through which they can exchange confidence, care, and tangible resources (Jones, 2014). For college students, friendship relationships are the primary sources of social support on college campus (Arifuddin et al., 2022).

<u>**Importance of social support**</u>: Existing empirical research has demonstrated the significance of social support for college students, as it contributes to their adjustment and promotes psychological well-being, particularly in stress relief (Rayle & Chung, 2007). Firstly, social support functions as a valuable resource that encourages positive adjustment in emerging adults (Para, 2008). It is believed to enhance one's sense of belonging, self-worth, and security, as well as to moderate the perception of threatening situations and increase self-confidence in coping with such situations (Villar et al., 2022). Secondly, studies on stress and coping have revealed that social support is one of the most effective strategies for individuals to cope with stressful events (Taylor et al., 2004). It can both prevent and alleviate stress, enabling

individuals with supportive social networks to encounter fewer adverse circumstances and successfully cope during stressful situations (Grant-Vallone et al., 2003). This buffering effect of social support makes individuals more resilient to stress when faced with challenging circumstances (Taylor et al., 2013).

For college students, the transition from high school to university represents a significant psychological phase. While attending university offers learning experiences and opportunities for psychosocial development, it can also introduce strains and acute stressors. College students in this life stage may experience loss of the familiar, fear of the unknown, separation from loved ones, depression, isolation, the search for independence, building new social support networks, making life-altering decisions, and academic stress (Rayle & Chung, 2007; Rayle & Chung, 2007). Difficulties in navigating these stressors associated with the transition can lead to decreased academic performance and heightened psychological distress, among other severe consequences (Friedlander, Reid, Shupak, & Cribbie, 2007). In this context, social support is an essential resource for emerging adults during the university transition, helping them cope with potential increases in pressure and other challenges, ultimately contributing to their success as college students (Grant-Vallone et al., 2003; Friedlander et al., 2007).

Identity Formation

In addition to the changes in social connections and social support system, existing empirical research supports the exploration and formation of college students' identity during emerging adulthood as another key feature of this developmental period (Lane, 2015; Arnett, 2006). Across different literatures, the concept of identity has been defined as "unitary" or "multiple", "real" or "constructed", "stable" or "fluid", "personal" or "social", and in many other ways that often appear contradictory (Vivian, 2018). In this study, we will review the concept of identity and its construction during emerging adulthood based on a social psychological perspective rooted in the works of Erikson (1950, 1968) and Marcia (1966) (Erikson, 1950; Erikson, 1968; Marcia, 1966).

Definition and Classification

For Erikson (1968), identity primarily refers to a subjective sense of sameness and continuity across time and across contexts (Erikeson, 1968; Luyckx, et al, 2011). Based on this definition, existing approaches to identity typically focus on two "levels" at which identity may be defined: individual and social identity (Schwartz, 2001).

- Individual (or personal) identity

  Personal identity is defined as a unitary and continuous awareness of oneself, emphasizing individual autonomy, continuity, integration, identification, and differentiation (Naomi, et al, 2002). This sense of individual autonomy distinguishes the self from others and maintains continuity across various contexts and time (Hitlin, 2003; Branje et al., 2021). In particular, personal identity encompasses goals, values, beliefs, religious and spiritual beliefs, standards for behavior and decision-making, self-esteem, desired future selves, and overall life story (Schwartz, 2001). Personal identity identifies an individual as a specific person, providing them with direction and purpose, thereby avoiding identity confusion (Albarello et al., 2017).

- Social (or collective) identity

  In addition to personal identity, individuals often classify themselves as belonging to various groups and their affiliations with these groups (in-groups) as well as groups with which they do not identify (out-groups) (Hornsey, 2008). This process leads to the development of collective identity, which refers to an individual's identification with the groups and social categories they belong to, the meanings they attribute to these social groups and categories, and the resulting emotions, beliefs, and attitudes associated with this identification (Vignoles, 2011). Tajfel (1978) thus defined social identity as “that part of an individual’s self-concept which derives from his knowledge of his membership of a social group (or groups), together with the value and emotional significance attached to that membership”. This definition highlights the focus of the "commonalities among people within a group and differences between people in different groups” (Hitlin, 2003).

Erikson-Marica’s Identity Status Model

According to Eriksen (1968), identity formation results from the dynamic interplay between identity synthesis and identity confusion. Identity synthesis refers to a cohesive and internally consistent sense of self that remains stable over time and across different situations (Dunkel, 2005). On the other hand, identity confusion refers to a fragmented or incomplete sense of self, which hinders the ability to make self-directed decisions (Schwartz et al., 2013). Marcia's identity status model is an important elaboration of Erikson's (1968) perspective on identity formation, proposing two complementary processes: exploration and commitment (Meeus, 2011). Identity exploration refers to actively searching among various potential identities in order to find a sense of self that aligns well with one's personal values and aspirations. On the other hand, identity commitment represents the outcome of the decision-making process, involving the choice to either adhere or not to a particular set of goals, values, and beliefs (Marcia, 1988; Ritchie et al., 2013; Schwartz, 2001).

According to Marcia's identity status model, an individual's identity formation is the result of the interaction between identity exploration and commitment. Specifically, individuals engage in an initial phase of exploration, during which they assess various identity options. After exploration, individuals often pause to reflect on their progress and make decisions regarding whether to continue exploring or to commit to a specific identity (Grotevant, 1992). For instance, if individuals feel satisfied with the identity they have developed during the initial exploration, they are unlikely to continue seeking further options (Grotevant, 1992; Schwartz, 2001). Conversely, if individuals remain unsatisfied with their current identity, they may continue exploring and engage in subsequent periods of reevaluation at a later time. These reevaluations are critical in the exploration process, as they represent necessary updates and adaptations in response to situational changes, personal growth, or new information (Grotevant, 1992; Schwartz, 2001).

Identity Formation for College Students

- **Key Life Stage for Identity Formation**

  Although Erikson (1968) posited that identity development is a lifelong process, the majority of research highlights adolescence, particularly emerging adulthood stage, as a crucial period for identity formation (Azmitia et al., 2008). From early adolescence onward, adolescents engage in active questioning and exploration of their identity, with identity-related questions playing a pivotal role in shaping their development. This period is characterized by an ongoing search for self-answers to questions (Branje et al., 2021), for instance, who am I? What are my values? How do I differ from others? Are my self-perceptions consistent over time? As they seek to understand who they are and what they aspire to become, adolescents reevaluate the identifications they formed in childhood and consider different identity possibilities, and make new commitments to these identifications (Schwartz, 2001; Branje et al., 2021). Identity formation thus occupies a central position as a fundamental developmental task during adolescence (Erikson, 1968; Meeus et al., 2010).

In recent empirical research, Arnett (2004) and other researcher (Azmitia et al., 2008; Luyckx et al., 2013) have emphasized social-structural and economic changes, particularly the prolonged period of education in many postindustrial societies, which have led to a delay in psychosocial maturity until the period of emerging adulthood (Waterman & Archer, 1990; Lane, 2015). Normatively structured life events such as marriage and entering the labor market, which were once predetermined, are now increasingly left for college students to decide on their own (Côté, 2002; Schwartz et al., 2005). Arnett (2005) has therefore argued that "Although identity development has traditionally been associated with adolescence, in reality, the primary phase of identity exploration occurs during emerging adulthood rather than adolescence".

- **The Heterogeneity of Identity Formation**

Empirical research has also highlighted significant heterogeneity in the development of identity processes at the individual level. For instance, while some emerging adults show changes towards lower self-certainty and increased identity confusion, there is also substantial evidence for stability in identity processes during this period (Branje et al., 2021): for a considerable proportion of emerging adults, there is notable stability in identity synthesis, identity statuses, and the underlying identity processes of commitment, exploration, and reconsideration across adolescence and young adulthood (Branje et al., 2021). For instance, relevant research reveals that the majority of individuals remain in the same identity status during adolescence (ages 12-20, Meeus et al., 2010) and young adulthood (ages 25-29, Carlsson et al., 2015). A study utilizing daily measures of identity over a five-year period also identified predominantly stable patterns. Approximately 50% of the sample displayed consistently high commitment levels, while the other 50% of adolescents experienced temporary discontinuity in their identity commitments, evidenced by a decline in commitments during middle adolescence (Becht et al., 2016). In summary, emerging adulthood college students exhibit significant heterogeneity in identity formation process, and the extent or manner in which individual identity stability is influenced by social context varies among individuals (Branje et al., 2021).

College Student's Drinking Behavior

The drinking behavior of college students is the primary focus within our research topic. Existing empirical research indicates that, compared to non-college peers, college students are often reported broader drinking behaviors and more severe drinking problems (Halim et al., 2012). For instance, Anderson et al. (2017) pointed out the differences in drinking behaviors between college-attending emerging adults (EAs) and non-college-attending EAs. They noted that although the category of EA encompasses individuals not enrolled in college, those within this subgroup attending college demonstrate a significant increase in heavy drinking from 12th grade into college, maintaining the highest levels and consistency of heavy drinking compared to non-college-attending EAs (Johnston et al, 2014). Additionally, college-attending EAs are more likely to report past-month drunkenness (Johnston et al., 2014), be diagnosed with alcohol abuse (Slutske, 2005), be diagnosed with an alcohol use disorder (Blanco et al., 2008), and less likely to receive treatment for alcohol-related issues in the past year compared to their non-college-attending peers (Blanco et al., 2008; Anderson et al., 2017). College students have thus long been identified as a high-risk population concerning alcohol abuse and drinking issues (Brownfield et al., 2003; Kypri et al., 2005; Dorsey et al., 1999).

Some researchers attribute part of the reason for college students' high-risk drinking behavior to the abundant opportunities available in college social environments to consume alcohol excessively (Conroy and de Visser, 2018). For instance, Borsari (2007) indicated that alcohol has long been perceived as a crucial aspect of college social life, frequently featured in student social activities, alumni events, and campus sports activities. As extensive empirical research has consistently demonstrated a correlation between exposure to a college environment characterized by heavy drinking and an elevated likelihood of transitioning into unhealthy alcohol consumption patterns (Kypri et al., 2005; Johnsson et al., 2008; Huckle et al., 2006; Hebden et al., 2015). College student drinking is thus seen more as behavior specific to certain social contexts rather than static individual behavior. Understanding the drinking patterns of college students necessitates an in-depth analysis and understanding of the social context in which their alcohol consumption takes place, as well as their interaction processes within that social context (Jackson, et al., 2016). This section will expound upon four aspects of the social contexts of college student drinking: (1) physical location, (2) interpersonal environment (companions), (3) drinking games, and (4) consequences of refusing to drink.

Physical Location

An important aspect of the college student's drinking context is the physical location where drinking occurs. It has been observed that college students commonly engage in alcohol consumption across various social milieus, including intimate gatherings, parties, celebratory events, athletic competitions, and licensed drinking establishments such as bars or restaurants (Stogner et al., 2015). Terry-McElrath et al., (2023)'s survey on the drinking behaviors of 818 American college students found that the most common drinking location was at home (48.8%), followed by the residences of acquaintances (35.9%) and bars/restaurants (25.6%). Clapp et al. (2006)'s large-scale study on college student drinking in New Zealand indicates that 43% of reported drinking episodes occurred at private residences, 37% at a bar, pub, or club, 8% at a residence hall, and 11% at other locations. Clapp et al., (2007) noted that college drinking evenly dispersed between bars and private gatherings as students typically frequent bars and private settings where formal alcohol controls are not rigorously enforced.

Existing research underscores the importance of the physical location of college drinking, as drinking patterns vary depending on the specific physical setting (Clapp et al., 2006). Heightened levels of alcohol intake are likely when individuals imbibe in settings populated by numerous intoxicated individuals (Clapp et al, 2006; Rodriguez et al., 2016). For instance, Perkins and Berkowitz (1986) found that college students tend to drink more frequently and extensively at large parties and social functions compared to other settings within the college environment. This may be because students generally perceive excessive drinking at large parties as inevitable and appropriate (Tran et al., 2020; Baer, 2002; Buettner et al., 2011).

Interpersonal Environment

The social settings in which alcohol consumption occurs represent another crucial aspect of the drinking context. Extensive existing empirical research indicates that college drinking primarily occurs within social environments (LaBrie et al., 2007; Simons et al., 2000). Terry-McElrath et al. (2023) conducted a survey on alcohol consumption behavior among 818 American college students and found that the most common social drinking settings were with friends (72.6%), followed by large groups (31.0%), and significant others/romantic partners (27.1%). Only 13.6% of surveyed American college students reported having consumed alcohol alone. Particularly, drinking activities within the Greek environment represent one of the most typical and prevalent interpersonal social drinking scenarios among college students (Lui, 2019).

Drinking Games

Drinking games accompanying alcohol consumption among college students represent another significant aspect of the social context of college drinking behavior. "Drinking games" constitute a specific highly specialized form of social interaction within college social drinking scenes. Beccaria and Sande (2003) define "drinking games" as situations where individuals consume alcohol based on explicit, standardized, pre-agreed rules. These rules typically include a core component determining who drinks, when they drink, and in many cases, how much they should consume. Drinking games are widely prevalent in college drinking activities across various university campuses worldwide (Beccaria and Sande, 2003). An empirical study by Borsari et al, (2007) on college student drinking behaviors estimated that 50% to 62% of college students have engaged in drinking games in the past month. Furthermore, individuals who refuse to drink during these games may face scrutiny (Borsari, 2004). Existing research indicates that drinking games within the social drinking context of college students typically serve three primary functions or purposes:

- **Ritualization**

  Tan (2012) highlighted the highly ritualized patterns of excessive drinking specific to the college environment, could be manifested in the form of drinking games. This involves students devising intricate drinking rules dictating when alcohol must be consumed, developing a specialized vocabulary for game mechanics, and associating specific alcohol brands with particular games. Analogous to organized sports, these elaborate rules create ritual-like ceremonies with components such as ritual artifacts (alcohol), scripted guidelines (rules governing drinking occasions), performance roles (methods of consumption), and audience (fellow participants or drinkers). For instance, the game "Icing" mandates participants to conceal bottles of a sweetened beverage throughout a residence, where discovering a bottle entail consuming its entire contents promptly. Such rituals imbue a sense of ceremony and tradition within the college drinking culture.

- **Social Facilitation**

  In the study of drinking games among young people in Italy, Beccaria and Sande (2003) noted that the design of drinking games appears to fulfill many functions in promoting group relationships, including fostering celebration, camaraderie, relaxation, interpersonal mingling, flirtation, group cohesion, and reducing inhibitions. Moreover, Borsari et al., (2007)'s empirical investigation indicated that there are over 500 different drinking games on college campuses, all of which share a common goal of enhancing social interactions among participants. These games may involve language skills (such as tongue twisters), physical abilities (such as beer pong), or group activities (such as taking a drink every time a certain phrase or word is mentioned in a song or TV show.

- **Facilitating Alcohol Consumption**

  Existing empirical research supports the role of promoting heavy drinking as one of the significant functions of drinking games in college social drinking. For instance, Borsari et al. (2003) found in a survey of over 1200 freshmen that more than half (63%) had engaged in alcohol gaming during their lifetime, viewing it as a means of rapid intoxication, socialization, exerting control over others, or inducing intoxication in others. Engs and Hanson (1993)'s research indicate that regardless of moderate or heavy drinking, individuals engaging in alcohol gaming exhibited a higher prevalence of alcohol-related issues compared to those not participating in such games.

Social Consequences of Abstinence

The participation of college students in social activities frequently involves alcohol consumption, rendering abstainers a minority within social settings. For instance, research on the culture of heavy drinking among youth at Australian universities, as exemplified by Supski and Lindsay (2017), underscores the marginality of young individuals opting out of alcohol consumption. Similarly, National Health Service (2012) indicate that in 2009, merely 20% of young people (aged 16-24) in England refrained from alcohol consumption (National Health Service Information Centre for Health and Social Care, 2012).

The treatment and attitudes towards students who reject drinking in social settings, as well as the potential social consequences faced by individuals who choose not to drink in collegiate social activities, represent another crucial aspect of the drinking context. Existing empirical studies suggest that in college social settings, although the majority of students may exhibit a certain degree of tolerance towards non-drinkers, refusing to drink can still be challenging and non-drinkers are often labeled as unsociable or boring, which may lead to exclusion and diminished invitations to social interactions. Furthermore, such social exclusion can be reciprocal in certain contexts, as some empirical studies indicate that non-drinking students with strong identity consciousness may ostracize drinkers and choose to interact only with fellow non-drinkers.

Specifically, college students discuss non-drinking in relation to not only how others view them, but also how they see themselves.

- On the one hand, for students who choose to abstain from drinking, their decision not to drink may influence how they are perceived by their peers in social settings. Non-drinking college students often encounter particular challenges in their social lives, as they are subject to close scrutiny by peers and friends, with their motivations often being detailed examined (Seaman & Ikegwuonu, 2010). Piacentini & Banister (2009) indicates that young people who choose abstinence from alcohol consumption often have to justify their behavior.

For instance, Conroy and De Visser (2014)'s study on UK college students indicate the necessity for non-drinkers to employ a variety of potential strategies to deal with challenges from other in college social settings, including: rejecting stereotypical labels (e.g., 'boring'); adopting alternative identities; ensuring that drinkers do not feel judged; alleviating situational tension using humor; setting boundaries for being out; and being assertive or resolute in discussing non-drinking (Herring et al., 2013). Nonetheless, according to Conroy and De Visser (2014), within the backdrop of social drinking, whether feigning participation or disclosing one's abstention, neither approach offers a fully satisfactory inter-situational framework for participants: feigning carries the risk of being exposed, while disclosure poses the risk of being labeled as a social outsider. Therefore, considering the evidence that abstaining from alcohol may entail social exclusion, the refusal to drink among students often entails the fear of "missing out" on social interactions and the anticipation of perceived or actual negative evaluations and social exclusions by peers (Conroy and de Visser, 2018).

- On the other hand, for college students who abstain from alcohol consumption, their choice not to drink does not only influence how others perceive them but also reflects their self-perception. For example, research by Supski and Lindsay (2017) highlights that for some strongly self-aware college students who resist drinking, abstaining from alcohol is often perceived as an act of self-control, self-determination, and accountability. This behavior requires individuals to position themselves within specific discourses to justify their sobriety. These highly self-aware students who abstain not only demonstrate self-respect but also encourage other young individuals to contemplate alternative identities, such as the identity of "non-drinkers." In Supski and Lindsay (2017)’s interview study of Australian college students, some students who opted not to drink exhibited a strong sense of self-identity, individuality, and confidence in their differences. This self-awareness was a defining characteristic of the young individuals who chose abstinence. Despite facing pressure to drink, they were comfortable asserting their choice to decline alcohol. For instance, some students acknowledged the prevalent drinking culture at university and anticipated resistance to their decision to abstain, expecting that their choice would set them apart rather than bring them closer to their peers. Several young individuals reported a strong awareness of "who they are" and embraced their identity as abstainers.

Furthermore, Conroy and De Visser (2014)’s interviews on five 19–22-year-old non-drinking English undergraduates revealed that although some non-drinking students indicated a willingness to withstand peer pressure regarding their decision not to drink, their assessment of the necessity for more dependable and loyal friendships represented a threshold beyond which such challenges became intolerable. This need for more dependable and intimate friendships partly entails accepting their decision not to partake in alcohol consumption. In other words, inadequate levels of acceptance of their non-drinking stance might lead to the dissolution of social bonds for some non-drinking students.

College Student’ Friendship Network

College students' friendship networks constitute a pivotal component of our research topic (Explanandum), particularly as the social relational structure within which college drinking behavior occurs and evolves. Understanding the characteristics, evolution, and relationship between college students' friendship networks and college drinking behavior through a review of existing literature is essential for comprehending the target social phenomena. In this section, we will review existing research on college students' friendship networks and their association with drinking behavior.

Introduction to SNA

Social Network Analysis (SNA) or Social Network Theory (SNT), serves as a theoretical and methodological paradigm rooted in a relational perspective, commonly utilized to analyze how social relational structures affect both individual and collective behaviors. SNA highlights the idea that individuals are embedded within complicated networks of social relations and interactions, thus being influenced by those they interact with. Furthermore, an individual's position within larger social structures can shape behavior, either through constraints or influences (Quatman and Chelladurai, 2008).

In practical research contexts, SNA offers not only a theoretical framework but also graph theory-based quantitative tools for representing, measuring and effectively analyzing the impact of a system's relational aspects on the social phenomenon under investigation. This includes exploring the structural patterns of social relations, such as social interactions, interpersonal connections, and resource flows (Butts, 2008; Valente et al., 2004).

The Graph Theory Foundation of SNA

Rand et al. (2011) emphasized that human societies are typically characterized by heterogeneity and high levels of organization, where individuals and their social relations may form a structured network exhibiting complex topological properties. To assess the interactions among individuals in these structured communities and the impact of social network structures on the dynamics of collective behavior, social networks have increasingly served as conceptual models and explanatory tools across various academic disciplines (Reifman et al., 2006). Nevertheless, due to the complex nature of structural elements that are not easily articulated in natural language, scholars in the field of social network analysis rely on specialized jargon and notation. Much of this terminology is derived from graph theory, a branch of mathematics that deals with discrete relational structures (Butts, 2008).

Specifically, for researchers in SNA, social entities such as individuals, groups, and organizations are typically conceptualized as "nodes." The social relationships between these social entities, as defined by Reitz et al. (2014) as enduring interaction patterns involving at least two individuals, are commonly represented as "edges." In a broader sense, a social network is built on relational data and can be described as a system of finite "nodes" interconnected by relationships or ties (referred to as "edges"). These established connections can encompass personal or professional relationships, ranging from casual acquaintanceships to close familial bonds. In addition to social bonds, links within the network can also embody the transmission of information, goods, resources, interactions, similarities, and other phenomena (Oliveira and Gama, 2012).

In graph theory notation, we can define a social network using a graph G where the graph $G = (V, E)$ is a 2-tuples consist of node set $V = \{v_1, v_2, \dots, v_n\}$ and edge set $E \in V \times V$. $B = \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{n1} & \cdots & b_{nn} \end{bmatrix} = [b_{ij}]_{n \times n}$ is the adjacency matrix of graph G, where b_{ij} is a Boolean variable characterize the existing of edge ($v_\mathrm{i}, v_\mathrm{j}$) (Newman, 2010). Denote $N_i = \{v_\mathrm{k} \in V | b_{ik} = 1\}$ by node v_i's Neighbour set, $d_i = |N_i| = \sum_{j=1}^{n} b_{ij}$ by v_i's degree, vector $\boldsymbol{D} = (d_1, d_2, \dots, d_n)$ by degree distribution. For weighted graph G, b_{ij} represent the weights of edge $(v_\mathrm{i}, v_\mathrm{j})$ to describe the connection intensity. The underlying structure of these social networks is the subject of study in SNA (Newman, 2010). Over the past several decades, SNA has developed numerous quantitative tools and algorithms based on the analysis of social structures to describe typologies and evolution of social networks. Moreover, SNA has advanced various technical methods applicable to tasks in social networks such as community detection, link analysis, node prediction, behavioral forecasting, and simulation.

The primary focus of this section is not on the detailed technical aspects of SNA. Scott (2012) pointed out that the primary objective of SNA is to analyze the contents and patterns of relationships within social networks and involves exploring these patterns, either mathematically or visually, to comprehend the interactions among actors and the significance of these relationships (Oliveira and Gama, 2012; Scott, 2012:1). Hence, in addition to the technical approaches based on graph theory, SNA researchers have also advanced social network theories to investigate the evolution of social relationships and behavioral interaction patterns within social networks. In the following sections, we will primarily review several key concepts within the frameworks of social network theory.

Formation and Evolution of Friendship Networks

The dynamic process underlying the formation and evolution of social networks is one of the focuses of SNA theoretical research. Existing research has identified key characteristics of friendship relationships that differentiate the process of formation and maintenance of friendships from other social relationships: Furman and Buhrmester (1985) define friendship relationships as close voluntary relationships characterized by companionship, intimacy, and mutuality. This description implies a relationship that is recognized and valued by both individuals (Burk et al., 2012).

Similarly, MacLean and Point (2016) emphasize that friendships are defined by intimacy and trust and have emerged as central reference points in contemporary selective relationships, distinguished from other significant relationships (MacLean and Point 2016; Ray, 2000; Allen and Adams, 2007; Badhwar, 2008; Smart et al., 2012). Specifically, MacLean and Point (2016) pointed out that familial bonds are substantiated by biological relationships, legal documents such as birth certificates, and predefined familial roles. Couple relationships can be formalized through marriage. In contrast, there are no institutionalized norms to confirm the existence of a friendship or prescribe its duration, the longevity of a friendship thus hinges on the consistent care and active engagement within the relationship (O'Connor, 1998).

Bolin et al. (2003) further argue that the density of a friendship network is not fixed permanently but rather diminishes over time if not actively nurtured. Friendships with little or no interaction are likely to weaken progressively. To cultivate and sustain their friendship networks and receive social support from these networks, individuals must invest their limited resources, such as time and energy, into social interactions.

Kitts and Leal (2021) and Rivera et al., (2010) summarized three structural expectations that influence the formation of friendship relationships: homophily (having a lot in common with me), transitivity or closure (having the same friends/belonging to the same group as me), and reciprocity (calling me a friend). This indicates the inclination to label someone as a friend due to their association with the same subset of similar and interconnected peers (cohesive in a structural sense). In the following sections, we will review existing studies on the formation and evolution of friendship networks based on these three main mechanisms mentioned above (Cheadle et al., 2013).

Reciprocity

Rivera et al., (2010) identifies relational mechanisms as a crucial factor in the formation of friendship relationships by proposing that the configuration and structure of social networks influence friendships through shaping trust, information sharing, and opportunities for interaction (Rivera et al., 2010; Cheadle et al., (2013). Reciprocity, as one of these relational mechanisms, is a fundamental process within social networks. Individuals are inclined to form preferences for those who reciprocate their feelings, thereby reducing the likelihood of rejection in reciprocal relationships (Montoya & Insko, 2008).

Drawing upon social resource theory and equity theory, Törnblom and Kazemi (2012) elucidates the concept of reciprocity in the formation of friendships. Social resource theory posits that individuals acquire necessary social resources through reciprocal exchanges within a network, encompassing resources like financial assets, information, and emotional support. Reciprocity, in this context, denotes the mutual exchange of support between two members of a social network (Wang et al., 2021).

Empirical evidence supports the role of reciprocity in both the formation of friendship ties and the reception of peer support. For instance, in van Rijsewijk et al (2020)'s study on collegiate friendship dynamics, findings indicate that if a student seeks and receives support from a peer, there is an implicit expectation for reciprocal support-seeking behavior from the peer in the future. Hence, predicated on the principle of reciprocity, friendships typically evolve into bidirectional relationships, wherein mutual investment and nurturing contribute to the strengthening of ties through enhanced interaction.

Transitivity

In addition to reciprocity, the formation and persistence of friendships are fundamentally grounded in the similarities between individuals, as people tend to establish and maintain social connections with those who resemble them or share significant activities (Cheadle et al, 2013; Bullers et al., 2001). Van Duijn et al. (2003)'s study on the formation of friendship relationships among college students delineates the process of friendship formation into two distinct stages: the meeting process and the interaction process, wherein similarities between individuals play a pivotal role. Van Duijn et al. (2003) classifies similarity into three different types: proximity, visible similarity, and invisible similarity. Proximity is defined as a special form of similarity characterized by individuals being in the same physical space concurrently, exerting a significant influence on the process of meeting (getting acquainted) and particularly on the initial phases of friendship network evolution and development. Visible similarity, apart from physical proximity, refers to similarities based on externally observable characteristics or easily accessible information, such as gender, ethnicity, behavior and age. Typically, variables of proximity and visible similarity serve as indicators of shared interests and behaviors among individuals. On the other hand, invisible similarity pertains to similarities based on less overt attributes, such as attitudes and activities that lie beyond the immediate context in which the friendship network is established. These variables of similarity often serve to enhance and solidify friendships based on shared beliefs, values, and interests that may not be immediately visible to others.

Van Duijn et al. (2003) particularly emphasize the significance of Proximity in the establishment of friendship relationships as a friendship can only develop between individuals when they cross paths initially; they must 'meet' before they can potentially form a bond. At the furthest extreme, in the scenario where two individuals never meet, regardless of their similarities, they will not become friends (Fehr, 1996).

Physical or social proximity is thus believed to increase the likelihood of encountering others and forming friendship. Empirical studies suggest that network mechanisms such as transitivity, which reflects high social proximity, can create relatively frequent and stable encounters, thereby contributing to the formation and strengthening of friendship relationships (Berndt and Perry, 1986; Van Duijn et al., 2003).

Specifically, Newman and Park (2003) contend that the closure of transitive triplets represents a prototypical phenomenon in the establishment of friendship networks: if individual A considers person B a friend and person B considers individual C a friend, then there is a high likelihood that eventually, individual A will also consider person C a friend, thereby leading to network closure. For instance, Van Duijn et al. (2003) observes that the extent of mutual acquaintances between two individuals positively correlates with the likelihood of their introduction and facilitates a heightened (whether consciously or unconsciously driven) inclination towards friendship. Franken et al. (2017) highlighted that a mutual friend can play a unique role in facilitating peer support between two adolescents. When two individuals share a mutual friend, they are more inclined to interact and spend time together with this friend. This iterative process potentially facilitates accessibility and familiarity between the two individuals, consequently fostering the cultivation of peer support dynamics (Simone et al., 2018).

Homophily

Van Duijn et al. (2003) pointed out that meeting one another is a primary prerequisite for developing friendships among college students. Following the initial encounter, the formation of friendship relationships transitions into an interaction (mate) stage. In the “mate” stages of friendship development, common interests, behaviors, and attitudes are considered more relevant as they become apparent in longer-lasting relationships and interactions (Van Duijn et al., 2003). Hence, besides proximity, both visible and invisible similarities are considered to influence the formation and sustenance of friendship through the mechanism of homophily (Van Duijn et al., 2003). In this context, homophily is defined as the tendency for individuals to befriend others who exhibit likeness in key characteristics or behaviors (Berten and Van Rossem, 2015). In practical terms, homophily within social networks is often illustrated by the adage "birds of a feather flock together," suggesting that individuals are more inclined to form connections, such as friendships, if they share similar qualities and attributes, such as participating in akin hobbies or leisure interests, considering it to be one of the most notable and consistent empirical regularities of social life (Montgomery et al., 2021; Kossinets and Watts, 2009).

In summary, existing research supports reciprocity, transitivity, and similarity-based homophily principle as important network mechanisms that shape the formation, maintenance, and evolution of friendship networks. These mechanisms do not typically act in isolation in the development and evolution of college students' friendship relationships; rather, their interactions collectively shape the dynamics of college friendship networks (Asikainen et al., 2020).

Network Homophily

Within the established collegiate friendship networks, the homophily of networks has been consistently observed across diverse social settings, representing a longstanding focal point and key concept within social network analysis (Asikainen et al., 2020). Network homophily refer to the observed tendency of individuals within social networks to exhibit similarities with their connected peers or "friends" (Reitz et al., 2014). This principle is considered one of the most fundamental characteristics of social networks and serves as a significant catalyst for various pertinent social phenomena, including inequality, segregation, and substance usage (Reitz et al., 2014). We are particularly interested in homogeneity within social networks, as a wealth of empirical research underscores the pronounced similarity in drinking behaviors among college students' friendship network (Bot et al., 2005; Prinstein et al., 2001; Engels et al., 1999).

The existing literature and empirical evidence support that the emergence of network homophily is a natural consequence driven by two primary network dynamic processes: peer influence and peer selection (McPherson et al., 2001; Valente et al. 2004, Kreager and Haynie, 2011).

On one hand, peer selection refers to the tendency of individuals to form relationships with others who are already similar to them (Kreager and Haynie, 2011; Skopek, 2023: 174). Peer selection is typically considered to be based on similarity (i.e., "birds of a feather flock together"): if two individuals share the same trait or characteristic, there is a higher likelihood of a friendship forming between them (Kreager and Haynie, 2011; McMillan et al., 2018). Supporters of peer selection argue that individuals might choose friends or peers based on the behavior of those peers, rather than adjusting their behavior to match that of friends they have already selected (Fletcher and Ross, 2012). Therefore, the similarity in substance use among individuals in a network is seen as a precursor, rather than a consequence, of friendship formation (KreagerHaynie2011; Gottfredson and Hirschi, 1990). Peer selection is extensively supported by empirical evidence as similarity in physical attributes such as gender, age, and ethnic background, as well as similarity in various behaviors, increases the probability of two previously unacquainted individuals becoming friends (Knecht et al., 2011; Berndt and Murphy, 2003; Moody, 2002).

On the other hand, peer influence refers to the tendency one has to adjust their own attitudes and behaviours when exposed to the attitudes or behaviours of others (Skopek, 2023: 147; Tajfel and Turner, 1986), particularly the phenomenon where individuals tend to emulate the behaviors of their friends. This social influence effect leads individuals to adopt behaviors demonstrated by their social connections (Mundt et al., 2012). Peer influence has also garnered considerable support from researchers. For instance, Mundt et al. (2012) maintains that an individual's behavior tends to converge toward the average behavior of their friends over time, which may be attributed to peer influence, or the diffusion of behaviors and behavioral norms through social relationships. McMillan et al. (2018) emphasizes that peer influence occurs when an individual's attitudes and behaviors are molded by those of a friend, resulting in the dyad becoming more homogeneous than before the relationship began. In addition, supporters of peer influence, particularly social learning theorists, suggest that friendship groups offer intimate settings for individuals to acquire behaviors and attitudes, including those related to substance use (Akers, 2009; Bandura, 1977). From a learning perspective, individuals adopt or intensify substance use behaviors as an outcome, rather than a cause, of peer friendships and other close social interactions (Kreager and Haynie, 2011).

Although numerous researchers have offered explanations of network homophily, particularly the emergence of behavioral homophily, from the perspectives of peer selection or peer effect, the prevailing consensus indicates that peer influence and peer selection are not mutually exclusive mechanisms. Rather, they often operate in tandem, mutually reinforcing each other to bolster network (behavioral) homogeneity (Berten and Van Rossem, 2015). Empirical research strongly supports the significance of both processes, indicating that both influence and selection play pivotal roles in fostering homophily, especially in the context of risky behaviors among college students, such as alcohol consumption (McMillan et al., 2018; Kretschmer et al., 2018; Mercken et al., 2010; Pearson et al., 2006).

Social Networks of College Students

The study of college students' social networks is a popular empirical topic within SNA research. In the following section, we will review existing studies pertaining to the characteristics of social networks among college students and the relationship between college students' friendship networks and individual drinking behaviors within the network.

Characteristics of Social Networks of College Students

One of the most significant characteristics of social networks of college students is the dynamic nature of these networks, the importance of social support derived from friendship networks, and the challenges associated with establishing friendships and accessing social support.

In the preceding literature review on the features of Emerging Adulthood, we synthesized the importance of Emerging Adulthood college students in establishing new social connections in the university environment and garnering social support from friendship networks (Skahill, 2002).

(1) Research on college students' social relationship networks suggests that the transition to university life necessitates adjustments in various life domains, particularly substantial changes in students' social networks and support systems (Klaiber et al., 2018; Skahill,

2002; Arthur and Hiebert, 2011; Brooks and DuBois, 1995; Schaefer et al., 2021). Buettner and Debies-Carl (2012) point out that the transition to college life for emerging adults is often characterized by a separation from existing social networks or an increase in distance from them. Consequently, the primary source of social support shifts from the family and high-school friends to new friendship connections in college context (Klaiber et al., 2018; Fraley and Davis, 1997; Oswald and Clark, 2003; Mayer and Puller, 2002).

(2) A wealth of empirical research suggests that making new friends and obtaining social support can be challenging in college environment. Particularly for new students, the college experience may be associated with feelings of loneliness, disconnectedness, and a lack of social engagement and support (Buettner and Debies-Carl, 2012; Pargetter, 2000; Perry and Allard, 2003). For instance, a study on alcohol consumption among American and Canadian college students conducted revealed that over half of the surveyed students in the US and Canada reported feeling "very lonely" in the past 12 months due to inadequate social support from their friendship networks (Klaiber et al., 2018; American College Health Association, 2016). Van De Bunt et al., (1999)'s research indicates that this challenge is particularly pronounced for first-year college students. They point out that the initial stage of a student's first year at university, a period where initiating conversation with strangers is socially acceptable and even expected, represents a unique opportunity to form new friendships.

The Relationship Between College Students' Friendship Networks and Drinking Behavior

Perkins (1997) notes that peers are the most influential social references within the college environment and play a significant role in shaping the patterns of alcohol use among college students. Although there is empirical evidence indicating that social network positive impact preventive health behaviors (Dorsey et al., 1999; Hibbard, 1985; House et al., 1988; Valente, 1994; Adler and Matthews, 1994), a substantial body of existing research suggests that social networks on college campuses may facilitate and reinforce risky and unhealthy behaviors such as excessive alcohol consumption, experimentation with controlled substances, and poor dietary habits (Dorsey et al., 1999).

Specifically, numerous social network researchers have conducted extensive studies on the relationship between college students' friendship networks and drinking behavior, particularly focusing on how an individual attaches to that social structure and how their actions may influence or be influenced by that structure (Valente et al., 2004). Existing research widely supports both the emphasis on the peer influence effects of friendship networks on college students' drinking behavior and the emphasis on the peer selection effects of college students' drinking behavior influencing the evolution of friendship networks (McCann et al., 2019; Reid et al., 2015; Knecht et al., 2011).

We will review existing research on the relationship between college students' friendship networks and drinking behavior by separately examining how peer effects influence the drinking behavior of individual college students within social networks (i.e., socialization effects), and how peer selection shapes college students' friendship networks (i.e., selection effects).

Influence of College Students' Friendship Networks on Individual Drinking Behavior

Existing research indicates that peer influence originating from friendship networks (also known as peer socialization) can affect college students' drinking behavior in both active and passive ways (Laninga-Wijnen and Veenstra, 2021; Borsari and Carey, 2001).

Active Peer Influence: Direct Peer Pressure

Active peer influence refers to the process where peers actively stimulate certain behaviors in college students, involving mutual encouragement and peer pressure (Studer et al., 2014). Peer pressure, often defined as the "pressure to think or behave along certain peer-prescribed guidelines" (Clasen & Brown, 1985: 452), has been commonly used in existing research to describe active peer influence in the context of risk behaviors, particularly drinking behavior (Laninga-Wijnen and Veenstra, 2021; Borsari & Carey, 2001; Larsen et al., 2009). It typically involves peers' explicit offers of alcohol, which is direct and demands an immediate response (Wood et al., 2001). If resistance occurs, it may be met with coercion, teasing, or taunting

(Laninga-Wijnen and Veenstra, 2021). Empirical evidence strongly supports this direct form of peer pressure. For instance, in Kandel (1985)'s study on college student drinking behavior, he highlighted direct (or active) peer influence as a widely accepted factor influencing alcohol consumption among college students. In various drinking scenarios, peer pressure often manifests through direct offers or explicit encouragement to drink, ranging from polite gestures such as offering to get a peer a drink or buying a round, to overt commands or encouragement to drink, such as forcing others to drink during drinking games (Kandel, 1985; Borsari and Carey, 2001).

Passive Peer Influence: Imitation and Normative Influence

Existing research suggests that in many cases, peer influence does not manifest in direct, coercive peer pressure. For instance, Borsari and Carey (2001) indicates that peer influences on drinking behaviors extend beyond direct offers or encouragement to drink. Both theoretical frameworks and empirical evidence propose that peer influence often comprises three distinct components: explicit offers of alcohol, modeling, and social norms. Among these, modeling (imitation) and perceived norms are indirect (or passive) influences that have been associated with drinking behavior (Borsari and Carey, 2001). Similarly, research by Laninga-Wijnen and Veenstra (2021) highlights that passive peer influence involves a more implicit influence process, characterized by imitation or normative influence.

Imitation

Laninga-Wijnen and Veenstra (2021) proposed that imitation is a passive, implicit form of peer influence, suggesting that individuals observe and imitate peer behaviors either consciously or unconsciously, without being explicitly encouraged or coerced to do so. Imitation behaviors have been widely reported in empirical studies concerning college students' drinking behaviors. For instance, Riedijk and Harakeh (2018) indicated that some observational studies (Harakeh and Vollebergh, 2012; Harakeh and De Boer, 2019) reported that imitation, rather than explicit peer pressure, influenced college students' drinking behaviors. Borsari and Carey (2001)'s studies demonstrated that young adults imitated drinking behaviors, such as drinking rate and speed, of their peers (Borsari & Carey, 2001; Larsen et al., 2009). Similarly, Hildebrand et al. (2001) explored the drinking behaviors of athletes in college, with their research indicating that members of athletic teams may model their drinking behavior after prominent figures in their social network (Hildebrand, Johnson, & Bogle, 2001; Jackson et al., 2005).

Normative Influence

In addition to imitation, normative influence is another widely recognized way in which friendship networks indirectly impact college students' drinking behaviors. For instance, Wright et al. (1986) indicate that imitation and peer pressure are likely to occur within relatively smaller networks, such as cliques. In the broader peer context, such as the classroom or within peer crowds, the influence of normative conformity may come into play. Norms serve as essential guidelines for how adolescents should behave to align with peer expectations and avoid being perceived as social "misfits" (Laninga-Wijnen and Veenstra, 2021). Normative influence within friendship networks is often used to explain the conformity tendencies in college students' drinking behaviors, and this type of influence is believed to be particularly evident among college students who are seeking to establish social connections and acquire social support in a new environment.

For example, Harakeh and Vollebergh (2012) described that young adults often engage in synchronizing their behavior with peers to establish social connections and avoid feelings of isolation (Harakeh and Vollebergh, 2012; Khan et al., 2014; Bainter et al., 2022). Seeking such social interactions can sometimes lead to maladaptive or potentially harmful conformity behaviors in an effort to enhance acceptance within the peer group (Robinson et al., 2015, 2016; Bainter et al., 2022). This phenomenon of conformity is evident in various behaviors, including alcohol use. Research by Bainter et al. (2022) on college students' drinking behaviors suggests that young adults who feel disconnected and undervalued in social relationships may engage in binge drinking as a form of conformity to boost their self-esteem and increase their perceived relational value. They propose that challenges to an individual's sense of belonging can have detrimental effects on mental well-being, leading to emotional distress and decreased self-esteem, which then drives individuals to seek validation through conformity behaviors in order to enhance their relational value.

Influence from Friends with Different Properties

Existing research indicate college students' friendship networks are believed to influence college drinking behaviors through passive and active peer effects, and friendships with distinct properties may yield differing degrees of peer influence on individuals' drinking behavior (Bot et al., 2005). Generally, current empirical studies often endorse the idea that peer influence from close friends or those with higher social status exerts a larger impact on the drinking behaviors of college students (de Water et al, 2017).

For instance, Urberg et al. (1997) observed that close friends significantly influenced the initiation and persistence of alcohol use among college students, and that both close friends and the friendship group played a role in drinking to the point of intoxication, the influence of the best friend surpasses that of other acquaintances.

According to Yanovitzky et al. (2006), previous studies suggest that students tend to regard friends and best friends as members of their ingroup: individuals with whom they interact regularly, seek advice and emotional support from, and trust more than other peers (Donohewet et al., 1999). Friends may either encourage or discourage the initiation and continuation of alcohol use, provide information about the consequences of alcohol consumption, and facilitate access to alcohol for the student (Oetting & Donnermeyer, 1998). Baer (2002) indicate that the drinking behavior best friends appears to exert the most significant influence on college students' alcohol consumption.

de Water et al. (2017) further emphasizes that best friends play a particularly influential role in peer influence. Adolescents are not only highly impacted by their best friends but also by peers who hold a high social status.

Burk et al. (2012) suggests that elucidate studies examining differences between reciprocated and non-reciprocated friendships indicate that adolescents' drinking behaviors are more similar to those of reciprocating friends than nonreciprocating friends. However, adolescents are more likely to adjust their drinking behaviors to align with those of nonreciprocating friends, especially individuals with higher status within the peer group. This implies that adolescents may be more inclined to modify their own drinking behaviors in order to gain acceptance from peers who do not yet acknowledge the relationship, compared to peers with whom they already share well-established relationships.

In summary, empirical research supports the notion that active or passive peer influence from best friends or friends with higher social status within college students' friendship networks may have a more significant impact on the drinking behaviors of individual college students.

Influence of College Students' Drinking Behavior on Friendship Networks Evolution

In addition to the impact of friendship networks on college students' drinking behavior through peer effects, existing research also supports the notion that the college students' drinking behavior can be instrumental in the formation and evolution of peer relationships and friendship networks, this is primarily facilitated through a process of similarity-based peer selection (Stogner et al., 2015; Burk et al., 2012; Leifmann et al., 1995).

For example, research conducted by Borsari (2007) emphasizes the significance of college students' drinking behavior in the development of friendships within the college campus. He points out that alcohol has long been perceived as a fundamental aspect of social life in college and is frequently present at various student gatherings, alumni functions, and campus sports events (Borsari, 2007; Rimal and Real, 2005). In comparison to abstainers, student drinkers tend to have a larger social network (Moffat, 1991), are perceived as popular among their peers, and may embody traits associated with success within the vibrant collegiate social scene, characterized by socializing, participating in recreational activities and sports, and engaging in romantic relationships (Ashmore et al., 2002). This underscores the pivotal role that alcohol consumption plays in shaping social connections and peer relationships on college campuses. Bullers et al. (2001) argues that while both selection and influence play a role in the connection between an individual's drinking behavior and that of their social network, the social selection effects are significantly more influential than social influences, as suggested by recent research on social network drinking and adult alcohol involvement. For instance, Teunissen et al. (2012)

indicated that the consistent correlation between the drinking patterns of college students and those of their friendship network associates, at least in part, due to the process of similarity-based peer selection, where individuals establish friendships with those who share comparable drinking habits.

In this section, we will review extant research pertaining to similarity-based peer selection in university settings which typically occurs in form of active peer selection, social exclusion and passive peer selection (Laninga-Wijnen and Veenstra, 2021).

Active Peer Selection

In research on college friendship networks, Laninga-Wijnen and Veenstra (2021) suggests that active forms of peer selection based on similarity refer to how college students may be drawn to peers who share similarities with them. Through perceiving these resemblances, adolescents may make decisions to socialize and form friendships with these individuals. This process is often referred to as “Preferential Attraction”, as likenesses between individuals can lead to easier interactions and stronger relationships (Byrne, 1971).

Existing studies indicate that in the active process of similarity-based peer selection that promotes the formation of college friendships, college students' drinking behavior plays a significant role as it contributes to creating three different types of similarity: (1) Proximity Similarity; (2) Behavioral similarity, and (3) Identity similarity.

Proximity Similarity

Proximity as a special form of similarity is a key factor in influencing the establishment and maintenance of friendships among college students (Van Duijn et al., 2003). Unlike other forms of relational ties, friendships necessitate sustained efforts in relationship affirmation, care, and interaction (McCabe, 2023; MacLean and Point, 2016; Van Duijn et al., 2003). MacLean and Point (2016) suggests that students often form friendships through regular and close contact that occurs when they attend classes together, reside in the same dormitories or residences, participate in clubs or student organizations together, or engage in other shared social activities (Marmaros & Sacerdote, 2006; MacLean and Point, 2016). Engaging in alcohol-related activities on campus is considered as one of the most effective means to enhance proximity similarity, fostering regular intimate interactions and exchanges, thereby facilitating the constitution of friendships by augmenting intimacy (MacLean, 2016).

Cheadle et al. (2013) points out college students' drinking behavior as social focal points influence social interactions in specific settings that students choose to participate in. The underlying concept is that successful interactions centered around social focal points, such as drinking and partying, generate positive feelings (Cheadle et al., 2013; Doty and De Wit, 1995), shared objectives, and cultural norms of sociability, thereby promoting relationship formation and encouraging individuals to frequent similar social environments (Collins, 2004; Kahler et al., 2003). Since this type of college social environment is centered around the use of alcohol and the majority of college individuals at the party are drinking, individuals who consume alcohol have more opportunities for interaction and forming friendships with others who also partake in drinking, leading to a higher likelihood of developing friendships with individuals who have similar drinking habits (Feld, 1981; Cheadle et al., 2013).

Behavioral Similarity

Social drinking activities among college students can create shared experiences, behaviors, and interests, and this behavioral similarity among college students contributes to the establishment and maintenance of friendship bonds. Research by Boman et al. (2013) suggests that although friendships may vary in nature, (e.g. some friendships form between individuals with diverse interests), studies have shown that the strongest connections often exist within pairs who share numerous common interests, activities, characteristics, and experiences (Boman et al., 2013; Way & Greene, 2006; MacLean, 2016). Cheadle et al. (2013) has highlighted that shared alcohol behavior facilitates the development of new friendships in college campus, subsequently influencing the longevity of friendships.

For instance, Arnett (2005) conducted interviews with 60 emerging adults aged 18-24 years from tertiary education institutions, each of whom had consumed at least one alcoholic drink in the previous six months and had visited a licensed venue at night at least once. The survey findings revealed that a significant aspect of young people's enjoyment of alcohol consumption revolves around the camaraderie shared with friends (Arnett ,2005; Brown and Gregg, 2012; Townshend, 2013). The bonding among peers is heightened when both the internal emotional states induced by intoxication and the communal act of drinking, termed "drinking enaction," are harmonized (Törrönen and Maunu, 2011). For many individuals, the connection established through drinking together is intensified when their drinking patterns align with those of their friends (MacLean and Point, 2016).

Identity Similarity

Drinking activities among college students can help create similarities in identity or values. In the college campus setting, alcohol consumption often carries cultural meanings and signifies the drinkers' identity, sense of belonging, or value preferences. Engaging in collective drinking can assist college students in confirming their shared values or collective identity. We will elaborate on this in the section about college drinking culture in this chapter.

Social Exclusion

Preferential attraction and dissimilarity repulsion are often considered as two ends of the same spectrum (Tan and Singh, 1995). Consequently, in addition to active peer selection, existing research supports social exclusion in college students' friendship networks driven by similarity-based social selection—a tendency for individuals to dislike those who are dissimilar, as dissimilarity may lead to negative perceptions and conflicts that undermine the stability of friendships (Laninga-Wijnen and Veenstra, 2021). Experimental studies indicate that both the preference for similarity and the repulsion from dissimilarity influence the formation of friendships, and it is evident that dissimilar friends are less likely to sustain their friendships compared to similar friends (Laninga-Wijnen and Veenstra, 2021).

Alcohol consumption among college students has been reported to be a critical role in the process of social exclusion (Laninga-Wijnen and Veenstra, 2021; Laursen, 2017). Specifically, while creating similarity among students with similar drinking behaviors, college students' social drinking activities also contribute to heterogeneity among students with different drinking behaviors or drinking patterns. Existing studies suggest that college students' alcohol consumption can create or enhance three different types of heterogeneity, thereby influencing college students' friendship networks: (1) Proximity heterogeneity; (2) Behavioral heterogeneity; (3) Identity heterogeneity.

Proximity Heterogeneity

Alcohol consumption can create proximity similarity among participants of social drinking activities, fostering regular close interactions. However, it may also generate spatial heterogeneity between drinkers and non-drinkers. Previous literature reviews on the consequences of refusing alcohol in college social drinking contexts have highlighted that abstaining from drinking is often stigmatized, leading non-drinking students to be excluded from social activities. This exclusion reduces the close interactions between drinkers and non-drinking college students. For instance, Monahan and Lannutti (2000) has pointed out that while alcohol can facilitate social interactions as a "social lubricant" in various social settings (Monahan and Lannutti, 2000; Stogner et al., 2015), those who choose not to drink or consume alcohol in moderation may feel estranged from their alcohol-using peers (Watten, 1996).Similarly, Stogner et al. (2015) pointed out that an individual who frequently uses alcohol or drinks excessively may feel out of place in a group of abstainers and light drinkers. Varying levels of interest in drinking can result in friends sharing fewer common activities, spending less time together, or potentially causing conflict that strains otherwise close relationships.

Behavioral Heterogeneity

Diverse patterns of alcohol consumption or levels of alcohol consumption among college students contribute to heterogeneity in their behaviors or habits, potentially undermining the establishment or maintenance of friendships. For instance, in Foucauldian discourse analysis conducted by Knecht et al. (2011) on the drinking behaviors of college students in New Zealand, it was indicated that students who participate in social activities but refuse to drink alcohol may experience feelings of social exclusion and isolation due to differing drinking behaviors.

As one interviewed student described, "When friends are together socially at a party, people not drinking feel left out of the fun." Furthermore, research by Knecht et al. (2011) also found that apart from abstaining from alcohol leading to exclusion, engaging in alcohol consumption but exhibiting distinct drinking patterns also generates behavioral heterogeneity, thus potentially resulting in social exclusion. For instance, individuals who drink alone may be positioned as having problems and lacking friends, individuals who do not remain together while enjoying drinking activities or individuals who depart from the group and return home may be negatively portrayed as being unsupportive companions (Knecht et al., 2011).

Identity Heterogeneity

While social drinking activities create similarities in identity and values among college students with similar drinking patterns, they also create identity heterogeneity among those with different drinking patterns. We will review existing research on the relationship between college students' identity formation and drinking behavior on the College Drinking Culture section in Part 2 of this chapter.

Passive Peer Selection (Default Selection)

In addition to active forms of peer selection and social exclusion, extant literature also supports the occurrence of similarity-based peer selection in college friendship networks in the form of passive peer selection. Laninga-Wijnen and Veenstra (2021) argues that default selection is another way in which similarity in social networks can arise. This passive process may come into play when some youth find themselves in a marginalized position within their peer group, often due to interpersonal challenges, which limit their options for forming friendships (Deptula & Cohen, 2004). Consequently, these individuals may end up befriending peers on the outskirts of the social circle not out of genuine attraction, but rather out of necessity to establish connections and receive some form of social acceptance.

In summary, existing literature supports that college drinking influence friendship network formation and evolution through similarity-based peer selection. College students who share similar drinking patterns may establish or strengthen their friendships through similarity-based active peer selection, while also engaging in social exclusion of those with different drinking patterns. Students who abstain from drinking are more likely to find themselves on the periphery of the peer network, where passive forms of peer selection may be more prevalent among obtaining college students.

Part 2: Key Concepts of the Explanans

In this study, we are particularly interested in two potential Explanans on targe Explanandum phenomenon: namely, social capital within college student social networks and the cultural significance of college drinking behavior. In the subsequent two sections, we will review the existing research pertaining to these two potential Explanans, focusing specifically on their conceptual frameworks and the analyses within the existing literature regarding their relationship with college student drinking behavior.

Social Capital

Social capital is a fundamental concept in SNA research, closely associated with social relationships and social support. We are interested in exploring the role of social capital in the diffusion of drinking behavior within college friendship networks. In this section, we will review the concepts of social capital and its relationship with college drinking behavior.

The Concept of Social Capital

Existing research has provided various definitions of social capital from different theoretical perspectives. Drawing from the functionalist tradition of Durkheim and Parsons, Coleman (1998) conceptualizes social capital as “a function of social structure producing advantage”. Bourdieu (1986) defines social capital as "the totality of actual or potential resources that are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition". Bourdieu (1986: 248–249) also emphasized that social capital is linked to group membership, providing individuals with collective capital that serves as a form of validation or credibility within various contexts.

Horvat et al. (2003) has pointed out that the influential definitions of social capital by Coleman (1988, 1990) and Bourdieu (1986) are considered "foundational" but are relatively brief and imprecise, leading to the issue of conceptual murkiness surrounding the use of the term "social capital."

The ambiguity of the social capital concept has allowed subsequent researchers to freely develop different meanings of the same term "social capital." Horvat et al., (2003) pointed out that subsequent studies on social capital have gradually formed an emergent consensus, primarily based on the work of Portes (1998) and Lin (2001). This emergent consensus posits that social capital should be understood as the material and immaterial resources that individuals can access through their social relationships (Horvat et al., 2003).

In specific terms, Portes (2009) delineates social capital as a property of individuals, wielded by them "to command scarce resources". Lin (2017) presents a more comprehensive and presently influential definition of social capital. Lin posits that social capital, conceptually, is grounded in social networks and relations and necessitates assessment relative to its foundational constructs. He defines social capital as resources embedded in a social structure that are accessed and mobilized in purposive actions. Under this framework, the conception of social capital comprises three key elements: resources embedded within a social structure, individuals' accessibility to such social resources, and the utilization or mobilization of these resources in purposeful actions by individuals.

Alaa et al. (2017) provides a synthesis of the prevailing consensus regarding the concept of social capital:

- Social capital is often perceived as a metaphor for gaining advantages. Lin (1982) introduced the theory of social resources, which highlights the significance of accessing and utilizing social resources embedded within social networks to achieve improved socioeconomic standing. Venkatanathan et al. (2012) indicated that through social ties and the structure of the network of these ties, certain individuals are able to access a wider array of resources, leading to their success. As a measure of the benefits individuals derive from their social environment, social capital is commonly viewed as a metaphor for advantage.

- Social capital is often conceptualized as "social-structural resources" that are accessible exclusively through interpersonal relationships and social frameworks (i.e. "without network connections, there is no social capital") (Macinko and Starfield, 2001; Prell, 2006). Licamele et al. (2005) highlighted that an individual's social capital is widely believed to depend on their position in the social network and the collective structure of network they are part of. Therefore, social capital is not static but rather dynamic and subject to change based on variations in the typology of social networks and the positioning of individuals within these networks, making individual's social capital relatively unstable. Generally, individuals who have strong connections possess higher capital, and networks characterized by strong connections hold a greater collective value (Alaa et al., 2017).
- The distribution of social capital that individuals are able to access within a social network is uneven. Alaa et al., (2017) concluded that the inequality of social capital reveals disparities driven by the diversity of characteristics and behaviors among individuals, which is evident in their network positions. Additionally, Macinko and Starfield (2001) pointed out that the context-dependent feature of social capital implies that the acquisition of social resources is not equally facilitated or uniformly distributed.

Classification and Measurement Methods of Social Capital

Classification of Social Capital

Existing studies on the classification of social capital are largely based on Putnam's work, he distinguishes between bridging and bonding social capital (Putnam, 2000: 22). He defines "bridging" social capital as open networks that are outward-looking and encompass people across diverse social cleavages, while "bonding" social capital consists of inward-looking networks that tend to reinforce exclusive identities and homogeneous groups. Subsequent researchers have supplemented and expanded upon Putnam's (2000) classification of social capital, gradually forming consensus on various categories of social capital (Patulny and Lind Haase Svendsen, 2007; Ceci et al., 2020; Claridge, 2018; Alaa et al., 2017).

Bonding Capital

Claridge (2018) suggests that bonding capital is established among individuals who share similar characteristics ("people like us") and maintain strong interpersonal relationships ("in it together"), typically involving family members, close friends, and neighbors. Therefore, bonding capital is often believed to be cultivated within tight-knit groups or communities characterized by a high degree of homogeneity among group members in terms of demographic features, interests, attitudes, and behaviors (Venkatanathan et al., 2012). This sense of shared identity, interests and belonging enables individuals to feel a strong sense of cohesion.

Social support, derived from college friendship networks, is widely recognized as a vital form of bonding capital. As Stadtfeld and Pentland (2015) observes, friendships typically take the form of strong ties between individuals who share common characteristics or interests. Consequently, support emanating from close friendship networks is regarded by researchers as a form of bonding capital (Venkatanathan et al., 2012). This perspective is consistent with the definitions of bonding capital posited by scholars, including Putnam (2000), Bourdieu (1986), Coleman (1988), Fischer (1981), and Cobb (1976), who collectively emphasize that bonding capital corresponds to the social support that individuals acquire through their social connections (Alaa et al., 2017). In the context of university settings, close friendships serve as a primary source of bonding capital (social support) for students, enabling them to access help, information, trust, a sense of belonging, and strong emotional backing from their friends (Stadtfeld and Pentland, 2015; Claridge, 2018, Zhao et al., 2020).

Bridging Capital

In contrast to strong ties, weak ties in social networks serve as a bridge between diverse and loosely connected groups, giving rise to bridging social capital. This type of social capital is generated through weak ties across individuals from different backgrounds. Although these ties may lack strength, they provide individuals with a broader perspective and open up opportunities for accessing new resources and information (Venkatanathan et al., 2012). As Adler and Kwon (2002) notes, the benefits of bridging social capital are far-reaching and can encompass increased information gathering capabilities, access to power or improved network positioning, and enhanced recognition of new opportunities (Adler and Kwon, 2002; Claridge, 2018).

Limitations on Dichotomous

Claridge (2018) proposes that while existing relevant research largely agrees that social capital is commonly categorized as either bonding capital or bridging capital, this binary distinction oversimplifies the complex nature of social relationships. For instance, if a relationship is with someone similar to oneself, who shares similar social circles, it is typically classified as bonding. Conversely, if the relationship is with someone different from oneself, who moves in different circles, it is characterized as bridging social capital. However, Claridge (2018) argues that relationships are not strictly dichotomous, and it is not a matter of either-or. He emphasizes that social relationships are intricate, often encompassing elements of both bonding and bridging. Additionally, any given network is also expected to display a mix of bonding and bridging features. It is challenging and difficult to operationalize a strict distinction between a social tie being a strong tie or a weak tie, or to categorize the social capital an individual derives from a social network as strictly bonding capital or strictly bridging capital. Therefore, attempting to make a strict categorization of social capital in practice may be unnecessary. Claridge (2018) notes that the binary nature of the distinction between bonding and bridging is primarily driven by practical considerations, aimed at reducing and simplifying analysis.[8]

Measuring Social Capital

Existing research lacks a commonly accepted standard method or indicator for measuring, particularly quantitatively, an individual's social capital. Different studies often determine their approach to measuring social capital based on their research objectives and areas of focus. In most existing research, an individual's social capital is typically considered a function of the typology of the social network they belong to and their position within that network, following

[8] In this study, as we are primarily interested in social support from college student friendship networks, which is often considered a form of bonding capital derived from strong ties, the terms social capital, bonding capital, and social support mentioned in the analysis are generally used interchangeably. However, adhering to the bonding-bridging dichotomy of social capital, it is strictly speaking inaccurate to categorize the social capital that university students derive from their friendship networks as solely bonding capital. For instance, the intensity of university students' friendships may vary, and it is difficult to determine whether social capital from friends with low friendship intensity is bridging capital or bonding capital. We do not make a strict distinction in this study.

the definition of social capital.

For instance, as Alaa et al., (2017) notes, an individual's social capital is contingent upon their position within the network and the network's structure - and these positions and structures are determined endogenously and evolve as the network forms and develops. Licamele et al. (2005) notes that most definitions concur that social capital is a function of the ties between actors within a social network. A systematic examination of social capital must distinguish between the "possessor of the capital" (actors who receive benefits), "sources of the capital" (actors who provide benefits), and the resources that have been received or given (Portes, 2009). Lin (2017) emphasizes that, given the significance of resources and relations in social capital, some researchers have chosen to focus on the locations of individuals in a network as the key to social capital.

In addition, another perspective considers embedded resources within social capital. In social resource theory, valued resources in most societies are represented by wealth, power, and status (Lin, 1982). Therefore, social capital is analyzed by the amount or variety of such characteristics of others with whom an individual has direct or indirect ties. For instance, in Alaa et al., (2017)'s research on measuring bonding capital, bonding capital is defined as the combined resources an individual obtains from its immediate neighbours in the network. They argue that bonding capital hinges solely on an individual's ego network (direct connections) and remains consistent regardless of the global network structure, as long as the local ego network is maintained.

In conclusion, there is no universally recognized standard method for quantitatively measuring social capital in current research. Researchers often need to determine the quantification method for social capital based on the study's objectives. In most current relevant studies, an individual's social capital is typically considered a function of the social network, individual network position, or ties between actors in a social network.

Social Capital and College Student's Drinking Behavior

Although existing literature has expressed interest in the relationship between social capital and university students' health behaviors, and some studies have provided empirical evidence on the impact of social capital derived from friendship networks on students' drinking behaviors, existing research on the role of social capital in the co-evolution process of college drinking and friendship network, remains relatively scarce.

Moreover, literature often presents conflicting findings on the relationship between social capital and drinking behavior. While some studies suggest that social capital increases the risk of adult binge drinking (Child et al., 2017; Martins et al., 2017), others argue that adequate social support have a positive and protective effect on college students' risky drinking behaviors (Weitzman and Chen, 2005; Weitzman and Kawachi, 2000; Klaiber et al., 2018; Fiorillo & Sabatini, 2011; Holt-Lunstad et al., 2010; Reblin and Uchino, 2008; Cohen and Wills, 1985; Broadhead et al., 1983; Leavy, 1983). Moreover, some studies have found evidence for both positive and negative associations (Fat et al., 2017; Villalonga-Olives et al., 2020).

As noted by Kawachi et al., (2013), the concept of social capital has broad appeal in explaining various phenomena in health behavior. However, the effects of social capital on health behavior can be ambivalent, with no clear direction of influence (Villalonga-Olives and Kawachi, 2017). According to Brechwald and Prinstein (2011), the mixed findings are not surprising, given the multiple mechanisms through which social capital influences behavior, including peer influences, social environment shaping, risk exposure, support availability, and social norms and monitoring mechanisms. Therefore, it is essential to gain a deeper understanding of how different aspects of social capital are associated with college drinking behavior (Tucker et al., 2021).

Cultural Significance of College Drinking Behavior

In addition to social capital, we are also interested in exploring the role of college drinking culture in the spread of drinking behavior within friendship networks. Existing research suggests that college students' drinking behavior, and their friendship networks interact and co-evolve through peer effects and peer selection, with college students' drinking culture seemingly playing a crucial role in this dynamic.

On one hand, the drinking culture within social networks is closely intertwined with social norms, which are believed to influence college students' drinking behavior through normative effects, acting as a form of peer influence. On the other hand, drinking culture is believed to play a crucial role in creating similarities or differences among college individuals, particularly in terms of identity. This can impact the process of similarity-based peer selection, leading to preferential attraction among similar individuals and social exclusion among heterogeneous individuals, thus shaping the friendship networks of college students.

In this section, we will review existing research on the cultural significance of drinking behavior, its conceptualization, main contents, and its potential relationship with college students' drinking behavior.

The Concept of Drinking Culture

The concept of drinking culture is relatively broad and ambiguous. According to Taras et al. (2009), culture is a "complex multilevel construct" that is formed over an extended period and is relatively stable, consisting of shared assumptions and values at its core, while practices, symbols, and artifacts constitute its peripheral aspects. Specifically addressing drinking culture, Dietler (1990) cites Heath (1976:43), who emphasizes that rules and expectations play a crucial role in defining drinking culture within various social contexts. Dietler (1990) highlighted that drinking occurs almost exclusively in the context of social interaction and is governed by cultural rules and expectations, which are often carry significant emotional weight. Elements of drinking that are typically regulated by these norms and expectations include the type and amount of alcohol consumed, the pace of consumption, the timing and location of drinking occasions, the rituals accompanying drinking, the gender and age of participants, the roles assumed during drinking events, and the appropriate behavior.

Similarly, Savic et al. (2016) argues that the concept of drinking culture extends beyond merely describing patterns of drinking, such as rates of alcohol use and types of beverages consumed, or problems associated with drinking, like the extent of drunkenness, the settings and places where drinking occurs. Instead, it also encompasses the meanings and values attributed to drinking and the ways in which drinking is controlled or regulated within a society. Based on this understanding, Savic et al. (2016) proposes a more influential, norm-perspective-based definition of drinking culture, which they conceptualize as "[...] the norms surrounding patterns, practices, use-values, settings, and occasions related to alcohol and alcohol problems that operate and are enforced (to varying degrees) in a society (macro-level) or in a subgroup within society (micro-level). Drinking culture also refers to the modes of social control employed to enforce norms and practices. […]".

Cultural Significance of College Student's Drinking Behavior

We are particularly interested in the meanings and values to college drinking behavior (i.e., what does drinking mean in college social activities? What purpose does it serve?).

Risk Taking

The symbolic significance of college drinking encompasses the notion that drinking behavior, particularly high-risk drinking (e.g., heavy drinking), is a form of adventure (Tan, 2012). For instance, Osgood et al. (2013) indicate that college drinking, which bears semblance to adult-like antisocial conduct, projects an appealing image of sophistication, independence, and adventurousness. This portrayal contributes to the perception of college drinking as a high-status adventurous activity, thereby enhancing the social attractiveness of participants (Osgood et al.,2013; Moffitt, 2017; Dijkstra et al., 2010). Tan (2012) notes that college students often deliberately engage in adventure through risky drinking behaviors, demonstrate calculated risk-taking while consuming alcohol, and sometimes exhibit reckless risk-taking behaviors. For instance, empirical studies have shown that some college students construct their risky drinking behaviors as elaborate narratives of adventure, where the process of circumventing risks associated with drinking is perceived as a quest or a challenge to attempt the forbidden and, more importantly, to get away with it. Descriptions of maneuvers and strategies to avoid detection, often with other conspirators, support this adventure narrative.

Hedonistic

The symbolic significance of college drinking also encompasses the notion that drinking behavior is a form of the pursuit of “hedonistic” pleasure (Fenton et al., 2023; Measham, 2006; Szmigin et al. 2008; de Visser et al., 2013). Qualitative investigations into the meanings of alcohol consumption for college students indicate that college drinking often signifies the pursuit of pleasure. This pleasure encompasses notions of fun, enjoyment, feeling good, relaxation, socializing, laughter, and sociability (Fry, 2011; Guise & Gill, 2007; Sheehan & Ridge, 2001). This pleasure is a communal experience entailing friends preparing and anticipating nights out together (MacNeela & Bredin, 2011) and enjoying the bodily sensations of intoxication, fostering a collective sense of joy and camaraderie in socializing (Fry, 2011). For instance, participants in college drinking often describe it as a means to "let go of inhibitions" and make "things a bit more exciting" (Supski et al., 2017).

Rite of Passage

Extensive empirical research indicates that college cultural norms endorse college drinking as a rite of passage during the undergraduate years (Prentice and Miller, 1993; Kolind, 2011). For instance, Schulenberg and Maggs (2002) suggest that at emerging adulthood, alcohol consumption is often viewed as a symbol of maturity or coolness rather than being dull, representing a symbolic transition into adulthood. In a similar vein, Capece and Lanza-Kaduce (2013) have elucidated that the use of alcohol serves as a signal of maturation among the youth, thereby signifying a rite of passage into the adult phase of life.

According to Tan (2012), the Rite of Passage meaning associated with college drinking behavior holds significant functional and developmental implications for students, as it forms an integral part of their individual identities in college. Schulenberg and Maggs (2002) notes that ideally, college students' personal identity formation occurs through a process of exploration and commitment (the Marican identity formation model), where individuals develop a secure and enduring sense of self that encompasses an integrated set of personal interests, values, goals, and commitments. During emerging adulthood, college students actively explore alternative behaviors and lifestyles by questioning previously taken-for-granted beliefs and assumptions (Schulenberg and Maggs, 2002). In this process, the Rite of Passage meaning associated with college drinking enables experimenting with drinking to become important for positioning college students within peer groups, as it is often seen as a way to demonstrate social maturity, an attempt to appear older, and a means for college students to experiment with mature identities (Demant & Østergaard, 2007; Johnson, 2013; Demant & Järvinen, 2006).

Confirmation of Collective Identity

In addition to serving as a rite of passage that contributes to the formation of individual identity, college drinking behavior in a college social setting is also commonly seen as an affirmation of one's social identity[9] within the college drinking culture. Hall (1996) notes that how we see ourselves and how others perceive us are crucial elements in the process of social identity formation, as individuals often categorize themselves as belonging to affiliation groups (in-groups) as well as groups with which they do not identify (out-groups). In this process, Livingstone et al. (2011) argues that college drinking behavior constitutes one of the signs that allow the recognition of someone as a member of the group (i.e., "we drink therefore we are") under the college drinking culture (Monaco et al., 2020; Livingstone et al., 2011).

Similarly, Tan (2012) pointed out that college drinking during campus social activities, such as sports or celebratory events, facilitates the expression of group solidarity and builds a sense of collective identity. Hiltunen et al. (2022)'s research on Swedish students' drinking behavior reveals that alcohol use becomes a symbol of student community, a sign of belonging to a group, and a way of constructing social identities in interaction with others. He notes that the use of war metaphors and "war stories" when students describe their drinking experiences highlights the intensity and shared recollections of memorable experiences of drinking and drunkenness, which may contribute to the affirmation and reinforcement of collective identity.

[9] The concept of social (or collective) identity refers to an individual's identification with the groups and social categories they belong to, the meanings they attribute to these social groups and categories, and the resulting emotions, beliefs, and attitudes associated with this identification (Vignoles, 2011).

Mode of Social Control

The norm-perspective-based definition of college drinking culture suggests potential norm-based social control, such as potiential sanctions on behaviors that deviate from cultural rules in college social settings. Existing research indicates that the aspect of confirming social identities plays a significant role in such social control within college drinking culture.

On one hand, Monaco et al. (2020) notes that as college drinking constitutes a part of "what it means to be a student" under college drinking culture, it thus appears necessary and essential for members who share that social identity to engage in drinking. For instance, Hiltunen et al. (2022) indicate that most private parties are organized by a host and come with explicit expectations from both the host and the guests. Norms dictate what is deemed appropriate and inappropriate. There is often an expectation to relax and have fun together, which alcohol facilitates. Failing to bring one's own alcohol or declining to drink are considered norm violations. By adhering to the alcohol norm and developing a clear alcohol identity, individuals gain attractiveness and respect in their surroundings. Those with a clear alcohol identity do not problematize these expectations but comply with the norms surrounding party life (Hiltunen et al., 2022). On the other hand, Jenkins (2000) notes that social identities are constructed by differentiating between groups: To construct an "us," we also need a "them". Therefore, students who refuse to drink or have different drinking patterns may be categorized as "them,", facing social ostracism due to the heterogeneity of collective identity.

In summary, to a large extent, college drinking culture achieves social control over college student's drinking behavior through homophily preference and social exclusion based on social identity similarity.

College Drinking Culture and College Drinking Behavior

Anthropological studies view drinking patterns as culturally regulated and learned traits, shaped by the local social-cultural context in which they exist. This perspective highlights that the practices and meanings associated with alcohol beverages are “culturally defined” and “situationally activated” (Singer ,1986; Mandelbaum, 1965; Graves et al., 1979). Tan (2012) notes that an increasing body of research portrays widespread alcohol consumption as an entrenched cultural phenomenon inherent to the college experience of many students as they transition from high school to higher education (Tan, 2012; Rabow and Duncan-Schill 1995; Workman 2001). The socio-culturally constructed nature of drinking behavior profoundly influences the dynamic interplay between alcohol and individuals within college students' social networks as it often fosters a social environment conducive to widespread drinking (Dorsey, 1999; Conyne and Von Holle, 1982; Von Holle, 1984; Read et al., 2003; Singer, 1986).

Specifically, current research supports the notion that the symbolic significance of college drinking transforms college students' social drinking behavior into a form of ritualized behavior and social performance with instrumental social functions and meanings that contribute to fostering widespread drinking among college students, solidifying their identities and shaping their friendship networks (Tan, 2012). For example, Treise et al. (1999: 19) theorized that college drinking can be framed as a ritual that consists of "an artifact (alcohol itself), a script (rules about who can and cannot drink legally, when and where the drinking will occur, agreements about transportation to and from the places where drinking occurs), a performance role (how to drink, how many drinks to consume, how to behave when drinking), and an audience (peers, bartenders, campus personnel)". Their research suggests that college drinking is a ritualized form of social interaction among students, providing them with various "social gifts", including a sense of order, community, and transformation. Furthermore, Tan (2012) pointed out that college drinking, as a form of ritualized behavior, manifests in the practice of drinking games. This is evidenced by students describing and creating intricate drinking rules dictating when participants must consume alcohol, developing a specialized vocabulary to define game intricacies, and associating specific alcohol brands or types with various games. One student draws a parallel between the elaborate rules of drinking games and those of organized sports. These drinking rules resemble ritualized ceremonies involving key elements such as ritual artifacts (alcohol), a script (regulating who can drink and when), a performance role (guiding how to drink), and an audience (fellow players or drinkers). For instance, the game "Icing" involves participants hiding bottles of a particular sugary beverage around the house for others to discover. Finding a bottle results in the individual being "iced" and required to immediately consume the entire contents while on one knee (Tan, 2012).

The cultural significance of college drinking, as a form of highly scripted ritualized behavior, is believed to contribute to the formation of individual and group identities among college students. Beccaria and Sande (2003) pointed out the significance of the drinking rite for young people: “the procedures of the rite, its regularity and often also its solemnity, sensitize the individual into adopting the values and norms of the group.” (Pedersen, 1990: 1488; Beccaria and Sande, 2003). For instance, hangovers and other indicators of widespread consumption are often perceived as a form of shared suffering ritual and serve as a focal point for campaigns, which contribute to the formation of collective identity. In addition, the expectation of the concern and care received from peers after experiencing a hangover is also considered ritualized behavior. Beccaria and Sande (2003) argue that this element is crucial not only for socializing and making friends but also for deepening friendships, discerning who are genuine friends, and cultivating shared social identities. As some students described, "If you're with your close friends, it's one of those things that kind of goes around. So, you know, it might be you one night, and they'll look after you, and we don't do it so much now, but like my friend the other night, then you look after them, but that's part of the friendship. You kind of help each other through it" (Beccaria and Sande, 2003).

Part 3: Extant Theoretical Explanations of the Explanandum Phenomena

In Part 3, we will review the primary explanations provided in existing research for the Explanandum phenomenon. The college drinking behavior within friendship networks is considered to be influenced by a wide array of factors, encompassing individual aspects such as genetic predisposition, personality traits, and cognitive processes, as well as the social-cultural milieu including societal, neighborhood, family, peer group, and situational characteristics (LaBrie et al., 2007; Ham and Hope, 2003; Kuntsche et al., 2004).Existing studies have provided explanations of the target social phenomenon from different perspectives or based on various theoretical assumptions. Among these, the following theoretical frameworks or models have been particularly influential and supported by empirical evidence: social contagion theory, social learning theory, social motives model, and social norms theory.

Social Epidemiology Approach

Definition and Concepts

Research in Social epidemiology based on the social contagion theory is a prominent field for explaining and analyzing the diffusion of alcohol consumption behavior among college students within social networks. Social epidemiology is typically defined as "the branch of epidemiology that studies the social distribution and social determinants of states of health" (Berkman & Kawachi, 2000). The fundamental premise underlying social epidemiology is that each society, through its distribution of advantages and disadvantages, establishes its unique distribution of health and disease. In accordance with this premise, social epidemiology strives to identify the societal attributes that influence the patterns of disease and health distribution within a population, with particular emphasis on the impact of exogenous socio-structural factors on the distribution and evolution of health behaviors (Fongo, 2004; Galea et al., 2004).

Within the realm of social epidemiology, the focus on "health and disease" extends beyond traditional infectious diseases to encompass the “social contagions” [10] of various non-communicable diseases, such as cancer, diabetes, and obesity (Martin and Martin-Granel, 2006, 979; Grøn and Meinert2017). Furthermore, social epidemiology also explores the social transmission of health behaviors (both good and bad) within social networks, including smoking, alcohol consumption, drug use, dietary habits, and physical activity (Hindhede, 2018).

Recent research in this area has demonstrated that various non-communicable diseases and health-related behaviors, both positive and negative, can propagate along and within social networks (Rosenquist et al., 2010; Christakis and Fowler, 2007; Christakis and Fowler, 2008; Fowler and Christakis, 2008; BearmanMoody2004). However, there remain critical

[10] The term "social contagions" refers to the set of all social phenomena that propagate through social networks (Hindhede, 2018).

controversial theoretical issues in how to explain transitions of behavior in the present prevalence of diseases related to health behavior or lifestyle, rather than viral or bacterial infections.

Specifically, the phenomenon under investigation in this study, the spread of college students' drinking behavior within friendship networks, is typically classified as non-conformist behavior and therefore often not regarded as a true epidemic, since no microorganism is involved in these diseases (Lozano et al., 2013). The crucial question is what exactly is being transmitted in this so-called epidemic (Hindhede, 2018)?

Regarding this question, Boero (2007) categorizes epidemiology into traditional epidemics involving microorganisms and postmodern epidemics characterized by non-conformist behaviors. In the context of social epidemiology, researchers acknowledge that all epidemiology phenomena including both traditional and non-conformist cases, are inherently social (Galea et al., 2004). They perceive individuals as complex entities shaped by both biological and social dynamics, thus emphasizing the interplay between social contexts and biological processes (Galea et al., 2004). For instance, according to structural analysts, social networks wield profound impacts on behavioral patterns, information dissemination, resource sharing, pursuit of opportunities, and community participation (Hindhede, 2018). These dynamics play a pivotal role in shaping the diseases we may be susceptible to and influencing our health-related behaviors. For social epidemiology researchers, the social contagion of nonconformist behaviors is more than a mere metaphor and more than the spread of diagnoses, it actually spread and emerge with very real effects (Seeberg and Meinert, 2015; Grøn and Meinert, 2017).

Explanations on the Explanandum Phenomenon

Research grounded in social epidemiology regarding college drinking behavior often employs mathematical models to simulate and analyze the impact of exogenous social-structural factors on the dynamics of drinking behavior (An et al., 2011). Specifically, social epidemiologists often use a few simple equations or rules, including dynamic state variable models, game theory models, systems dynamics models, and statistical methods to model the explanandum as a social contagious process of drinking behavior within a social network environment (Manthey et al., 2008; Xiang et al., 2018; Bhunu, 2012; Mubayi et al., 2010; Thomas and Lungu, 2010; Wang et al., 2016; Song et al., 2016; Manthey et al., 2008). Among these models, system dynamics models based on differential equations are the most commonly used and effective analytical models. Researchers typically use empirical data to calibrate the parameters in the differential equations and conduct dynamic system analysis on the simulation results of the infectious disease models. The primary goals of these models are to determine the spread speed of drinking behavior, the equilibrium distribution of individual drinking states within social networks, and the social structural factors that influence these outcomes, such as the topology features of social networks and the sensitivity of the model results to transmission threshold parameters.

Manthey et al. (2008)'s research on college student drinking behavior is a typical example of a study based on social contagion theory. They conceptualize college students' drinking behavior as a 'disease' that can propagate through social interactions. The interrelationships between social drinkers and problem drinkers are modeled using a system of ordinary differential equations, a variant of the classical susceptible, infectious, susceptible (SIS) model. The findings of Manthey et al. (2008)'s study reveal the intricate transmission dynamics of alcohol abuse on college campuses, highlighting the significant impact of social factors such as the delayed effects of parental drinking patterns, peer influences, and the proximity of liquor stores to campuses on the dynamics of drinking behavior among the college student population.

In essence, existing social epidemiology-based research on the Explanandum assumes that college student drinking behavior has real social contagiousness properties. The diffusion of college drinking behavior within college social networks is observed as a consequence of social propagation under the influence of specific social factors such as social network structure and the contagion rates prevalent in a particular culture.

Summary

Research on college students' drinking behavior based on social epidemiology approaches provides valuable theoretical insights, particularly in leveraging concise and efficient mathematical models to help us understand to what extent social structural factors influence the spread of drinking behavior within social networks. However, since social epidemiology tends to focus on exogenous social factors, the majority of studies grounded in social contagion theory analyze the relationship between macro-level social conditions (e.g. social structures situations) and macro-level outcomes (e.g. the distribution of drinking behavior in the social network), that is, macro condition-macro outcome. This leads to:

- Social epidemiology studies often neglect the interaction processes among individual at micro-level (Bräker and Soellner, 2017; El-Sayed et al., 2012). For instance, as An et al. (2021) points out, although statistical models and system dynamics models are powerful in characterizing systems at an aggregate level, they fail to capture the heterogeneous actors that interact with each other. Equation-based and game theoretic models (Polasky et al., 2011) and system dynamics models are useful for representing feedback between systems and explaining macro-level characteristics, but they lack the ability to represent micro-level processes and interactions (Heckbert et al., 2010).

  In addition, social epidemiologist approaches often assume that health behaviors can spread similarly to infectious diseases, with the transmission of behavior being entirely dependent on exposures (Bräker and Soellner, 2017). However, El-Sayed et al. (2012) notes that, unlike infectious diseases, individual behavior is initiated by psychological processes such as motivation, outcome expectations, and motivation to comply. Bräker and Soellner (2017) highlight out that the dynamics of health behaviors within social network exhibit nonlinearity with feedback loops, which are not extensively explored in traditional social epidemiology but can have significant implications for population health.

- Social epidemiology overlooked the reciprocal influence of health behavior on social structural factor (micro to macro), especially the shaping of social context (e.g. friendship network typology) by college drinking behavior. A substantial body of existing research has demonstrated that college drinking behavior co-evolves with friendship networks through peer influence and peer selection mechanisms, a process that research based on infectious disease models struggles to comprehend and analyze.

Regarding the roles of social capital and college drinking culture in social epidemiology-based research: social capital is a concept that is rarely mentioned in social epidemiology research, possibly because these studies focus on exogenous social factors and neglect the individual-level effects of social capital. As for college drinking culture, it is usually treated as a factor that influences health behavior through “infectious” parameters that affect exposures, that is, as a variable in “variable sociology”, Social epidemiology research lacks mechanism-based explanations that place individuals within their social and cultural contexts.

Social Learning Theory

Definition and Concepts

A prevailing assumption in current research on the spread of college drinking is that college students engage in drinking behavior due to peer pressure, which implies an active peer influence (Harakeh et al., 2012). However, this active peer influence has been questioned by some researchers (Perrine and Aloise-Young, 2004; Slater, 2003; Michell and West, 1996; Arnett, 2007). Alternatively, some researchers emphasize it is the passive peer influence, or more precisely, the observation and imitation of peers' drinking behaviors by college students without direct solicitation, explaining the diffusion of college student drinking behaviors within social networks.

Harakeh et al. (2012) identified that two explanations regarding imitation have gained support in existing literature.

- One explanation is the perception-behavior link paradigm (Chartrand and Bargh, 1999), which emphasizes that individuals often imitate the behavior of others spontaneously and unintentionally. For example, empirical evidence has consistently shown that during interaction with another person, individuals unintentionally mimic their postures, mannerisms, facial expressions, eating behavior, and other behaviors (Chartrand and Bargh, 1999; Tanner et al., 2008).

- Bandura's social cognitive/learning theory (SLT) (1977, 1986) provides an alternative explanation, emphasizing that imitation of others' behaviors is conscious rather than unintentional. This theory suggests that individuals observe and intentionally imitate, also known as "modeling," the behavior of others. The behavior being modeled is perceived as positive and attractive, which may result in immediate positive rewards, such as a sense of belonging to the group or being liked (Phua, 2011).

  Furthermore, although SLT emphasizes the conscious imitation of peer behavior, as Oostveen et al. (1996) points out, within the SLT framework, the observed peer behavior is not directly imitated but rather mediated by cognitions that might stimulate imitation in similar situations, even when the model behavior is not observed (Bandura, 1977, 1986; Abrams and Niaura, 1987; Wood et al., 2001).

Explanations on the Explanadum Phenomenon

Borsari et al. (2006) 's research is a typical example of applying the SLT to study the spread of college student drinking behavior in social networks. They summarize that three key constructs of SLT describe how peers' drinking behavior influences personal alcohol use: social reinforcement, modeling, and cognitive processes.

- Social reinforcement (or differential reinforcement) refers to receiving consequences for an observed behavior. According to Maisto et al. (1999), this is often dependent on the setting in which the observed behavior occurs. The different environments in which college drinking occurs provide varying degrees of acceptance of certain behaviors. For example, heavy drinking may be accepted and encouraged at a campus party but frowned upon and punished at a faculty social event.

- Modelling, also known as vicarious learning, is the process through which individuals acquire new behaviors by observing others or through verbal or written communication (Maisto et al., 1999). This process is a central concept of SLT, as it proposes that learning occurs by observing others' behaviors and the resultant positive or negative consequences experienced by others (Abrams and Niaura, 1987). SLT posits that the environment offers individuals information that shapes their cognitions (thoughts), which then influence their overt drinking behaviors. In this process, behavior patterns that are rewarded are more likely to be imitated than those that are punished.
- Cognitive processes, rooted in past experiences, often serve as mediators of environmental or social influences on behavior. Two key cognitive processes, self-efficacy and alcohol expectancies, have consistently been associated with college student drinking (Werner et al., 1996). Self-efficacy refers to the belief in one's ability to engage in a behavior to achieve a desired outcome, such as declining a drink to maintain sobriety. On the other hand, alcohol expectancies encompass beliefs regarding the cognitive, affective, or behavioral effects of alcohol consumption and can be either positive (e.g. "drinking makes me more sociable") or negative (e.g. "when I drink, I often say things that I regret later") (Jones et al., 2001). These expectancies are thought to play both causal and sustaining roles in alcohol use among college students, with positive alcohol expectancies in particular being influential (Jones et al., 2001).

Borsari et al. (2006) notes that within the SLT framework, these three constructs: social reinforcement, modeling, and cognitive processes - cannot be considered independently; a change in one will facilitate changes in the other two. Additionally, the relative influences exerted by these constructs are thought to vary in different settings and for different behaviors (Abrams and Niaura, 1987). Therefore, the influence of these constructs is constantly changing, being adjusted and altered as peer environment changes. They enumerate three different peer environmental scenarios and explain how the three constructs of SLT have different influences on individual drinking behavior in each scenario (Borsari et al., 2006).

- First, a lack or breakdown of quality peer relationships can facilitate solitary drinking. The relationship between a breakdown or lack of peer relationships and increased solitary alcohol use is evident in research that links alcohol use to reduced levels of intimacy with others (Karwacki and Bradley, 1996), alienation (Senchak et al., 1998), emotional pain (Thombs et al., 1993) and low levels of social support (Moos et al., 1976; Steptoe et al., 1996).
- Secondly, excessive alcohol consumption may ensue if alcohol use becomes deeply embedded within peer interactions. A longitudinal study, which tracked students throughout their college years, identified the social environment as a highly significant predictor of college drinking behaviors (Bartholow et al., 2003). This phenomenon can be attributed to socialization, where alcohol use becomes pervasive, accepted, and encouraged in previously alcohol-free peer interactions. As Watt (1999) notes, when students are regularly exposed to valued peers who model and provide social reinforcement for alcohol use, it can lead to increased drinking in social situations. In such a peer environment, it is likely that social drinking by students is both modeled and socially reinforced by valued and popular peers, making it challenging for students to resist offers of alcohol.
- Thirdly, a student is more likely to drink lightly or abstain from drinking if their peers disapprove of alcohol use or refrain from drinking. Within the framework of SLT, this peer environment can be viewed as the converse of what occurs when peers support heavy alcohol use. Peers promote abstinence or light drinking through social reinforcement (creating an environment that condones this style of alcohol use), modeling (peers themselves abstain or drink lightly), and cognitive processes (strong self-efficacy in refusing drinks, low expectations that alcohol is necessary for socializing or popularity) (Borsari et al., 2006).

In summary, according to SLT, college drinking behavior, like any other aspect of human behavior, is acquired through learning (Durkin et al., 2005). Alcohol expectancies, as significant individual cognitions, serve as a mediating factor between peer drinking behavior and personal alcohol use. Neighbors et al. (2007) highlighted findings from empirical studies (e.g., Neighbors et al., 2003; Fromme et al., 1993; Read et al., 2004) indicating that alcohol expectancies, involving beliefs regarding the likelihood and subjective evaluations of the effects of alcohol consumption, have consistently been associated with heavy drinking among college students. Alcohol expectancies encompass individuals' beliefs about the probability of experiencing positive outcomes (e.g., social facilitation, enhanced social integration, improved sexuality, and stress reduction) as well as negative outcomes (e.g., cognitive impairment, increased risk, and aggressive behavior). Positive alcohol expectancies have demonstrated a stronger correlation with drinking behavior compared to negative expectancies (Jones et al., 2001; Valdivia and Stewart, 2005).

SLT indicate that non-drinking college students are exposed to models of drinking behavior, such as observing peers' alcohol consumption and its consequences, receiving social reinforcement for drinking behavior. Through these experiences, cognitions about the effects of alcohol are formed, giving rise to (positive) alcohol expectancies (e.g., beliefs like "drinking alcohol will make me more outgoing" and "alcohol makes people act stupid at parties") (Tomlinson and Brown, 2012; Svensson, 2003)which directly influence college students' decisions related to drinking (Brown, 1985; Christiansen & Goldman, 1983), particularly leading to the imitation of peers' drinking behavior (Trucco et al., 2011; Svensson, 2003; Kehayes et al., 2020). For example, Brechwald and Prinstein (2011) indicates that adolescents who observe that popular peer students drink alcohol will be motivated to conform to drinking behaviors in pursuit of similar status among peers (i.e., a social reward).

Summary

Research based on SLT provides a unique insight into how college students imitate their peers' drinking behavior and contribute to the emergence of the target social phenomenon. However, the SLT framework still has several notable limitations:

- SLT emphasizes the role of imitation, which is considered a form of passive peer influence. The SLT framework neglects the roles of active peer pressure and normative influence in producing the target social phenomenon.
- SLT overlooks the role of college students' drinking behavior in shaping friendship

networks via peer selection, as well as the co-evolution of college drinking and college friendship networks.

- While SLT emphasizes the mediating role of alcohol expectancies in the influence of peer environment on college students' drinking behavior, a substantial body of recent research suggests that social motives are a more proximal and important predictor of drinking behavior (Merrill et al., 2014; Halim et al., 2012).

Motivational Models

Definition and Concepts

Motivational models emphasize that individual drinking motives are the most important proximal predictors of college students' drinking behavior (Halim et al., 2012; Smit et al., 2015; Merrill et al., 2014; Villarosa et al., 2014). The concept of drinking motives is based on the assumption that drinking motives serve as a personally derived decision-making framework for alcohol use based on individual experiences, situations, and expectations, with the objective of achieving certain valued outcomes (Cooper, 1994; Kuntsche et al., 2005; Carpenter and Hasin, 1998; Cox & Klinger, 1988). Motivational models highlight the structure and role of the functions that drinking fulfills, suggesting that drinking behavior is motivated by different needs or serves various functions, and that specific drinking motives are linked to a distinct pattern of precursors and consequences (Merrill et al., 2014; Kuntsche et al., 2005). For instance, individuals who experience stress and drink to cope, as well as those who socialize with heavy-drinking friends and who drink for social reasons, are more likely to engage in heavy drinking (Abbey et al., 1993).

Furthermore, Kuntsche et al., (2005) pointed out that the motivational model assumes that individual’s decision to drink is a combination of emotional and rational processes based on the affective change that the person expects to achieve by drinking compared to not drinking. This affective change can be related to the direct chemical effects of alcohol, such as tension reduction or mood enhancement, or indirect effects, such as peer acceptance. Notably, research indicates that individuals do not need to be consciously aware of having made a decision to drink or the factors influencing this decision. In many cases, decisions regarding drinking are unconscious and automatized (Kuntsche et al., 2005).

Researchers have proposed various motivational models to explain college students' drinking behavior, with Cox and Klinger's (1988; 1990; 2004) model being the most widely known and influential (Cooper et al., 2016; Kuntsche et al., 2005). Unlike the SLT framework, which emphasizes the mediating role of alcohol expectancies in the influence of social factors on college students' drinking behavior, Cox and Klinger's motivational model prioritizes drinking motives as more closely associated with alcohol use than alcohol expectancies (Cronin, 1997; Kuntsche et al., 2005). Although alcohol expectancies and drinking motives may appear similar and are often confused, but as Ham et al. (2007) notes that there are distinct differences between them within motivational models: On the one hand, drinking motives denote the underlying intentions, goals, and purposes that drive individuals towards alcohol consumption, reflecting a desire or need to achieve specific anticipated outcomes from drinking which form the direct foundation for one's decision to drink (Cooper, 1994; Ham et al.,2007). For instance, an individual may drink alcohol to seek excitement or to cope with stress. Motives reflect the intentions and goals that drive individuals towards drinking.

On the other hand, alcohol expectancies refer to individuals' beliefs or expectations regarding the potential consequences of drinking behavior (Lindgren, 2016). They are viewed as part of long-term memory, and implicit thought processes surrounding current and future alcohol consumption (Jones et al., 2001; Hasking et al., 2011). As indicated by SLT framework, alcohol expectancies can be learned directly or indirectly through one's experience with alcohol (Linden et al., 2014) which constitute individuals' subjective evaluations of the positive or negative behavioral, emotional, and cognitive effects of alcohol intake. For example, people may expect that drinking will make them feel happier, more relaxed, or alleviate anxiety. Although the perception of alcohol's likely effects reflects expectancies, the endorsement of an outcome expectancy does not necessarily mean that an individual will drink to obtain that expected effect (Lindgren, 2016).

To summarize, motives serve as intrinsic driving forces that trigger individuals' decision to drink, while outcome expectancies represent individuals' subjective beliefs about the specific outcomes of alcohol (Cox & Klinger, 1988, 1990). Expectancies can be established well in advance of initiating drinking behavior (Linden et al., 2014), while motives may undergo daily fluctuations (Arbeau et al., 2011; Linden et al., 2014).

In predicting college students' drinking behavior, the motivational model of drinking asserts that an individual's drinking motivations for alcohol consumption play a more crucial role in initiating and sustaining drinking behavior than one's alcohol expectancy. These motives act as a mediator through which more distal factors, such as personality traits and alcohol expectancies, influence drinking behaviors (Kuntsche et al., 2007; Kuntsche et al., 2010; Cooper et al., 2016; Kuntsche and Kuendig, 2012; Linden et al., 2014; Ham et al., 2007).

Explanations on the Explanadum Phenomenon

According to Cox and Klinger (1988, 1990, 2004) and Cooper (1994), motives for college alcohol consumption can be categorized along two main dimensions - valence and source - which pertain to the objectives individuals seek to achieve through drinking. The valence dimension refers to the type of reward individuals hope to attain through drinking, which can be either positive reinforcement (e.g., pleasure) or negative reinforcement (e.g., relief from negative emotions). The source dimension, on the other hand, refers to the location of the expected reward, which can be either internal (e.g., changes in emotional state) or external (e.g., changes in social situations). By crossing these two dimensions, four distinct drinking motives emerge (Cooper, 1994): (i) enhancement motives, where individuals drink to enhance their emotional state (e.g., "to feel good"); (ii) social motives, where individuals drink to achieve positive social outcomes (e.g., "to have fun at a party"); (iii) coping motives, where individuals drink to alleviate negative mood states (e.g., "to feel more confident"); and (iv) conformity motives, where individuals drink to avoid peer disapproval or negative social consequences (e.g., " So you won’t feel left out ") (Stewart et al., 2006; Carey et al., 1997; Ham et al., 2007; Cooper, 1994; Kuntsche et al., 2005).

While it is important to consider all these drinking motives, some studies have shown that college students tend to have stronger positive motives than negative ones, with positive motives being more influential in predicting alcohol-related outcomes in this population (Read et al., 2003; Linden et al., 2014). Additionally, research has shown that of the four drinking motives, social motives tend to be the most commonly endorsed across all drinkers and may be particularly useful in explaining the etiology of drinking during the college period (Mooney et al.,1987; Van Damme et al., 2013). According to Arnett (2000), the college period is a key time of self-discovery, increased autonomy, and the formation of new social connections, factors that can heighten social motives for drinking.

Cox and Klinger's (1988; 1990; 2004) motivational model of alcohol use has been widely applied in research on college student drinking behavior, and numerous empirical studies have identified drinking motives as one of the most proximal indicators of college student drinking patterns (Villarosa et al., 2014; Martens et al., 2007; Martens et al., 2008; Ratliff & Burkhart, 1984; Read et al., 2007; Carey & Correia, 1997; Kassel et al., 2000).

Summary

Cox and Klinger (1988; 1990; 2004)'s motivational models have garnered substantial empirical support and provide individual internal state foundation at micro-level for understanding college drinking behaviors. It is considered one of the most influential and effective theoretical frameworks in helping us comprehend these behaviors.

The two-dimensions motivational models also reflect the multi-determined nature of college drinking behavior within friendship networks. Brown et al. (2011) pointed out that the pathways to college alcohol-related problems are multifaceted and multiply determined. Cox and Klinger's (1988) motivational model of alcohol consumption suggests that college alcohol intake is influenced by interplay of biological, psychological, and environmental factors. These factors operate through a common motivational pathway, ultimately influencing the decision to consume or refrain from alcohol.

Despite the significance of motivational models in analyzing and understanding the target social phenomenon, this framework still has several limitations.

- The emphasis within motivational models on the relationship between external sources drinking motives and social integration, such as enjoying being with others (social motives) and fitting in with the crowd (conformity motives) - does not explicitly clarify how these drinking motives emerge through individual interactions (i.e., the origins of drinking motives).
- Due to a primary focus on the individual internal state at the micro-level, there is a lack of focus within motivational models on the co-evolution process of college students' drinking behavior and their social networks, it fails to dynamically analyze the role of drinking motives in the co-evolution of college students' drinking behavior and their social networks.

Social Norms Theory

Definition and Concepts

The Social Norms Theory (SNT) serves as the conceptual framework for understanding the relationship between social norms and college drinking behaviors (Rinker et al., 2016). It highlights how individual college students' perceived beliefs regarding the prevalence and social acceptability of their peers' drinking behavior significantly influence their own alcohol consumption patterns (Cox et al., 2019; Ahern et al., 2008).

The concept of social norms within SNT originated from the work of Room (1975: 359), who characterizes social norms as "a cultural rule or understanding affecting behavior, which is to a greater or lesser degree enforced by sanctions". He emphasizes that a norm is culturally constructed, and it is "not a property of an individual or a private understanding between people interacting with one another but is a relatively permanent rule shared by a class of individuals who may not ever have met each other". Building upon Room's definition of social norms, Cialdini and Trost (1998: 152) expound social norms as "rules and standards known by group members, influencing and potentially limiting social conduct without legal enforcement. These norms arise from interpersonal engagements, may be implicit, and any repercussions for non-conformity are enforced through social connections".

Cialdini et al. (1990) delineated the concept of social norms into two distinct categories:

- Descriptive norms (or “behavioral norms”) encompass an individual's perceptions of the customary or typical actions exhibited by members of a social group (Perkins, 200; Blanton et al., 2008).
- Injunctive norms (or “prescriptive norms”) pertain to an individual's beliefs concerning the moral or social evaluation of behaviors, reflecting others' assessments of specific actions (the norms of "ought") (Cialdini et al., 1990; Miller & Prentice, 1996; Ajzen & Fishbein, 1980; Perkins, 2002; Blanton et al., 2008).

Furthermore, Descriptive norms and injunctive norms can be categorized as actual norms or perceived norms (Lee et al., 2007). A fundamental argument in SNT posits that individuals within social networks engage in or restrain health behaviors to conform to perceived norms rather than actual norms. This highlights that peer influences from social networks are shaped more by individuals' perceptions of others' beliefs and actions (the “perceived norm”) rather than the reality (the “actual norm”), as discrepancies typically exist between the two (Berkowitz, 2003). This discrepancy, termed a “misperception,” occurs when there is an overestimation or underestimation of the prevalence of attitudes and/or behaviors within a group or population. The impact of “misperception” on behavior forms the foundational basis of SNT approaches (Berkowitz, 2004).

Specifically, according to the SNT framework, individuals within a social network construct perceived norms by evaluating raw data from three primary sources: observable behaviors, direct and indirect communications, and knowledge of the self (Miller and Prentice, 1996; Borsari and Carey, 2003). However, perceived norms derived from these three sources of raw data may deviate from the actual norms within the social network.

For instance, Miller and Prentice (1996) highlighted that observable behaviors, as the primary source of normative information, are often the most accessible information about others but are susceptible to the fundamental attribution error. This error entails individuals interpreting others' behaviors as indicative of inherent traits rather than considering situational influences (Ross, 1977). The second source of normative information, direct (explicit) and indirect (implicit) communication, is also subject to limitations. Information may be intentionally or unintentionally distorted. Additionally, the third source of normative information, personal attitudes and behaviors also influence individuals' perceptions of norms because people tend to assume others think and act similarly to themselves (Mullen and Hu, 1988). These different sources of normative information are combined in an additive manner (Miller and Prentice, 1996), which can sometimes lead to inaccurate estimates of others' behaviors and attitudes in the social network (Borsari and Carey, 2003).

Based on existing empirical research, Berkowitz (2005) identifies two main types of "misperceptions" that can influence health behavior:

- Type 1 "misperceptions": “pluralistic ignorance” refers to situations where individuals incorrectly perceive their peers and community members' attitudes or behaviors to be different from their own (Miller & McFarland, 1991). Specifically, the majority who engage in healthy behaviors may wrongly believe they are in the minority. One consequence of pluralistic ignorance is that it leads individuals to adjust their behavior to align with the misperceived norm (Prentice & Miller, 1993). This adjustment can result in the normalization of problematic behaviors and the suppression of healthy behaviors (Berkowitz, 2003). This phenomenon has been extensively observed in behaviors such as alcohol consumption, smoking, drug use, and various attitudes, including prejudices.

- Type 2 "misperceptions": “false consensus”, occur when a minority of individuals with unhealthy attitudes and/or behaviors mistakenly believe they are in the majority (Berkowitz, 2003). These misperceptions of a norm can discourage individuals from expressing opinions and behaviors that they falsely perceive as non-conforming, thereby creating a negative cycle in which unhealthy behavior is expressed, and healthy behavior is inhibited (Baer et al., 1991). Furthermore, misperceptions can enable individuals who engage in problem behaviors to deny or justify their actions, as they believe their behavior is normative. For instance, heavy drinkers may incorrectly assume that most other students are heavy drinkers, or prejudiced individuals may mistakenly believe they represent the views of their group (Berkowitz, 2004).

Notably, false consensus and pluralistic ignorance are mutually reinforcing and self-perpetuating. For instance, Perkins (2002) has indicated that perceptions, once perceived as real, manifest actual consequences, with perceptions of reality potentially influencing behaviors that contribute to a "self-fulfilling prophecy". In the context of alcohol use and misuse among students, behaviors may escalate as individuals conform, at least partially, to their misperceived peer expectations regarding drinking, thus creating a self-fulfilling prophecy. Consequently, actual drinking norms may be elevated by these misperceptions more than would naturally occur, perpetuating the exaggerated perceptions in a continuous cycle (Perkins, 1997; Perkins, 2002).

Furthermore, SNT posits that all individuals who misperceive the norm (termed "carriers of the misperception" by Perkins, 1997) play a role in fostering an environment that permits problematic behaviors, regardless of their actual engagement in such behaviors. This phenomenon occurs as the perceived majority remains silent due to their mistaken belief that they are in the minority, while the vocal minority (“subculture custodians”) expresses themselves assuming they represent the majority. These misperceptions regarding social norms deter more responsible individuals from openly voicing their disapproval of excessive drinking and intervening in potential instances of peer alcohol misuse (Perkins, 1997). This viewpoint is supported by empirical research. For instance, Prentice and Miller (1993) demonstrated that students with moderate or conservative attitudes towards alcohol use, when mistakenly perceiving their views as greatly different from the norm, experienced increased feelings of alienation from their university and peers. The lack of visible opposition to heavy drinking then perpetuates and strengthens the misperceived norm regarding acceptable behavior. Consequently, students with the most permissive personal attitudes and engaging in extreme drinking behaviors are reinforced by their own and others' misperceptions, leading them to believe they are part of a fictitious majority. In contrast, students who are at the highest risk due to their permissive attitudes but happen to have a more moderate (i.e., more realistic) perception of their peers' norm for alcohol use are in a more cognitively dissonant situation, making it more difficult for them to act on their attitudes and drink heavily (Perkins and Berkowitz, 1986; Perkins, 2002).

In summary, the combination of "false consensus" and "pluralistic ignorance" enables the influential heavy drinking "subculture custodians" to wield a disproportionately strong influence by amplifying their voice while silencing the "silent majority" (Prentice & Miller, 1996). In order to break or reverse this cycle, the SNT emphasizes the importance of providing accurate information about peer group norms in a credible manner. This can help reduce perceived peer pressure and increase individual empowerment to promote healthy existing attitudes and beliefs (Berkowitz, 2005). If misperceptions of norms are not corrected, there is a risk of creating a self-fulfilling prophecy where individuals drink more simply because they believe everyone else is drinking more (Berkowitz, 2005). Therefore, offering normative feedback to address misperceptions of norms is a crucial aspect of the SNT Approach (Berkowitz, 2004).

Explanations on the Explanadum Phenomenon

SNT has been widely applied in research on college students' drinking behavior, asserting that misperceptions of the drinking behavior of the typical college student in the social network contribute to the spread of drinking behavior (Fitzpatrick et al., 2016; Perkins, 2002).

Some empirical research indicates that college students often tend to make inaccurate judgments about the actual drinking behavior (i.e., norm misrepresentation) within the college institution, particularly overestimating drinking norms (Fournier et al., 2013). For example, it has been found that college students have incorrect perceptions of normative drinking (Fitzpatrick et al., 2016), with 71% overestimating their peers' drinking (Perkins et al., 2005).

Perceived norms are thus considered to be a strong predictor of excessive alcohol consumption among college students (Borsari and Carey, 2003; Neighbors et al., 2007; Fitzpatrick et al., 2016; Neighbors et al., 2006; Perkins, 2002).

For instance, Borsari and Carey (2003) provides substantial evidence of a self-other norm discrepancy regarding alcohol use among college students. They describe a two-step process through which this "misperception" affects alcohol consumption among college students:

- In the first step, individuals compare their own alcohol consumption and attitudes with perceived descriptive and injunctive norms, such as those of a best friend or the typical student, often resulting in perceived discrepancies. This incongruity is explained by pluralistic ignorance and attribution theory. Pluralistic ignorance occurs when individuals believe their private attitudes are more conservative than their peers, despite aligning public behaviors. This leads to two perceptual errors: misjudging the target group's attitudes and seeing oneself as differing from the norm. Attribution theory suggests students have limited knowledge of peers' actual behaviors and attitudes, leading to assumptions that heavy drinking is standard, thus elevating perceived norms. These misperceptions are more likely when interactions with the target group are limited, resulting in generalized attitudes and behaviors. Both theories suggest students tend to overestimate peers' alcohol consumption and approval.
- In the second step, these amplified norms influence personal alcohol consumption among college students. Students often align their behaviors with perceived group norms rather than personal beliefs, leading their drinking patterns to mirror observed and endorsed behaviors (descriptive and injunctive norms). This norm influence can be complex and reciprocal; students perceiving peers as heavy drinkers may adopt similar patterns, reinforcing excessive drinking as the norm. This cycle can pressure students to comply with heightened norms, perpetuating a culture of heavy alcohol consumption (Perkins, 1997).

In summary, according to SNT, misperceptions among college students regarding the actual social norms on campus can contribute to escalated drinking behaviors and may also serve as a rationalization for excessive drinking among individuals with alcohol-related problems which is considered a primary factor in the spread of drinking behavior among college students (Berkowitz, 2003).

Summary

SNT is recognized for offering a theoretical foundation for potential social interventions and SNT-based interventions have been reported to yield positive effects in various higher education institutions (Johnson, 2012; Wechsler et al., 2003; Keeling, 2000; Berkowitz, 2004). However, SNT still exhibits several limitations that cannot be overlooked.

- SNT emphasizes the impact of passive normative influence in peer influence on college students' drinking behaviors, often describing tendencies of conformity. Additionally, the concept of "false consensus" to some extent indicates an active peer influence, where a minority mistakenly believes they represent the majority and thereby exert direct pressure on peers. However, SNT does not directly explain the imitation tendencies in college students' drinking behaviors, which limits its explanatory power in this context.

- SNT primarily emphasizes the influence of social norms in social networks on college students' drinking behaviors through peer influence but overlooks how college students' drinking behaviors shape social network relationships and the dynamics of individual perceived norms in this process. Furthermore, the dynamic co-evolution of social relationships and college students' drinking behaviors is not adequately illustrated within the SNT framework. In reality, friendships among college individuals, their drinking behaviors, and their perceived norms influence one another and co-evolve in the social network environment. The SNT framework does not provide an effective theoretical perspective to analyze this dynamic process.

- SNT fails to provide a comprehensive explanation for why some college students do not conform to social norms. Empirical research on college students' drinking behaviors indicates that while a minority of students refuse to drink in social environments, there are individuals who choose to abstain from drinking rather than conform to the prevailing norms, as suggested by SNT. The framework does not offer a satisfactory explanation for this phenomenon. According to the Bernheim (1994), individuals who do not conform to social norms are labeled as "individualists" with markedly distinct preferences that lead them to reject conformity. These individuals exhibit behavior that diverges significantly from the social norm, illustrating a lack of "trivial" nonconformists. However, this explanation is not sufficient as it only considers individual preferences. In the context of college student drinking behaviors, nonconformity is not merely a matter of individual preference but is also culturally influenced and situationally driven (Singer, 1993). Cultural norms and situational factors play significant roles in shaping college students' decisions regarding alcohol consumption, and these aspects are not adequately addressed by the SNT framework.

Part 4: Research Gaps and Potential Contribution

In Part 1 to Part 3 of this chapter, we have conducted reviews on the explanandum phenomena and its key components, explanans factors, and explanatory theories on the explanandum phenomenon. In this section, we will pinpoint principal limitations and research gaps in the current literature. Furthermore, we aim to illustrate how this research has the potential to address these research gaps and provide a unique contribution to the existing body of knowledge in the field.

Research Gaps

Existing research on the substantive topic of this study has conducted analyses and provided explanations for the target social phenomenon from a range of theoretical perspectives, yielding some valuable insights. However, there remain several key limitations and research gaps in the existing explanatory research on the substantive topic:

(1) Existing studies fail to offer a multi-level (micro-, macro-, micro-macro) systemic analysis grounded in social complexity theory. For instance, studies employing a social

epidemiology approach provide a macro-conditions to macro-outcomes analysis (e.g., how social network structure influences drinking behavior distribution), while neglecting micro-level analysis on the interaction process. Studies grounded in Social Learning Theory offer a macro-to-micro analysis, indicating that widespread drinking behavior in college friendship networks increases the risk of individuals imitating their peers' drinking within those networks. Similarly, Social Norm Theory studies provide a macro-to-micro analysis, suggesting that "misperceptions" of social norms at the macro level increase the risk of individual drinking behavior at the micro level within the network. Studies on social motives theory, focusing on social and conforming motives, offer a macro to micro analysis, such as how peer pressure from the social environment increases the risk of individuals drinking for external motives. Social Norm Theory studies provide a macro to micro analysis, suggesting that "misperceptions" of perceived norms at the macro level increase the risk of individual drinking behavior at the micro level within the network.

In summary, existing research predominantly focuses on individual attributes at the micro level (such as individual drinking motives, alcohol expectations, network position, number of friends, etc.) and lacks analysis of the non-linear interaction processes among college students (micro-micro interactions). Furthermore, there is a lack of focus on how college drinking behavior shapes the friendship network (micro-to-macro) and the coevolutionary process between college drinking and the friendship network, which are emphasized in empirical research. More importantly, existing studies lack attention on how the target social phenomenon emerges in the social context through the interaction process among college students, i.e., the micro-macro transition issue, which is considered a core issue in the research shifts called for by the social complexity approach.

The absence of analysis regarding the non-linear interactive processes among individuals and the micro-macro transition reflects a deficiency in traditional analytical research frameworks to provide an effective theoretical framework. This theoretical framework is needed to analyze the interrelationships between micro and macro factors, to clarify the connections between factors at various levels, and to demonstrate how these diverse elements interact, culminating in the emergence of the target social phenomenon.

(2) The emergence of the target social phenomenon is multi-determined, resulting from the interaction of multiple social mechanisms. For instance, Halim et al. (2012) note that while social norms and social motives for drinking independently predict drinking behavior, they also interact in influencing drinking patterns. Specifically, social motives have been found to both mediate and moderate the association between social norms and drinking behaviors. In addressing such complex social phenomena, research based on single-factor, single-mechanism theoretical assumptions are often viewed as oversimplified, simplistic, and limited in explanatory capacity. There is a lack of clear analytical frameworks that systematically organize multiple explanatory factors or potential explanatory social mechanisms to elucidate the specific social mechanisms and their interactive relationships contributing to the emergence of the target phenomenon.

(3) Existing explanatory research on the target social phenomenon predominantly relies on statistical analyses characteristic of "variable sociology" or qualitative methods (e.g. ethnographic research, narrative research, and case studies) that utilize qualitative data obtained through interviews, surveys and observations. There is a current absence of mechanism-based explanations that encompass a clearly defined and complete causal chain to illustrate the emergence process of the target social phenomenon.

(4) When examining the impact of peer influence from social networks on college students' drinking behavior, current research often underscores the connection between this process and students' efforts to foster social integration but has not fully elucidated the role of social capital in this context. Social capital plays a crucial role in understanding social integration, as the acquisition and maintenance of social support from peer networks are important motivations for college students to enhance their social connections. Related questions such as the extent to which college students' pursuit of social capital from friendship networks impacts the diffusion of their drinking behavior in social networks and how this influence of social capital operates in mechanisms remain to be explored and explained.

(5) Empirical studies indicate that one of the most important aspects of drinking culture among college students is its ability to transform drinking behavior into a highly scripted

and ritualized activity, serving as a desirable social performance. This allows drinking behavior in college social settings to create identity similarity among students with similar drinking patterns and identity heterogeneity among those with different drinking patterns. The identity similarity/heterogeneity among college students influences the evolution of friendship networks through a similarity-based peer selection process, particularly through mechanisms of social exclusion and inclusion. Whether and to what extent these social inclusion and social exclusion mechanisms affect the diffusion of drinking behavior within social networks, and how they exert their influence, remain unexplored questions in current research.

In summary, the existing research on the substantive topic lacks analysis and interpretation grounded in social complexity theory. Specifically, current studies predominantly focus on individual attributes and do not adequately address the interactive processes among individuals within the social context or the micro-macro transition, which is essential for explaining the emergent properties of social phenomena. This research, grounded in the social complexity theory, aims to address the research gap by focusing on the interaction processes between individuals within the social context, seeking to provide mechanism-based explanations (MBEs) for the target social phenomenon.

In addition to the research gap on the substantive topic, there are also methodological challenges in social complexity-based research method which have been discussed in Chapter 1, and I will not repeat them here.

Potential Contribution of This Research

This research offers original contributions on both methodological innovation and substantive knowledge:

- We will analyze and explain the substantive target social phenomenon based on the social complexity framework, contributing to bridging research gaps in the following aspects:

(1) This research conducts social simulation studies to illustrate and analyze the nonlinear interactive processes among college student individuals, particularly by placing these

individuals within the social context of the co-evolution of drinking behavior and friendship relationships, helping us observe and explain how the target social phenomenon emerges from the interactive processes among individuals.

(2) This research will propose mechanism-based explanations with a "macro-micro-macro" based complete causal chain for the target social phenomenon, which is currently lacking.

(3) This research contributes to understanding the role of social capital in the co-evolutionary process of college drinking and friendship networks and the extent to which college students' pursuit/maintenance of social support influences the dynamics of their drinking behavior within friendship networks.

(4) This research contributes to the role played by drinking culture in the co-evolutionary process of college drinking and friendship networks and how the social exclusion and inclusion facilitated by identity similarity created through drinking culture impact the dynamics of college drinking behavior within friendship networks.

- This research also has the potential for original contributions in exploring and advancing social complexity-based research method: We develop the "generative methodology" analytical toolbox proposed by analytical sociologists (Bearman and Hedström, 2009: 16; Manzo, 2021: 3), exploring and implementing the use of RL-based ABM social simulation methods to test mechanism-based explanations of complex social phenomena in social networks, providing a feasible and replicable research paradigm. In this process, this study provides exploratory responses to the challenges in this field of research methodology, including clarify the epistemological foundation of structural individualism, refining “Coleman's boat” analytical framework, constructing appropriate MBE theoretical hypotheses, formalizing the hypotheses into an RL-based ABM model, and testing the MBE hypotheses under the abductive reasoning principle.

Chapter 3: Research Methodology

This chapter is dedicated to tackling one of the central challenges of this research by attempting to bridge the existing gaps in methodological approaches to explaining the emergent properties of complex social phenomena. To achieve this objective, we will build upon the existing social complexity theory framework and sequentially address the challenges faced in explaining complex social phenomena, including establishing a proper philosophical foundation, developing a practical analytical framework, constructing well-formed causal explanatory hypotheses, and exploring a feasible and replicable research paradigm for testing these hypotheses through the generative approach.

Specifically, in this chapter, we will:

(1) Clarify the concept of "complex social phenomena" from the perspective of social complexity and define how the diffusion of drinking behaviors within college students' friendship networks is characterized as a complex social phenomenon within this theoretical framework.

(2) Review the epistemological challenges in gaining knowledge about complex social phenomena and the existing debates on how to address these challenges. Based on the current academic discourse, we will clarify the epistemological stance adopted in this study, which is structural individualism.

(3) Based on the study's epistemological stance, explain the concept of social mechanisms and clarify why causal mechanism-based explanations (MBEs) are considered the ideal form of scientific explanation for complex social phenomena under the structural individualism epistemological foundation.

(4) With the desired scientific explanation paradigm, MBE, explicitly defined, we will then elaborate and refine an analytical framework grounded in the "Coleman’s boat" diagram, ensuring alignment with the epistemological foundation of structural individualism. This refined framework enables us to systematically analyze and construct MBE hypotheses pertinent to our target social phenomenon, thereby bridging the explanans of interest and the target explanandum phenomena through a “Macro-Micro-Macro” approach.

(5) We will develop a feasible and replicable research path based on the social simulation approach for testing the causal MBE hypotheses. We will design and develop an agent-based model (ABM) following the abductive reasoning principle to test the causal MBE hypotheses.

Section 1: Epistemological Foundation

The three fundamental components of social research encompass ontology, which denotes the phenomena existing within the human realm that researchers can acquire knowledge about; epistemology, which concerns the processes through which knowledge is generated; and philosophical perspective, which delineates the philosophical orientation of the researcher guiding their actions (Moon and Blackman, 2014). A significant obstacle impeding the advancement of social complexity theory lies in the scarcity of firmly established, enduring philosophical frameworks explicitly tailored to complexity (Castellani and Gerrits, 2024:38). This section endeavors to clarify the specific ontology and epistemology stances embraced in the present study, providing a clear philosophical compass that guides our understanding and explanation of the complex social phenomena under scrutiny.

The Concept of "Complex Social Phenomena"

In this study, the target social phenomenon under investigation: the diffusion of drinking behaviors within college students' friendship networks, is recognized as a complex social phenomenon. This concept is grounded in social complexity theory, signifying the emergent properties of a social system that are repeatedly observed with certain statistical regularities. To elucidate this concept, we will dissect and clarify the individual notions of "social," "social phenomena," and "complex" within the term "complex social phenomena".

"Social"

The ontological status of the term "social" is a subject of controversy. Guala and Hindriks (2013) summarized three main concepts of the nature of the social based on different ontologies:

- Individualism or reductionism: Society is considered as merely a collection of individuals, with each property being the result or collection of the properties of its members.

- Holism or collectivism: A society is viewed as a whole entity that transcends its membership, and its attributes cannot be traced back to the attributes of its members, nor to the interactions between the latter.
- Systematism: A society is neither just an aggregate of individuals nor a supraindividual entity; rather, it is a system composed of interconnected individuals. In other words, it is a system wherein some attributes are derived from the collection of attributes of its constituent parts, while others arise from the relationships (and interactions) among these parts.

Both purely individualistic and holistic approaches to defining and understanding social phenomena have faced extensive criticism and are deemed inappropriate for this study. We will further elaborate on this in the subsequent sections.

This study adopts a systematist definition of the term "social," which encapsulates two critical components essential for understanding social systems within the framework of complexity theory:

- First Key Component: Interconnected individuals

  Society is conceived as a system composed of interconnected individuals. Drawing on Meadows' (2009) description, a system is defined as "an interconnected set of elements that is coherently organized in a way that achieves something". This definition explicitly identifies three fundamental components of a system: elements, interconnections, and function or purpose (Wright and Meadows, 2012). From a systemic perspective, a social system is understood as concretely structured groups or collectives of individual agents who communicatively interact with each other in relatively stable and enduring ways within the social structure (Kaidesoja, 2007).

  In addition, in Meadows' (2009) definition, system function is attributed to its emergent attributes, which are inherent characteristics of the system and not manifest in any individual component independently, thereby introducing the conceptually critical second component of the definition of "social" in systems theory.

- Second Key Component: Resultant Properties and Emergent Properties

The attributes of a social system can be classified into resultant properties and emergent properties.[11] Resultant properties exhibit reducibility as they are properties of the whole that can be possessed by its parts in isolation or in unstructured aggregation. An example of a social resultant property is total wealth, where the wealth of a group is simply the sum of the wealth of its individual members. Similarly, attributes of the social system such as income inequality and average age, although not possessed by their component parts (individuals), are still aggregative or resultant as they result from the simple addition of the properties of the parts. Greve (2012) reconceptualizes resultant properties as weak emergence properties, indicating a distinction between "macro" (social) and "micro" (individual) properties, yet allowing for the macro-properties to be reduced to micro-properties. Herein, social resultant properties are reducible and predictable, as they derive logically from the micro-level structure of components.

Conversely, social properties are characterized as emergent properties when they are irreducible to the properties of the individual components of the system in a lawful and regular manner (Sawyer, 2005: 4; Cilliers, 1998). Social properties are considered emergent properties when they exhibit novelty, meaning they are not inherent to any single component of the system (Sawyer, 2005: 4; Cilliers, 1998).The emergent properties of social entities explain how a social entity can exert a causal impact on the world in its own right: an impact that is not merely the sum of the impacts its parts would have if they were not organized into this kind of whole (Elder-Vass, 2010: 5).

[11] To grasp the concept of "property" in this context, it's essential to delineate the relationships among "entity," "whole," "parts," and "properties." According to Elder-Vass (2010: 16-18), an entity is essentially a durable unity, or "whole," that arises from a collection of components, with the arrangement and interactions among these parts giving it its unique structure. Applied to human society, a social system serves as this "persistent whole" is constituted by a group of human individuals acting as the "set of parts", which are structured by the social relations that exist between these individuals. A "property," in this schema, refers to an inherent aspect of the entity that possesses the potential to exert a causal influence on the world (Elder-Vass, 2010: 16-18).

In summary, strong emergent properties in a social system are those that the system as a whole possesses, which are not found in any of the individual parts and would not be present in the complete set of parts without the organized structure of relations among them (Elder-Vass, 2010:17)[12]. Furthermore, despite conceptual disparities, resultant and emergent properties within social systems are not mutually exclusive; A social system may harbor a combination of both emergent and resultant properties.

“Social Phenomenon”

In the field of social science, the term "social phenomenon" is generally used to encompass a wide range of objects, including processes, culture, events, structures, institutions, individual cognitive states, perceptions, and attitudes (Anzola, 2021). Although the concept of "social phenomenon" is rarely explicitly defined, it is often associated with the concept of "social fact." In a significant body of social science literature, "social phenomena" and "social facts" are not strictly distinguished and are frequently used interchangeably. In Durkheim’s limited sense of the term, "social fact" refers to anything that can be categorized as 'social' (Smith, 2014), while Durkheim's concept of the 'social' pertains to a noteworthy property that exists outside of individual consciousness (Durkheim, 1964: 2). Within the context of this study, with our understanding of "social" and "social system," social facts refer to any noteworthy social property within a social system.

On the other hand, "social phenomenon," as pointed out by Smith (2004), builds upon the notion of "social fact" but is properly called 'phenomena' rather than simply 'facts'. Social phenomena are generally used to refer to those social facts that can be recognized solely through sensory intuition. Here, intuition does not refer to the five senses of sight, sound,

[12] Irreducibility is a defining characteristic of emergent properties, often used to distinguish them from resultant properties. For instance, Elder-Vass (2010: 25, 26) proposes a counterfactual distinction between the two: by comparing the causal power of a whole and the causal power that its parts would have if they were not organized into such a type of whole. A resultant property can be explained without reference to the relations between the parts of the higher-level entity, whereas emergent properties depend on the existence of specific sets of relations between the parts of the entity possessing the property. For example, a university is composed of various real entities (e.g. academics, students, buildings, equipment) and social structures (e.g., departments, university culture, institutions, rules, legal frameworks), whose structural relationships empower the university to recruit staff, raise funds, conduct research, teach students, and award degrees. These emergent properties define the university's independent ontological status, rather than merely being an aggregation of its components (Sorrell, 2018).

touch, smell, or taste, but rather to the observation of a statistical regularity that becomes apparent to our minds only when a sufficient number of individual events are examined (Smith, 2014). For instance, a riot occurring in a city can be regarded as a social fact within a social system. When such riots are repeatedly observed across different cities and times, exhibiting certain statistical regularities (such as all "riots" being characterized by large-scale violence and being more likely in economically depressed areas) then "riots" can be defined as a social phenomenon. In order to avoid delving into a deeper discussion of social ontology, which is beyond the scope of this study, the term "social phenomena" is used in this study to refer to any social facts that have been repeatedly observed to exhibit a certain regularity, for practical and conceptual clarity.

"Complex"

The term "complex" in this study refers to the complexity within social systems, which is generally considered one of the most important characteristics of social systems from the social complexity theory perspective. Castellani and Hafferty (2009:44) noted that social systems are commonly characterized as "emergent, self-organizing, bounded, functionally autonomous, thematically centered, differentiated, agent-based, rule-following, and complex". In this research, the distinction between complexity and emergent properties is not strictly made, the complexity of a social system is indicative of its emergent properties, which are irreducible.

The origins of complexity or emergent properties within social systems remain nebulous, contentious, and unresolved in academic discourse. One influential perspective on this matter is offered by the relational approach to emergence, which attributes the genesis of emergence to the specific relationships that exist between the parts: the preservation of a stable configuration of substantial particular characteristic relations must exist between the parts for integrating them into an emergent higher-level entity as a whole and endowing them with emergent properties beyond the sum of the parts (Elder-Vass, 2010: 20).

In the present study, we abstain from delving into ontological discussions regarding the genesis of emergent properties in social systems, acknowledging that such inquiries surpass the ambit of our research. However, a review of the existing literature reveals that complexity theorists have discerned certain characteristics that render systems more conducive to the emergence of complexity:

- Numerosity of Individuals: definitions or descriptions of complexity frequently cite 'many elements' as a key characteristic (Ladyman et al., 2013). Cilliers (2002:3) notes that a large number of elements are necessary, but not sufficient for complexity. Complex systems typically consist of a multitude of elements, as complexity only arises when a substantial number of parts engage in numerous interactions. When the number of components is relatively small, their behavior can often be formally described using conventional terms (Cilliers, 2002:3).
- Autonomy of Individuals: Agency refers to the human capacity to 'act' in the world (Hager and Beckett, 2019:13). In complex systems, individuals are often considered to possess a degree of decision-making autonomy. It has been pointed out that in a truly complex system, components behave autonomously while undergoing various direct and indirect interactions (Heylighen et al., 2006).
- Heterogeneity of Individuals: Although social complexity theory emphasizes interactions between components over individual attributes as the source of social complexity, some scholars argue that individual heterogeneity may contribute to the emergence of system complexity. For instance, Hanseth and Lyytinen (2010:1) note that the proliferation and diversity of components, relations, and their unpredictable dynamics enhance system complexity. Strathern and McGlade (2014:12) similarly contend that self-organization emerges from the interplay, interactions, and feedback loops among heterogeneous components.
- Adaptivity of Individuals: Individuals within social systems often possess learning capabilities and the ability to adapt to changing circumstances (deMattos et al., 2012: 1550). It has been highlighted that complex systems consist of interdependent agents that interact, learn from each other, and adapt their behaviors accordingly (Beck and

Plowman, 2014: 1246).

- Individuals Embedded in Social Structure: In complex social systems, interactions among components are typically socially embedded rather than entirely random. Ladyman et al. (2013) note that it is a consensus that a complex system possesses structure. Complex systems are not characterized by parts performing random walks. Interactions within social systems are often constrained and influenced by the social structure.
- Non-linear Interactions Among Components: Non-linear interactions among components are often cited as a necessary condition for a complex system and are a core concept within the social complexity theory framework (Ladyman et al., 2013).

Firstly, for a set of elements to be considered a system, they must have the capacity to interact, which is one of the fundamental concepts defining a system. Interaction can involve the exchange of energy, matter, or information through forces, collisions, or communication. Without interaction, a "system" would merely be a collection of independent particles (an independent "soup" of particles), lacking the means to form patterns or establish order (Ladyman et al., 2013).

Secondly, for a system to generate emergent properties, interactions among components must be non-linear. Nonlinearity is considered a prerequisite for complexity in most existing social complexity research. A system is linear if solutions to its equations can be added or multiplied to obtain new solutions (Ladyman et al., 2013). Nonlinearity implies that this superposition principle does not apply, and the outcomes of changes in a non-linear system, such as the effects of certain actions or interactions, are not proportional to the magnitude of the change (Ladyman et al., 2013).

Non-linearity often implies the presence of closed feedback loops within a social system. According to Heylighen et al. (2006), since the actions of components are local, their effects propagate gradually to more distant agents, diffusing across the entire network formed by the agents and their interactive relationships. The same action can have multiple effects in different parts of the network at various times, with some causal chains closing in on themselves, reverting to influence the conditions that initiated them, thereby creating closed feedback loops. This makes the system inherently non-linear, with no proportionality between cause and effect within these loops.

Non-linear feedback can be positive or negative. Positive feedback or "autocatalysis" can amplify small fluctuations into substantial, systemic effects. This sensitive dependence on initial conditions, known as the "butterfly effect," is characteristic of deterministic chaos, where globally unpredictable changes arise from locally deterministic processes. However, complex systems can exhibit chaotic behavior without being deterministic. Negative feedback can suppress large perturbations, potentially stabilizing a global configuration. The combination of these effects leads to a global evolution that is not only unpredictable but also creative, fostering emergent organization and innovative solutions to problems (Heylighen et al., 2006). Non-linearity allows for small causes to have large results, and vice versa (Cilliers, 2002:4), rendering social systems unpredictable and irreducible.

- Co-evolution: As mentioned in the context of non-linear interaction, is a fundamental aspect of complex dynamical systems (Ladyman et al., 2013). The impact of any individual's action in the social system can feed back onto itself through non-linear interactions and subsequently influence other individuals, sometimes directly and sometimes after a series of intervening stages. This feedback can be positive, enhancing or stimulating the process, or negative, detracting or inhibiting it (Cilliers, 2002:4). This dynamic feedback mechanism results in an ongoing process of mutual adaptation among agents within a system (Heylighen et al., 2006). Agents co-evolve through this process: they continually adapt to changes initiated by other agents, but in doing so, they also modify the environment of these others, thereby necessitating further adaptation. This reciprocal adaptation is a hallmark of co-evolution, as described by Kauffman (1995).

“Complex Social Phenomena”

Based on the aforementioned concepts of “complex” and “social phenomena”, this study employs the term "complex social phenomena" to describe social phenomena within social systems that exhibit emergent properties. complex social phenomena are defined by three key features:

- Complex social phenomena are first and foremost social phenomena, implying that they refer to social properties that are frequently and repeatedly observed to exhibit certain statistical regularities. These social phenomena are relatively stable, aggregated, and macroscopic in nature (Srbljinović and Škunca, 2003).
- Secondly, complex social phenomena refer to social emergent properties that typically arise from the non-linear local interactions among structured lower-level entities within the social system (Elder-Vass, 2007).
- Thirdly, complex social phenomena are characterized by their irreducibility and regularity. This means that we cannot deduce or explain complex social phenomena by simply aggregating individual properties within a social system, nor can individual properties and their relations be fully inferred from the complex social phenomena. Additionally, regularities imply a certain level of abstraction, requiring explanations of complex social phenomena to have generalizability to accommodate explanations across different social systems.

In summary, in this study, complex social phenomena refer to social emergent properties within social systems that are repeatedly observed and exhibit certain statistical regularities, signifying an intrinsic attribute of a social system as an entity. Complex social phenomena are believed to emerge from ongoing non-linear interactions among a multitude of heterogeneous and adaptive individuals within a structured social environment, characterized primarily by irreducibility and statistical regularities.

Based upon the previous discussion on the definition of complex social phenomena, we argue below that the research object in this study, which is the diffusion of drinking behavior among college students in friendship networks, aligns with the descriptive characteristics of complex social phenomena:

- Firstly, as outlined in the literature review chapter, the phenomenon of drinking behavior diffusion among college students in friendship networks has been repeatedly and consistently observed across different social backgrounds and is considered a social phenomenon with stable macro-level characteristics and regularities. The target social phenomenon exhibits certain statistical regularities. For instance, college students in industrialized societies share similar typical drinking patterns, motivations for drinking, drinking cultures, and modes of drinking control characterized by social inclusion and exclusion.

- Secondly, the target social phenomenon occurs within the college social context, which is a social system comprising a large number of heterogeneous, adaptive college individuals. These individuals engage in extensive non-linear interactions within structured friendship networks: college students' drinking decisions shape the friendship networks they are embedded in, and these newly shaped friendship networks, in turn, influence college students' drinking behavior, creating a closed feedback loop.
- Thirdly, the target social phenomenon demonstrates typical characteristics of irreducibility, non-predictability, and statistical regularities. It is not feasible to fully describe or accurately predict the diffusion of college drinking within a friendship network by merely aggregating the drinking behaviors of all college individuals in the network (this is partly due to the adaptivity of college students' decision-making process regarding drinking behavior).[13] The diffusion of college drinking behavior represents a novel emergent property arising from complex non-linear interactions among a multitude of college student individuals within the friendship network.

Therefore, based on the aforementioned points, we consider the diffusion of drinking behavior in college friendship networks as a prime example of a complex social phenomenon within the social complexity theory framework.

[13] Existing empirical evidence (reviewed in the literature review chapter) indicates that college students' drinking behavior typically occurs in social settings, and the dynamics of college drinking within friendship networks are the outcomes of interactions among college students within a social context. For instance, the drinking behavior of friends within a social network, the pressure to drink from friends, and perceived social norms can all influence the drinking behavior of individual college students. Conversely, the drinking behavior of individuals can also reshape the social context and friendship networks. Merely understanding and aggregating the drinking behaviors of all individuals does not facilitate comprehension or elucidation of the interactive processes among individuals. On the contrary, we must situate individuals within a social context to observe and study the interactive processes among them.

The Ontological and Epistemological Foundations of the Explanation on Complex Social Phenomena

We have previously defined the concept of complex social phenomena and have identified the target social phenomena under study as a complex social phenomenon. The next question is how we can acquire knowledge about complex social phenomena and provide scientific explanations. This task is challenging due to the inherent properties of complex social phenomena, particularly their irreducibility and unpredictability. Simply analyzing and aggregating individual behaviors or lower-level properties is insufficient for understanding complex social phenomena, as it only involves examining the resultant properties of the system instead of irreducible emergent properties.

For instance, Alaimo (2022) argues that the evolution of complex social phenomena is not determined by individual causalities in isolation, but rather by complex interrelated causal complexes with non-linear dynamics, thereby increasing the difficulties in explaining complex social phenomena. Brenner (2010) highlights the major challenge in studying complex social phenomena, which is obtaining a satisfactory conceptual representation of emergent macroscopic social phenomena while accounting for the discontinuity between microscopic and macroscopic representations.

To address the epistemological challenge of explaining complex social phenomena, it is crucial to first clarify our philosophical stance, especially in establishing a clear and appropriate ontological and epistemological foundation for our research. This is essential as it deals with fundamental questions that guide us in overcoming the aforementioned challenge (Castellani and Gerrits, 2024:30), such as defining a knowledge claim of complex social phenomena and understanding how knowledge about complex social phenomena can be produced or acquired.

Within the field of social science, there is an ongoing discussion regarding the appropriate ontology and epistemological foundation for explaining complex social phenomena, particularly the individualism-holism debate. This debate is considered one of the most intense and long-standing discussions concerning the most suitable explanatory model for complex social phenomena (Epstein, 2014; Salgado and Gilbert, 2013). Although many viewpoints within this debate have been widely criticized and will not be adopted in this study, the individualism-holism debate provides background knowledge for the structural individualism epistemological stance adopted in this research. Below, we will provide a brief introduction on this debate.

The Focus of the Debate on Individualism-Holism

The individualism-holism debate revolves primarily around two fundamental issues. Ontologically, the debate focuses on the ontological status of social structures and their relationship to individuals. Epistemologically, the debate centers on how complex social phenomena should be interpreted, particularly in terms of the extent to which social scientific explanations "should" prioritize individual agency or social structures. The term "should" in the methodological debate is used to convey advice directed at researchers prepared to study complex social phenomena. It presents a 'technical' norm indicating that, unless observed, no good or genuine explanations of complex social phenomena will emerge. The individualism-holism debate offers different perspectives and answers to these questions.

The Main Points of Purely Individualism- and Purely Holism-

Ontological individualism, specifically in its atomistic form, is a metaphysical proposition that pertains to the relationship between social properties and individualistic properties. The "local" claim posits that the social properties of any given social entity depend solely on the individualistic properties of its constitutive components, while the "global" claim posits that the social properties existing in a particular world are contingent upon the prevalence of individualistic properties among the individuals in that world (Epstein, 2014; List and Spiekermann, 2013).

Proponents of individualism in social ontology assert that the social world is composed of individual human beings, and the notion of supraindividual totalities is conceptual rather than concrete and real. They argue that social totalities are abstractions and, therefore, purely ontological individualists only consider resultant properties while rejecting the emergent properties of social systems. According to this view, no part of a social system will acquire new relevant properties or causal powers solely due to its relations within that system, as the structure of any system can be exhaustively described in terms of the intrinsic properties and relations of its lower-level parts (Santos, 2021).

Regarding methodological issues, methodological individualism asserts that effective explanations of social phenomena within the realm of social science should exclusively reference facts about individuals and their properties, without involving higher-level social entities, properties, or causes. In other words, the qualitative and causal identity of any entity must be completely independent of its exogenous relations with other entities, including within the context of higher-level systemic relational structures (Santos, 2021). When seeking knowledge about social phenomena, purely methodological individualism typically repudiates the existence of any social law governing the trajectory of social macro-processes and maintains that only laws of individual action are tenable. The assertion that "social phenomena may be regarded as having been explained only when their genesis, operation, and reorganization (in the final analysis) is accounted for on the basis of the individual adaptive actions of individual actors" encapsulates their epistemological stance (Schmid, 2011:144; Pérez-González, 2020). Purely methodological individualism is considered an atomism or micro-reductionism doctrine, suggesting that any macro-attribute of social phenomena can be represented as a mere combinatorial product of the intrinsic microproperties and micro-relations of the parts of that system (Santos, 2021).

In research practice, the position of methodological individualists demands that all concepts in social theory be ultimately analyzable in terms of the interests, activities, etc. of individual members of society. The ultimate explanations for all social outcomes should be directly based on facts about individual actions, with no other elements involved (Bunge, 1979). Furthermore, all sociological hypotheses and theories are tested by observing the behavior of individuals

(Bunge, 1979).

On the other hand, proponents of holism in social ontology argue that social entities form a totality with a fully independent ontological status, transcending the individual entities that comprise it (Bunge, 1979). According to this perspective, social facts or structures exist independently of individual behavior and possess their own inherent existence (Gilbert, 1996). The parts are ultimately seen as derived from the dismantling of their wholes, while the wholes themselves are considered primitive or self-imposed entities whose origins are not fully understood (Santos, 2021).

Methodological holists, therefore, assert that the social behavior of individuals should be explained in terms of their positions or functions within a social system and the governing laws that regulate it (Bunge, 1979). For explaining social properties, methodological holists argue that adequate explanations of social phenomena must employ non-individualistic or supraindividual concepts. They suggest that social properties, rather than individual-level properties, exhibit the most systematic causal effect in social phenomena (List and Spiekermann, 2013).

A classic example of a purely holist explanation might be the statement that "the economic depression was the main cause of the outbreak of the war" (Stanford Encyclopedia of Philosophy, 2023). Methodological holists may argue that this explanation is sufficient on its own and does not require additional micro-level details that specify how the economic depression influenced individuals' beliefs, actions, etc., which in turn led to the war. Pure holism is often contrasted with pure individualism, as it rejects the search for subjective meanings or reasons behind individual actions and instead attributes the meaning and general logic of social action to social wholes.

Critiques and Development of Purely Individualism and Purely Holism

Both purely individualism and holism have faced significant criticism in the past few decades and have been rejected by the majority of social scientists, particularly in their attitudes towards the ontological and epistemological status of social structure. In the field of social science, the concept of social structure is widely used and considered one of the core concepts in explaining complex social phenomena. However, the term itself is often vague and diverse, lacking a clear ontological status. Different social scientists with different ontological positions rely on different conceptions of social structure, leading to a lack of consensus and potential misunderstandings (Elder-Vass, 2010; Ross, 2023).

From their respective ontological stances, pure methodological individualists and holists have developed their own concepts of social structure and have provided explanations for its ontological status and causal efficacy. However, the perspectives of both pure individualists and holists on the concept of social structure have faced extensive criticism in subsequent research. Here, we summarize some of the more influential critiques:

- The criticism of purely methodological individualism (MI) perspectives revolves around the core problem of structure and individual agency: whether there is something social that can have causal effectiveness on its own, rather than being a mere side-effect of individual behavior (Elder-Vass, 2010). For purely MI, the answer is “no”. Purely MI insists that all social phenomena are in principle explicable only in terms of individuals – their properties, goals, and beliefs. Social structure refers to the “patterns of aggregate behavior that are stable over time” (Porpora, 1998; Ritchie, 2020; Porpora, 1989); the concept of social structure for individualists is thus ontologically epiphenomenal – a by-product of individual behavior that has no causal efficacy in the explanation of social phenomena. However, the individualist social structure position is often considered vague and contradictory, as MI does not clearly specify whether interactions between individuals or social relations are “properties of individuals” or not. In other words, "does methodological individualism simply point to the importance of individuals in explanations of social phenomena, or does it insist that explanations should be reduced to individuals alone?" (Hodgson, 2007).

  Some questions have therefore been raised (Hodgson, 2007), including whether methodological individualism implies either of the following: (a) social phenomena can be completely explained by individuals alone, or (b) social phenomena should be explained by considering individuals and their relational dynamics (Hodgson, 2007). The first version (a) represents a more purely narrow MI, which is untenable and has never been practiced as it involves the denial of social relations. While social relations are the very glue of a community that distinguishes it from a mere arbitrary set of humans, no one can consider social relations in isolation (Bunge, 1979). In fact, all satisfactory and successful explanations of social phenomena involve interactive relations between individuals. In other words, when explanations are reduced to individuals, interactive relations between individuals are also always involved (Hodgson, 2007). Meanwhile, the second version (b) poses an ontological challenge to purely methodological individualism because structures are typically related to the collections of interactive relations between individuals. Accordingly, (b) can be seen as equivalent to asserting that social phenomena should be explained by considering individuals and their interaction with social structures (Hodgson, 2007). As Hodgson (2007: 211) pointed out, "explanations in terms of individuals plus relations between them amounts to the introduction of social structure alongside individuals in the Explanans". In summary, the purely individualist (MI) perspective, which denies the ontological status and causal efficacy of social structure in explaining complex social phenomena, is either untenable or self-contradictory in both its narrow and broader senses.

- For holists, social structure refers to the "lawlike regularities that govern the behavior of social facts". On this sociological holist view, social structure operates mechanically and naturalistically over the heads of individual actors (Porpora 1998: 342). This is the mirror image of reductionism – a denial of the causal influence of the lower level (human individuals) from which social entities emerge – and it is equally untenable as an ontological position. Fleetwood (2008) points out that holists erroneously reduce individual actions and intentions to social structures. The rejection of this position is almost universal among contemporary sociologists.

The debate between individualism and holism, in terms of explaining complex social phenomena, has long transcended the binary opposition, as evidenced by the widespread critiques of pure individualism-holism. Both perspectives have been found unsatisfactory in explaining complex social phenomena, particularly regarding the ontological status and causal effects of social structure. The majority of methodological individualists have come to acknowledge that individuals' actions are typically constrained by the macro social structure, which shapes their internal states and the available opportunities for action, thus exerting a degree of causal effect (Bruch and Atwell, 2015).

Consequently, scholars (particularly methodological individualists) have sought to reconcile individualism and holism, as well as to explore the potential for incorporating the causal effects of social structure within methodological individualism. The key insight required for this reconciliation is that one can consistently hold individualist perspectives in certain aspects while being holistic in others (List and Spiekermann, 2013; Bruch and Atwell, 2015).

As a result, methodological individualists have further distinguished between strong and weak versions of methodological individualism (MI). "Strong" versions of MI advocate for the purely methodological individualism approach introduced above, asserting that all social phenomena should be explained solely in terms of individuals and their interactions, which has been widely rejected as it denies the emergent properties of social phenomena. On the other hand, the weak versions of MI incorporate elements of both individualism and holism, recognizing the significant role played by social structure in social science explanations (Udehn, 2001: 347, 2002: 479). The shift from the "strong" to the "weak" version of MI reflects scholars' efforts to reconcile individualism and holism. As documented by Udehn (2002), the entire history of MI across authors and disciplines can indeed be thought of as a slow evolution from “strong” to “weak” versions of MI, where the distinction essentially refers to the proportion of collective and institutional (versus individual) variables, entities, and properties that are accepted within the explanation of social phenomena (Manzo, 2010; Udehn, 2002: 479).

The weak version of MI is often referred to as structural individualism, as Coleman calls it, which emphasizes the explanatory importance of the social and relational structures within which individuals are embedded (Bulle and Phan, 2017). It represents a non-reductionist variant of MI that seeks to reconcile individualistic perspectives with the role of social structure in explaining complex social phenomena, recognizing the causal power of social structure. Structural individualism is the ontological and epistemological position adopted in this study. Below, we will provide a detailed introduction to the concept of structural individualism, as well as the ontological status and causal effect of social structure within the structural individualism.

Structural Individualism

Most social structuralists, such as Coleman (1990: 300), have criticized the strong (reductionism) interpretation of ontological individualism, which insists on the "fiction that society consists of a set of independent individuals, each of whom acts to achieve goals that are independently arrived at, and that the functioning of society consists of the combination of these actions of independent individuals". In contrast, advocates of structural individualism recognize that the notion of a truly isolated individual, devoid of all social relations, is untenable. They believe that individuals are 'embedded' in social situations that can be called 'social structures' and are in no respect isolated atoms moving in a social vacuum. The explanation of social phenomena cannot be detached from the relationships and behavioral interactions among individuals embedded in "social structure" situations (Demeulenaere, 2011).

As a result, structural individualists reject the view of social structure as a "by-product of individual behavior" or "patterns of aggregate individual behavior." This view is considered atomistic and reductionist, since it implies that social structure is a simple aggregation of isolated individual actions or properties, and is considered to be entirely dependent on individual action. Instead, structural individualists believe that social structure is ontologically and causally irreducible to individual activities, emphasizing its independent ontological status as an emergent property of social systems. This perspective enables social structure to operate relatively independently of individuals, or at least of any individual (Udehn, 2002; Demeulenaere, 2011), and to exert causal influence "in their own right" (Törnberg, 2017:47).

Specifically, the concept of social structure in structural individualism refers to "a set of relations among members of a given social system and its environment (Törnberg, 2017:49)". In this view, social structure is a nexus of connections among human individuals, understood as patterns of causal interconnection and interdependence among individuals and their actions, as well as the positions that they occupy (Lopez & Scott 2000: 3; Fleetwood, 2008; Elder-Vass, 2010: 78). This definition conceives social structure in a broad sense, encompassing all kinds of structural forms likely to be encountered in the social sciences defining the social situations, including cognitive, interpersonal, rules, organizational, institutional, cultural, conventions, customs, and so forth (Bulle and Phan, 2017).

Within this, Hodgson (2007) summarized two main forms of social structure: (1) relational structure, where social structure is narrowly conceived as comprising the social relations themselves. And (2) institutional structure, where Hodgson (2007) emphasizes that social institutions are the kind of structures that matter most in the social realm, defining institutional structure as systems of established and embedded social rules, conventions, norms, values, cultures, and customs that structure social interactions. These cultural or normative patterns delineate the expectations that agents hold about one another's behavior and that organize their enduring relationships (Fleetwood, 2008; Hodgson, 2007; Elder-Vass, 2010:78).

In the concept of social structure within structural individualism, both human individuals and social structure are recognized to have causal efficacy in their own right. Specifically, in providing a reasonable explanation for emergent complex social phenomena, structural individualists distinguish between causal powers[14], representing the direct driving forces

[14] The concept of causal power is a key ontological element in critical realism (Törnberg, 2017: 45-46). Bhaskar (1978 :51) asserts that the world consists of things, not events, and that most things are complex objects possessing an ensemble of tendencies, liabilities, and powers. It is through the exercise of these tendencies, liabilities, and powers that the phenomena of the world are explained. This critical realist ontological perspective on causal power highlights two key points: (1) By dint of their intrinsic nature, only concrete, material entities possess causal powers that combine and interact to produce actual and observable events. Causal power is thus an inherent (emergent) property of concrete entities. This implies that causal power is defined as the capability or capacity of a concrete object or entity to exert a certain causal effect on the world autonomously (Elder-Vass, 2010; Kaidesoja,

arising from the intentions and actions of concrete entities, and structural properties, which do not exert direct causal power but nonetheless do have causal influence by defining situational properties that may shape, enable and constrain the intentions, preferences, capacities and dispositions of concrete entities that condition social action, which in turn may generate change (Wan, 2012; Fleetwood, 2008; Törnberg, 2017: 49).

Nathalie (2018) proposed the following propositions, which elucidate the interplay between individual agency and social structure within the framework of structural individualism-based explanation:

(A) Individuals, as the centers or producers of meaningful actions, serve as driving forces within society. Structural individualists insist that the explanation of social phenomena must be grounded in the analysis of individual behavioral interactions.

(B) While individuals hold a central role in causality, social structures define the situational properties that serve as the irreducible background conditions, providing the subjective meanings that drive individual actions and interactions. Social structures are considered to hold a causal role, as they effect changes that would not occur in the same manner under different circumstances (Carter and New, 2004: 10; Törnberg, 2017: 47). However, unlike the causal power attributed to individuals, the causal effect of social structures on complex social phenomena is indirect rather than direct. Social structures are not "efficient causal entities" (such as an organism, a person, or a group); they do not possess

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2007). human individuals are inherently concrete entities with causal power. Moreover, social entities with emergent properties are "concretively structured groups and collectives (and perhaps combinations thereof) that function as relatively enduring dynamic social systems" (Kaidesoja, 2007: 84; Törnberg, 2017: 47). The emergent properties endow social entities with a form of emergent causal power not possessed by their constituent parts (Törnberg, 2017: 48). In this context, possessing causal power means "to have a capacity or potentiality to produce a certain kind of outcome in the presence of appropriate antecedent conditions" (Little, 1998: 205). (2) In the ontological discourse of critical realism, "causes" are not understood as variables or events but are seen as those things, forces, powers, or sets of relations that make things happen or trigger events (Kurki, 2008: 174; Törnberg, 2017: 45-46). Therefore, seeking to explain social phenomena involves "the description of the real properties, structures, and generative mechanisms that underlie the actualization of events and their empirical observations" (Kurki, 2008: 166). This implies a shift in the stance on causality: moving from the dependence account of causality commonly adopted in variable-based sociology to a production account of causality (Törnberg, 2017: 46; Miller, 2015). We will further discuss this shift in the subsequent section concerning mechanism-based explanations.

effective causal power, nor do they consume, act, or produce independently. Instead, they exert influence by affecting the subjective meanings or reasons for individual actions through the contextual properties they define (Törnberg, 2017: 47; Elder-Vass, 2006). For instance, social structures act as a "causal constraint" on individual behavior, limiting the options available to individuals, while their agency makes the selections (Ross, 2023; Wan, 2012). Therefore, in structural individualism, social structures have a causal role in the macroscopic representation of emergence only to the extent that they influence the subjective meaning or reasons for individual actions through the contextual properties they define (Bulle and Phan, 2017).

To differentiate from individual interaction effects, Elder-Vass (2010: 22) describes the causal effect of social structure as the "structural effect," viewing social structure as the "latticework of relations," with individuals occupying positions and entering into relations dependent on these positions. As Fleetwood (2008) aptly encapsulates this perspective, "a social structure is a latticework of internal relations between entities that may enable and constrain (but cannot transform) the intentions and actions of agents who draw upon, reproduce, and/or transform these relations."

Furthermore, Hodgson (2003) and Archer (2003) have further pointed out that while there is a consensus that social structures enable and constrain individuals' actions, it is also believed that social structures do not directly cause individuals to formulate or modify their actions (Fleetwood, 2008; Archer, 2003; Hodgson, 2003). Instead, sociologists assert that the influence of social structures on individuals' intentions and actions is primarily mediated through reflexive deliberation and unconscious habituation, in addition to directly enabling and/or constraining interactions among individuals through social relational structures (Wan, 2012):

- According to Archer (2003), reflexive deliberations serve as the mediating process between social structure and individual agency. She explains that agents engage in reflective consideration of the social circumstances they face. With a personal identity shaped by their unique set of concerns, they understand what is most important to them and what they aim to achieve within society. Through internal deliberation about themselves in relation to their social context, they craft projects they believe will fulfill some of their societal aspirations, albeit fallibly. Since pursuing a social project typically involves interaction with social powers, manifesting as constraints and opportunities, the ongoing internal dialogue mediates how agents perceive these structural and cultural influences. Essentially, our personal capabilities are exercised through this reflective internal conversation, which is causally responsible for shaping our concerns, defining our projects, diagnosing our situations, and ultimately determining our societal practices. Reflexive deliberations thus serve as the mediating process between structure and agency, representing the subjective component that consistently interacts with the causal powers of objective social forms (Archer, 2003: 130).

In summary, the effects of relational structure on individuals' intentions are manifested in structured interests, resources, powers, constraints, and predicaments that are built into each position by the web of relationships, especially social capital. These comprise the material circumstances in which people must act, and which motivate them to act in certain ways (Elder-Vass, 2010). Thus, Archer (2003, 2006) claims that individuals would consciously take social structures into consideration (deliberations) when they reflexively deliberate upon some potential course of action. This reflexive deliberation occurs via the internal conversation, whereby agents literally talk to themselves (and sometimes others) about their needs, concerns, beliefs, attitudes, and goals and the social structures that might constrain or enable them. They then formulate (fallible) courses of action, or agential projects, they think might result in their needs being met and their concerns addressed. In essence, reflexive deliberation, via the internal conversation, is the mediatory process that links social structure and agency, and it is characterized by being reflective and relatively rational (Törnberg, 2017:44).

- Hodgson (2003) believes that the influence on the intention of an individual's behavior is not solely the result of rational deliberations; unconscious habits also play a significant role. He posits that habits and processes of habituation link institutional structure and individuals' intentions (Hodgson, 003; Fleetwood, 2008). From this viewpoint,

> institutional structures (rules, conventions, norms, values, culture, and customs) that transcend individuals become internalized or embodied within individuals as habits through habituation. Consequently, these habits predispose individuals to think and act in certain ways, without deliberation. Here, the term "habit" generally denotes an unconscious self-acting disposition or tendency to engage in a previously adopted or acquired form of action. A habitus, then, is an agential disposition generating a tendency for the individuals to do x. Habituation involves three main processes: (i) repetition, regularity, routinization, and continuity; (ii) reinforcement, or incentive and disincentive; and (iii) intimacy, familiarity, or close proximity (Fleetwood, 2008; Hodgson, 2003).

In summary, the primary means through which social structure exerts its influence on individual intention and behavior are seen to be through reflexive deliberations and unconscious habits. Moreover, these two pathways: reflective contemplation and habitual patterns – are not viewed as mutually exclusive in the shaping of individual agency. Fleetwood (2008) points out that intentions and actions are sometimes caused by habit alone, sometimes by reflexive deliberation alone, and sometimes by a combination of habit and deliberation in a complicated iterative process.

In this section, we described how social structure influences individual intentions and thereby constrains their actions, allowing social structure to have an indirect causal effect on social phenomena. For most structural individualists, the relationship between social structure and individuals is not just a unidirectional causal effect of social structure on individual actions; rather, there is a continuous cycle of interaction between social structure and individual actions (Elder-Vass, 2007). In the short run, individuals respond to and are constrained by their social situation, as mentioned above. Meanwhile, in the longer run, social structures are produced (and reproduced) from the accumulation of individuals' actions and non-linear interactions in the past (Bruch and Atwell, 2015). Social structures are thus sustained (reproduced) only through the activities of individuals, and individuals may also modify or transform social structures (Ross, 2023).

Archer (1995: 73-79) employed a continuous cycle to summarize the interaction between individual agency and social structure: structure necessarily pre-dates the action(s) which transform it; and that structural elaboration necessarily postdates those actions (Archer, 1995: 76; Greve, 2012)[15]. Therefore, there is a continuous cycle of interaction between social structure and individual actions. The examination of this interaction is based on the pre-existence of structure and the temporality of its interplay with human individuals (Elder-Vass, 2007).

Summary on Structural Individualism

We emphasize three main characteristics of Structural individualism:

- Structural individualism represents a weak version of methodological individualism (MI). It criticizes and rejects the strong MI's positions of atomism and reductionism, attributing substantial explanatory importance (with causal effect) to the social structures in which individuals are embedded (Hedström and Bearman, 2011). Structural individualism insists that a proper explanation of complex social phenomena, especially their emergence properties, should be based on the analysis of non-linear interactions among individuals within the social situation, as these interactions have direct causal power (Bunge, 2000). Social structures, by defining situational properties, can constrain and shape individuals' intentions and actions, thereby indirectly explaining social phenomena.

- Structural individualists recognize the relatively independent ontological status of social structure from individuals, as it is not merely a pattern of aggregation of individual behavior. According to Wan (2012), structural individualists argue that social structure is

[15] Archer (1995: 73-79) delineates a continuous cycle of interaction between individual agency and social structure as encompassing: (1) structural conditioning (which occurs prior to the exercise of agency), (2) social interaction (taking place within the context of these structural conditions), and (3) structural elaboration (the outcome derived from the interaction between the first two phases over time). Törnberg (2017: 43) emphasizes that the social world is inherently pre-structured: structure precedes agency because agents occupy structural positions before they act upon and modify them. As Archer (1995: 253) puts it, "[w]e are all born into a structural and cultural context which, far from being of our making, is the unintended result of past actions among the long dead." Therefore, social structures have historically emerged from the social interactions of individuals (who may have long since passed away), and individuals consequently always confront and transform pre-existing social structures rather than constructing them from scratch (Kaidesoja, 2007). This interplay between structure and agency unfolds over time, constituting a continuous causal chain and a cyclical relationship.

actually precedes concrete individuals and significantly shapes their actions. However, it still needs to be emphasized that while structures are objective and represent real commonalities among individuals, they emerge as a result of individuals' non-linear interactions, thus representing a property of social systems rather than a substantial entity (Törnberg, 2017: 47; Bunge, 1999: 69). Equating social structure with something akin to structures in nature that have a completely independent ontological status from individual behavior is inappropriate, as it is not "intrinsic to nature" (Di Iorio, 2022). Geoffrey (2010) has warned about the potential danger of reifying social structure in structural individualism, treating it as something separate from the interacting patterns of individuals that would persist even if all individuals were to disappear. In structural individualism, social structures are maintained in existence only through the interactions of individuals, meaning they are ontologically dependent on the individual activities (Kaidesoja, 2007). Although the emergence properties of social structure bring about autonomy and relative stability, ensuring the continued existence of most social structures even after the death or disappearance of a few individuals or individual interactions, social structures would still cease to exist if a significant number of individuals or their interactions were to vanish. Unlike structures in nature, social structures are only relatively enduring (are 'space–time-dependent'), and therefore, in practice, we cannot overlook the analysis of the ongoing interaction between social structure and individual interactions, especially how individual behavior shapes social structure (Benton and Craib, 2023).

As Manzo (2014) pointed out, the core theoretical proposal behind structural methodological individualism is that "structure" and "action" are related by a dynamic, circular relation that should be broken down analytically precisely in order to explain how a given high-level connection came into existence (Manzo, 2014).

- The influence of social structure on individual action and interaction is not direct but is mainly mediated through relatively rational reflexive deliberations and relatively unconscious habits. Therefore, any assertion of the explanatory power of social structure must be supplemented by some kind of account of how it shapes the relatively rational deliberations part of individual intentions, such as motivation, desire, and goals. Additionally, it must also account for the relatively unconscious habitual part of individual intentions, such as preferences, values, identity, and beliefs.

The Ontology and Epistemological Stance in This Study

This section briefly introduces the existing ontological and epistemological debates for explaining complex social phenomena in the field of social science philosophy and elucidates our own stance to clarify the philosophical background for selecting the subsequent research framework. We reject the idea of pure individualism or holism and embrace structural individualism as our ontological and epistemological stance in this study. Adopting this social research philosophy implies the following key points:

- The scientific explanation of the diffusion of college drinking in friendship networks, considered as a complex social phenomenon, must be grounded in the analysis of a multitude of heterogeneous and autonomous individuals (i.e., college students) and their non-linear interactions within the social situation defined by social structure. This approach aligns with the shifts in research focus advocated by the social complexity framework.
- Individual behavior has direct causal power over complex phenomena. Our analysis should focus on the non-reductive emergent properties of the complex social phenomena, necessitating an adequate explanation of the micro-macro transition, specifically how the interactions of college students lead to the emergence of the phenomenon of alcohol diffusion.
- Social structure mainly includes relational structure, i.e., the social network structure in which college students are embedded, and institutional structure, i.e., the influences of norms and cultural aspects within the social network of college students in this study.
- Social structure exerts indirect causal effects on the emergence of complex social phenomena by defining situational properties that constrain and shape the intentions and actions of individual college students, thereby indirectly explaining social

phenomena.

- Social structure primarily influences individual intentions and actions through rational reflection and habituation. Therefore, when explaining the emergence of the target social phenomena, we need to consider the impact of relational structure and institutional structure on the motivations, goals, preferences, habits, and identity of individuals.
- The relationship between social structure and individual action involves continuous interaction. We must account for how social structure is perceived by individuals and influences their actions, how social structure is shaped within the process of individual interactions, and how the co-evolutionary process between individual actions and social structure unfolds.

Section 2: Mechanism-Based Explanation

The preceding section on ontology and epistemology provides a foundation for addressing two fundamental questions: what constitutes a valid knowledge claim of complex social phenomena and how such knowledge, along with explanations for these phenomena, can be attained (Moon and Blackman, 2014). Structural individualism, building upon methodological individualism's emphasis on individual actions and interactions, accentuates the "explanatory importance of relations and relational structures" in shaping these interactions. Grounded in our methodological individualist epistemology, acquiring knowledge and explanations of complex social phenomena necessitates a dual focus: not only on the micro-macro transition from the nonlinear dynamics of individual interactions to the emergent properties of complex social phenomena, but also on how the structured situational context constrains and situates individual behavioral interactions.

Following the epistemological foundation of structural individualism, we can obtain or construct various forms of scientific explanations for complex social phenomena.[16] The question arises: what kind of explanation is appropriate, sufficient, and ideal? Hedström

[16] In the social sciences, (causal) 'explanation' means an account of how a social phenomenon comes about or why it varies. Building an explanation of a social phenomenon entails then establishing a link between antecedent fact(s) A (the 'explanans') and an outcome B (the 'explanandum') (Skopek, 2023:148).

(2005:14) identifies three main types of explanations in social science: covering-law explanations, statistical explanations, and mechanism explanations. He outlines the primary differences among these types of explanations in the following table:

Table 1: Three Types of Explanations

	Covering Law Explanations	*Statistical Explanations*	*Mechanism Explanations*
Explanatory Principle	To subsume under a casual law	To identify a statistical relationship	To specify a social mechanism
Key Explanatory Factors	"No restriction, except that the factor must exhibit a law-like relation to the event to be explained"	"No restriction, except that the factor must be statistically relevant to the event to be explained"	"Action-relevant entities and activities and the way in which they are linked to one another"

The covering law explanation is a deductive argument in which the explanandum phenomenon serves as a conclusion, supported by one or more empirically validated general laws and a set of statements outlining specific initial conditions as premises. Within the covering law approach, explanation and prediction are essentially equivalent (Hedström and Ylikoski, 2010). However, covering law approach is considered a failure as a theory of explanation in social science research, primarily due to the scarcity of observable empirical regularities that could serve as explanatory (Hedström and Ylikoski, 2010; Cummins, 2000). Statistical explanations are prevalent in variable sociology, which typically focuses on variables describing the attributes of social systems or their components. These analyses employ empirical data derived from randomized controlled trials (RCTs) or observational studies, utilizing statistical causal inference to explore causal dependencies between variables (Goldthorpe, 2001; Manzo, 2022). In this study, grounded in our position on the production account of causality,[17] we adopt Hedström's (2005) categorization of scientific explanations

[17] The concept of "causality" can be interpreted in different ways in social science. Goldthorpe (2001) classified three types of causation interpretations:

(1) "Robust dependence": the causal claim depends on demonstrating that X continues to affect Y when a set Z of other variables, which may also be related to Y, are introduced in the analysis (Goldthorpe, 2001:2; Manzo, 2022:14-15);

(2)"Consequential manipulation": "genuine causation is that if a causal factor, X, is manipulated, then, given appropriate controls, a systematic effect is produced on the response variable, Y" (Goldthorpe, 2001:4-5; Manzo, 2022:14-15);

(3)"Generative process": "[...] what is important is the nature and the validity of the account given of the process that underlies the association appealed to [...]" (Goldthorpe, 2001: 9; Manzo, 2022:14-15).

Casini and Manzo (2016) synthesized these three interpretations into two philosophical concepts of causality, where "robust dependence" and "consequential manipulation" belong to <u>the first category: dependence (or</u>

and consider a generative causal mechanism-based explanation (MBE) that satisfies the criteria of generative sufficiency to be a suitable and comprehensive explanation for a complex social phenomenon under the structural individualism epistemological foundation. To elucidate this stance, we will first define the concept of mechanism and MBE.

Social Mechanism

The definition of mechanism varies in different academic contexts. Hedström and Bearman (2009: 6) summarize several of the most frequently cited definitions of mechanism by scholars in the following table:

difference-making) accounts of causality, encompassing regularity, probabilistic, and counterfactual views of causality. Conversely, "generative process" falls under the second category: production accounts of causality, which include process, entities-and-activities, and dispositionalist accounts (Casini and Manzo, 2016; Hall, 2004). Casini and Manzo (2016) pointed out that the fundamental idea behind dependence accounts is that causes make a difference to their effects, while production accounts emphasize that causes help generate or bring about their effects.

The causal inference paradigm based on the Rubin causal (potential outcome) model pertains to a type of dependence, or difference-making, account of causality. In contrast, research based on generative methods interprets causality in terms of the "production accounts of causality" as proposed by Casini and Manzo (2016), where causal relationships are regarded as generative in nature.

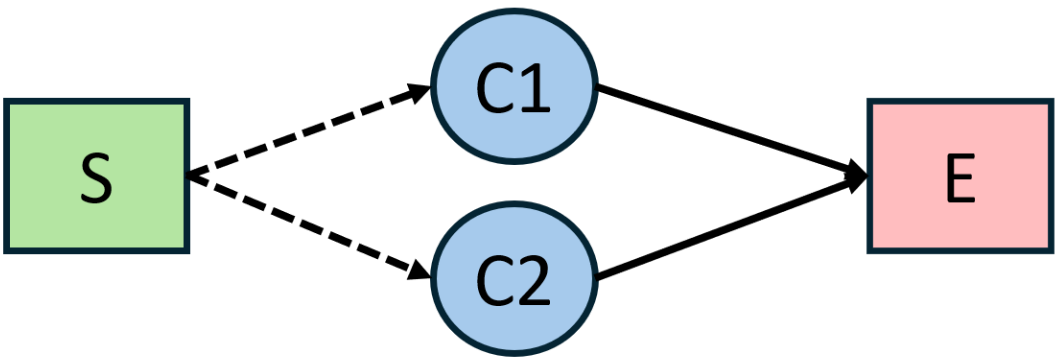
Table 2: Alternative Social Mechanism Definitions

Reference	***Definations***
Mayntz, 2003: 4	Mechanisms state how, by what intermediate steps, a certain outcome follows from a set of initial conditions
Machamer et al., 2000: 15	Mechanism refers to recurrent processes linking specified initial conditions and a specific outcome; in the case of social mechanisms, social phenomena are to be explained. If social mechanisms refer to recurring processes, mechanism concepts must be "truncated abstract descriptions"
Boudon, 1998: 172	"the well-articulated set of causes responsible for a given social phenomenon
Elster, 1989	A mechanism explains by opening up the black box and showing the cogs and wheels of the internal machinery. A mechanism provides a continuous and contiguous chain of causal or intentional links between the explanans and the explanandum.
Hedström and Swedberg, 1998	Mechanism is the part of a process that "links" cause (or input, initial conditions) and effect (outcome), or formally expressed as I—M—O. The mechanism M serves to explicate an observed relationship between specific initial conditions and a specific outcome
Mayntz, 2004	Mechanism refers to recurrent processes linking specified initial conditions and a specific outcome; mechanisms state how, by what intermediate steps, a certain outcome follows from a set of initial conditions.
Elster, 1999	Mechanisms are frequently occurring and easily recognizable causal patterns that are triggered under generally unknown conditions
Hedström, 2009	Mechanism is "a constellation of entities and activities that are linked to one another in such a way that they regularly bring about a particular type of outcome"
Hedström, 2005: 11	Mechanism represents a fixed causal relation which regularly leads from an initial state to an observed outcome.
Bunge, 1997	Mechanisms are frequently occurring and easily recognizable causal patterns that are triggered under generally unknown conditions

Manzo (2022: 18-22) classifies the existing definitions of mechanisms into two perspectives: "horizontal" and "vertical" views. The horizontal view refers to sets of counterfactual dependencies between variables[18], while the vertical view typically denotes a collection of entities and activities that dynamically generate an outcome through iterative aggregation across various levels (or scales) of analysis. Grounded in the realist ontological stance of this study, the concept of causal mechanisms discussed here refers to vertical mechanisms.[19] The most comprehensive conceptual analysis of the vertical mechanism concept is provided by Machamer et al. (2000). Their framework characterizes mechanisms as a causal pattern consisting of structured entities, along with their properties, and the activities in which these entities engage, either individually or in collaboration with other entities. These activities lead to changes, and the specific type of change that occurs depends on the properties of the entities and the way in which they are interconnected. In the context of social science, a social mechanism thus refers to a configuration of entities (with their properties) and the corresponding activities that are organized in a manner that consistently produces a particular type of regular outcome. In their own words, "mechanisms are entities and activities organized such that they are productive of regular changes from start or set-up to finish or termination conditions" (Machamer et al., 2000: 3; Manzo, 2010).

The following figure 1 illustrates a typical social mechanism unit model (Hedström, 2005: 30):

Figure 1: A Typical Social Mechanism Unit Model



The nodes C in the figure represent conditions, node S represents the social situations defined

[18] Although much of variable sociology research involves mechanism analysis aimed at "opening the black box," this analysis is based on the horizontal view of mechanisms. In this context, opening a black box equates to uncovering intermediate variables between a treatment and an outcome, such as chains of intervening variables, or "as an intervening variable or set of intervening variables that explain why a correlation exists between an independent and dependent variable" (Manzo, 2022: 22-24; Mahoney, 2001: 578).

[19] The pursuit of vertical MBE does not imply a rejection of horizontal MBE. Both horizontal and vertical MBE explanations can offer essential and complementary insights for constructing compelling causal statements to explain social phenomena, it will be discussed further in Chapter 7.

by social structure, and node E represents the effect or outcomes. The solid lines in the figure represent the detailed causal processes through which Conditions (C1) and Conditions (C2) can lead to the effect (E), while the dotted line represents the "ensuring condition" that holds in social situation S (Hedström, 2005: 30). A social mechanism indicates a causal chain where, under social situation S, if C1 fails to occur, C2 would occur, and C2 would bring about E (and vice versa if C2 fails to occur) (Hedstrom, 2005).

Given our epistemological stance of structural individualism, there are four key points to consider regarding the above social mechanism model:

- Conditions (C1) and (C2) describe the real entities with causal powers and the configuration of their activities: their internal states, attributes, actions and interactions.
- The shaping and constraining of individual properties by the social structure situation (S) should not be overlooked as a mechanism consists of a structured constellation of entities and activities. The effects of mechanisms are typically dependent on the social context defined by social structure in which the mechanisms are activated (Pozzoni, and Kaidesoja, 2021). As Falleti and Lynch (2009: 1151) pointed out, "the same mechanism operating in different contexts may lead to different outcomes". Hedstrom (2005) similarly pointed out that the same entities (individual actors) strung together in different ways can be expected to regularly bring about different types of outcomes. Furthermore, due to structural individualism support for ongoing interaction between social structure and individual interactions, the dashed arrow from S to C might be bidirectional rather than unidirectional in the long run.
- Mechanisms can be hierarchically nested. A mechanism at one level presupposes or takes for granted certain entities and activities, but there are often lower-level mechanisms that account for them. For example, if the effect (E) in one mechanism is a micro-level fact, that effect (E) may play a part or the whole as the conditions (C) in other mechanisms. Similarly, if the effect (E) in one mechanism is a macro-level facts outcome, that effect (E) may play as a part or the whole as the social situation (S) in other mechanisms. Through such nesting, we can allow different mechanism units to be structurally combined, forming a nested hierarchy structure to present a more complete and detailed causal

chain (Hedström and Ylikoski, 2010). Such combinations of social mechanisms are crucial, as scholars widely acknowledge that most effects or outcomes of interest arise not from a singular mechanism but from an interplay of multiple mechanisms that operate either sequentially or through various combinations (Gross, 2018).

- In the above figure, both conditions C1 and C2 could bring about the social phenomenon E. This represents a common case of causal overdetermination (or "multi-realizability"): in the same social context, there may be multiple social mechanisms leading to similar results. Conte and Paolucci (2014) pointed out that multi-realizability is a property not only of social mechanism but also of the real world.

Furthermore, existing research has highlighted two key characteristics of social mechanisms:

1. Distinction between "mechanism" and "process": Manzo (2014: 7) emphasizes that a mechanism is a "causal notion" (or causal pattern) without causal power (Elster, 1999:1; Hedström and Ylikoski, 2010; Elder-Vass, 2015), as mechanisms themselves are not real entities. A mechanism describes a set of structured entities and activities that are likely to trigger a sequence of events (i.e. a process) to bring about the observed outcome with a certain degree of regularity. Therefore, the "process" is triggered by the mechanism, and therefore, "mechanisms" always logically precede "processes" (León-Medina,2017b; Manzo, 2014).
2. Social events typically result from the simultaneous operation of multiple causal mechanisms associated with the contingent combination of various entities (Sorrell, 2018). Consequently, one can only expect an invariant association between specific causal mechanisms and particular types of events under rather exceptional conditions—specifically, when both the relevant entities and mechanisms remain stable, along with the conditions that govern the operation of those mechanisms (Sorrell, 2018).

Mechanism-Based Explanation (MBE)

Building on the previously defined concept of social mechanisms, we define Mechanism-Based Explanation (MBE) of a given complex social phenomenon as a causal statement that encompasses a set of social mechanisms or a nested form of social mechanism units. These social mechanisms or their combinations bridge the gap from initial conditions of a generative process to resulting social phenomena, unfolding the "linked chain of causes" that adequately constitute a scientific explanation of the target social phenomenon (Conte, 2009; León-Medina,2017b).

Particularly, in the context of scientific explanation, providing a scientific explanation of a given social phenomenon is understood as answering a "why-question" about its occurrence (Pozzoni and Kaidesoja, 2021), rather than merely focusing on a "what-question" about which factors (variables) influence the occurrence of the phenomenon. This includes questions like why events or social phenomena occur, why changes happen over time, or why states or events covary in time or space (Hedström, 2009). For MBE, answering these "why" questions imply answering a series of "how" questions.

The focus on social mechanisms thus breaks down the original explanation-seeking "why-question" into a series of smaller "what-questions" and "how-questions" about the causal process that must be answered to satisfactorily explain a phenomenon: What are the participating entities, and what are their relevant properties? How are the interactions of these entities organized (both spatially and temporally)? Etc. (Hedström and Ylikoski, 2010; Pozzoni, and Kaidesoja, 2021). As Elster pointed out: "A mechanism explains by opening up the black box and showing the cogs and wheels of internal machinery. An MBE provides a continuous and contiguous chain of causal or intentional links between the explanans and the explanandum" (Elster, 1989; Hedström and Bearman, 2009).

Pursuing MBE for Complex Social Phenomena

In this study, we seek to provide generative causal Mechanism-Based Explanations (MBEs) for complex social phenomena, for two main reasons:

- Pursuing MBE for complex social phenomena is an inevitable consequence of the epistemological stance of structural individualism which insists on the need for causal explanations of social phenomena to be grounded ultimately in accounts of the action and interaction of individuals embedded within social structures (Goldthorpe, 2001). Specifically, the commitment to structural individualism leads to a specific answer regarding the components of a causal mechanism that explains a social phenomenon.

Hedström and Bearman (2009: 7-8) articulate that the principle of causal MBEs is intrinsically linked to the epistemological stance of structural individualism: the fundamental principle behind the MBE approach is that proper causal explanations must identify the entities (their properties, actions, internal states) and relations that collectively produce the collective outcome to be explained (Di Iorio, 2016; Pérez-González, 2020). Therefore, adhering to the epistemological stance of structural individualism, MBE illustrates the accepted standard for explaining complex social phenomena, addressing the question of what constitutes a good causal (mechanism) explanation.

- MBE is suitable for explaining complex social phenomena that have a certain level of abstraction. Hedström and Ylikoski (2010) point out that MBE has two types of Explananda.

Firstly, Explanandum may address specific empirical facts or cases. In such cases, the description of the mechanism often involves modifying and combining more general mechanism schemes (Hedström and Ylikoski, 2010).

Secondly, Explanandum may address stylized facts. Although explaining specific empirical facts may be the ultimate goal of mechanistic theory development, most of the time theorists are addressing highly stylized theoretical Explananda that do not necessarily closely resemble any particular empirical fact. Hedström and Ylikoski (2010) further notes that a mechanistic explanation selectively describes the causal process, aiming to capture the crucial elements while abstracting away irrelevant details. The relevance of entities, their properties, and their interactions is determined by their ability to make a relevant difference to the outcome of interest. If the presence of an entity or changes in its properties or activities do not make any difference to the effect to be explained, they can be ignored (Hedström and Ylikoski, 2010). Therefore, the process of dissecting and abstracting is crucial in pursuing MBE in practice. By dissecting, a complex totality is decomposed into its constituent entities and activities, focusing on what is believed to be the most essential elements or disregarding those elements believed to be of lesser importance. This process makes the important cogs and wheels of social processes visible and intelligible (Hedström, 2005). Thus, MBE is suitable for explaining complex social phenomena with a certain level of abstraction and regularity. In existing research, a significant amount of MBE is not fully dependent on specific empirical contexts and often involves a certain level of abstraction. Balancing the realism and abstraction of MBE can to some extent reduce its reliance on specific empirical scenarios and social conditions, thereby contributing to the explanatory power and generalizability of MBE for a class of social phenomena. Renate (2004) summarizes that all MBEs explicitly position themselves at equilibrium points between general applicability and empirical adequacy, which are two inherently trade-off goals. Pozzoni and Kaidesoja (2021) point out that any given mechanism-based explanation statement can be characterized by (1) the level of reality it refers to, (2) its degree of conceptual abstraction, and (3) the scope of its claimed applicability at a given level of abstraction. The abstract nature of MBE makes it particularly suitable for the present study, as our target phenomenon is not a purely empirical case-based phenomenon but rather regularly observed social phenomena with a certain level of regularity and abstraction.

Section 3: "Coleman's Boat" Diagram and Theoretical Hypothesis

So far, we have elaborated on our epistemological stance of structural individualism, which indicates that in order to achieve explanations for complex social phenomena, we need to analyze the actions, attributes, and relationships of entities with causal power. Additionally, we need to analyze the influence of social structure situations on the interactions between entities with causal power, as social structure possesses indirect causal effects. Seeking vertical causal MBE for complex social phenomena is an inevitable choice and requirement under this epistemological stance of structural individualism. Seeking MBE for the target social phenomena indicates that we need to abstract and analyze the social mechanisms that give rise to emergent properties of the target complex phenomena, as well as the structural relationships between these social mechanisms. This process bridges the complete causal chain from initial conditions of a generative process to the resulting complex social phenomenon, opening the black box and revealing the cogs and wheels of the internal machinery.

In research practice, constructing a suitable MBE for a complex social phenomenon typically entails developing a "generative model" for the target social phenomena, followed by calibrating and validating this model (Manzo, 2014). The term "generative models" here refers to a set of theoretical hypotheses that constitute the MBE hypotheses for the target phenomenon, making theoretically informed guesses about the set of entities, properties, activities, relations, and interactions that are potentially responsible for a given observed connection of the target phenomenon.

Manzo (2014) points out that the connection between the target complex social phenomenon and its postulated MBE should be proven by recreating the connection itself, rather than just verbally stating or sketching the existence of this connection. The functioning of a potential MBE must be carefully designed, and its consequences must be triggered, not just inferred based on the supposed signature of the mechanism (Manzo, 2014). As stated by Epstein (2006: xii), "to explain an observation is to generate it," or in Macy and Flache (2009:263)'s words, “if you don’t know how you grew it, you didn’t explain it”.

We thus need to first address how to construct a potentially reasonable MBE hypothesis to explain the target complex social phenomenon. Is there a mature and effective thinking tool or theoretical framework that can help us analyze complex social phenomena and propose a reasonable potential generative model for subsequent testing through generative methods? In this study, we believe that “Coleman's Boat” diagram (1987, 1990) provides a diagram for theoretical analysis and a powerful cognitive tool for thinking. By following the research framework provided by "Coleman's Boat" diagram, we can construct a potentially feasible MBE hypothesis for the target complex social phenomena. To clarify this point, we first introduce what "Coleman's Boat" diagram is.

"Coleman's Boat" Diagram

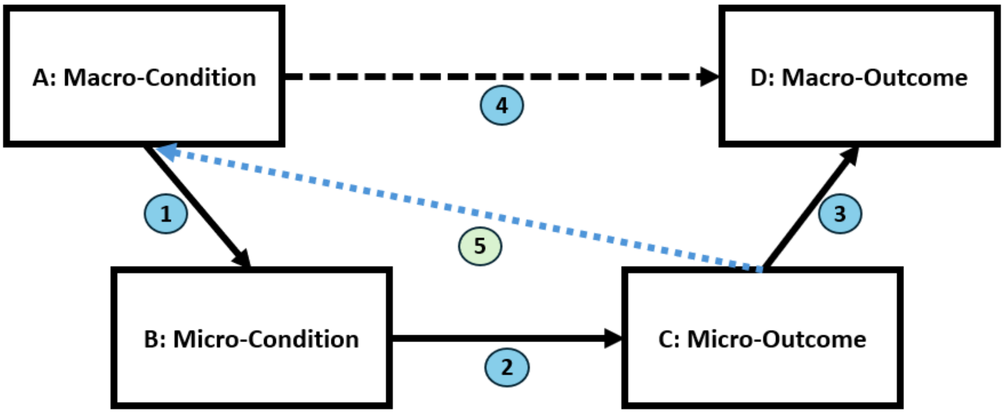
Coleman's boat diagram, also known as Coleman's Boat, provides a meta-model of mechanisms linking macro social facts to micro social facts (Vu, et al., 2020). It helps to illustrate one of the central analytical issues in exploring complex causality sociologically; specifically, it addresses whether there exist fully macroscopic explanations—explanations linking one "macro-" property to another macro-property, similar to Durkheim and social facts, that are separate from explanations that link one macro-property to another via micro-causal pathways. If so, what is the nature of the difference? (Jepperson and Meyer, 2011). To address these questions, Coleman, in fact, follows the epistemological stance of structural individualism, positing that social structures have only indirect causal effects, not direct ones. He discourages macro-macro mechanisms explanations and instead develops a macro-micro-macro research model to open the "black box" of the causal process.

In this sense, "Coleman's Boat" provides an ideal depiction of a mechanism-based sociological explanatory narrative pattern, a viable research path to help us identify the processes that link a causal relationship between two macro social facts (the Explanandum and Explanans). These processes are as follows:

- How social structures constrain individuals (Macro-Micro);
- How individuals make decisions under restrictions (Micro-Micro);
- How individuals interact and arrive at certain social outcomes (Micro-Macro) (Mills et al., 2006b).

By doing this, Coleman's Boat shows three analytically distinct explanatory subtasks among four nodes (Vu, et al., 2020; Raub, et al., 2011). The following figure provides a visual representation of these nodes and arrows.

Figure 2: Coleman's Boat Diagram



The nodes A-facts and D-facts in Figure 2 refer to various sorts of macro social facts that function as Explanans and Explanandum in sociological explanations. A-facts represent macro-social structure situation factors that might influence individuals and might be cited as causes of social phenomena. D-facts are macro-complex social phenomena to be explained (Ylikoski, 2021). The node B-facts refers to the intentions and properties of individuals, which include relatively rational deliberations and internal states such as desires, motives, goals, as well as relatively unconscious habits, values, beliefs, preferences, emotions, and identities. All these internal state concepts are used in the explanation of individual behavior, and their purpose is to mediate between social situation influences and individual behavior. B-facts are essential in the diagram since they explain individual behavior (C-facts) and mediate the situational influence of A-facts on individual behavior. The node C-facts refers to individual behavioral outcomes, which may include choices, behaviors, or actions, depending on the contextual analysis (Ylikoski, 2021).

Social mechanisms are embedded in Coleman's conceptual framework as the key concept to explain social phenomena (Billari, et al., 2006), which is depicted in the diagram as arrows connecting the various nodes. By doing this, Coleman's conceptual framework forms different social mechanisms into a nested hierarchy structure to present a more complete causal chain. The explanatory relationship arrows in the diagram can be understood as follows:

- **Arrow 1**: Situational mechanisms (macro-micro) explain how individuals' internal states are impacted by exposure to social structure situations that individuals are embedded in. It "link a social structure or other macro-sociological event to the beliefs, desires, and opportunities of some individual actor" (Raub, 2021), which attributes substantial explanatory importance to the social structures in which individuals are embedded (Wan, 2012).
- **Arrow 2**: Action formation mechanisms (micro-micro) represent a micro-theory which explains how individuals perform actions because of their internal states, showing "how a specific combination of individual desires, beliefs, and action opportunities generate a specific action" (Raub, 2021). It typically delineates the regularities of individual behavior and perhaps encapsulates a general theory of behavior (Raub et al., 2011).

  Concerning micro-level behavioral regularities, while some early researchers, such as Coleman, advocated the use of rational choice assumptions (Gërxhani et al., 2022:7), subsequent micro-level theories have diverged from standard rational choice postulates, employing a variety of individual behavioral regularities (Raub, 2021).

- **Arrow 3**: Transformational mechanisms (micro-macro) specify or reconstruct the complex processes whereby the actions and interactions of interconnected actors generate the intended or unintended macro-level outcomes (Wan, 2012). The micro-macro transition is the most interesting and important part of the model, moving from the individual level to the societal level, or in Coleman's words, "the central theoretical problem in sociology is the transition from the level of the individual to a macro level" (1986:347), since "[t]he interaction among individuals is seen to result in emergent phenomena at the system level" (Bunge, 2000).
- **Arrow 4:** directly connects the Explanans of the study to the Explanandum, representing propositions about empirical regularities observed at the macro-level, such as the associations between macro-conditions and macro-outcomes (Raub et al., 2011). The use of a dotted line for this arrow signifies the absence of specific macro-level mechanisms

within Coleman's boat, as Coleman insists that "explanations that simply relate macro properties to each other (arrow 4) are unsatisfactory" (Coleman, 1990; Elster, 2015). Bearman and Hedström (2009) noted that macro-level relationships per se reveal little about why we observe macro-level outcomes or about micro-level processes that bring about macro-level outcomes and macro-level relationships. Instead, macro-macro level factors are interconnected through a combination of situational, individual action, and transformational mechanisms (indicated by arrows 1 to 3) (Hedström and Swedberg, 1998: 99). An assertion of a structure or process at the macro-social level (causal, functional, structural) must be supplemented by some kind of account of how it is that ordinary actors, situated in specified circumstances, come to act in ways that produce the stipulated structures and causal processes (Little, 2012).

Rather than being seen as a metaphysical or theoretical proposition, it is more appropriate to view Coleman's boat diagram as an efficacious analytical thinking tool. It illustrates how MBE under the principle of structural individualism is generated, as macroscopic complex social phenomena are conceptualized as a long chain of successive "macro-micro-macro" transformations.

In this study, we will apply the "Coleman's Boat" Diagram as an analytical tool for analyzing the target complex phenomenon and formulating our MBE hypothesis for the phenomenon. Nonetheless, before proceeding, it is important to recognize that the original version of the "Coleman's Boat" Diagram is inconsistent with our structural individualism epistemological stance and thus cannot be directly applied to analyze the complex social phenomenon of this research. We need to make two appropriate modifications to the original "Coleman's Boat" Diagram to align it with the structural individualism epistemological stance:

- The "macro-micro-macro" framework in the original "Coleman's Boat" Diagram represents only the unidirectional influence of the social structure on individual internal states and behaviors through situational mechanism, neglecting the reciprocal shaping of social structure by individual-level interactions. Structural individualism emphasizes that the relationship between social structure and individual action involves continuous interaction. While considering how how social structure is perceived by individuals and influences their behavioral interactions, it is also important to focus on how social structure is shaped through the process of individual interactions, and how the co-evolutionary process between individual actions and social structure unfolds (Benton and Craib, 2023).

Therefore, it is essential to consider an additional arrow originating from the Micro-Outcome Node (C) and pointing towards the Macro-Condition Node (A) (referred as arrow 5 in Figure 2), representing the mechanism through which micro-level interactions among individuals shape the social structure in which they are embedded. In this context, arrows 1, 2, 5 form a closed feedback loop, illustrating the co-evolutionary process between social structure and individual interaction, and also highlighting the nonlinearity of individual interactions within complex social systems. This continuous bidirectional interplay between individual behavior and social structure is pivotal to our research and will be integrated into our analytical framework.

- Secondly, strictly speaking, the situational mechanisms represented by arrow 1 in the original "Coleman's Boat" Diagram do not conform to the definition of a "social mechanism" within the structural individualism framework, as the social structure cannot act as a condition within a social mechanism model.[20] Hence, we clarify that the term "situational mechanisms" in this context is a broad characterization, actually depicting the situational influence of the social structure on individuals embedded within it, normally mediated through rational reflections and ingrained habits.

By addressing these conflicts between the Coleman's Boat Diagram and our epistemological stance of structural individualism with the aforementioned modifications, we will apply the adapted Coleman's Boat Diagram to analyze the target complex social phenomena in this study and propose the MBE hypothesis for the phenomenon.

[20] While social structure exerts causal effects, it is not a real entity endowed with causal power and, therefore, cannot serve as a condition for social mechanisms.

Research Questions and Hypotheses

Explanandum and Explanans

Based on the framework of "Coleman's Boat" Diagram, the first step is to clarify the macro-social facts represented by node A and node D, which are the Explanans and Explanandum of the study, respectively:

The Explanandum (Node D) represents a complex social phenomenon of interest, which is the diffusion of drinking behavior in social networks of college students. This phenomenon is the main focus of the study, representing the macro-level social phenomenon that we aim to explain.

The Explanans (Node A) serves as the starting point of the study, aiming to investigate the relationship between the Explanans (macro-conditions) and the Explanandum (macro-outcome) in terms of mechanisms.

In this study, we are particularly interested in two social structural elements that make up the Explanans:

- Cultural Significance of College Drinking Behavior: Current research indicates drinking behavior in college social networks is seen as a highly scripted ritualized behavior (as discussed in the literature review chapter). The cultural significance of drinking behavior is considered an important social institutional structure that may potentially contribute to explaining the emergence of the target social phenomena via situational influence on the college students.
- Social Capital: college friendship network describes the social relational structure in which college students are embedded, while social capital refers to the resources that are embedded within the friendship networks of college students, indicating a structure of potential resource flow relationships among college students (as discussed in the literature review chapter) which may also potentially contribute to explain the emergence of target social phenomena via situational influence on the college students.

Research Questions

According to Coleman's diagram, as indicated by arrow 4, the aim of this study is to understand how the Explanans (Node A) causes the emergence of The Explanandum (Node D). Therefore, we need to address the following two "How" research questions:

- Research Question 1: How does the cultural significance of drinking behavior contribute to the emergence of the spread of drinking behavior in friendship network of college students?
- Research Question 2: How does social capital contribute to the emergence of the spread of drinking behavior in friendship network of college students? [21]

Based on "Coleman's Boat" diagram, to answer these two "How" questions indicated by arrow 4, we need to address the following four "How" questions following the macro-micro-macro path indicated by arrow 1 to arrow 3, namely:

Following arrow 1, we need to investigate:

- Research Question 3: How does the cultural significance of drinking behavior influence the internal state of individual college students?
- Research Question 4: How does social capital influence the internal state of individual college students?

Following arrow 2, we need to answer:

- Research Question 5: How do the internal states of individual college students influence their behavioral decision-making and interactions process?

Following arrow 3, we need to address:

- Research Question 6: How do the behavioral interactions of individual college students lead to the emergence of the diffusion of drinking behavior in friendship networks?

Additionally, due to the modification to the application of Coleman's diagram in this study, we also need to address an additional research question to complement the main research questions:

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[21] Strictly speaking, in the research questions, social capital and college drinking culture, as explanans, have a limited causal power. This is because individual actions and interactions possess direct causal efficacy, whereas social structural factors exert causal power only through situational mechanisms that influence individuals within the social structure.

- Research Question 7: How do the behavioral interactions of individual college students co-evolve with friendship networks?

MBE Hypotheses

In order to address the research questions raised above, we will analyze the social mechanisms represented by Arrow 1, Arrow 2, and Arrow 3 in the "Coleman's Boat" Diagram and propose an MBE hypothesis to bridge the gap between Explanandum and Explanans. The MBE hypothesis is composed of the following five main hypotheses:

- **Hypothesis 1**: Consistent with Coleman's diagram, as indicated by arrow 1, we propose that social capital and the cultural significance of drinking within the social network will influence the internal state of individual students through situational mechanisms. Specifically,
    - **Hypothesis 1.1**: We hypothesize that the cultural significance of drinking behavior influences the identity formation of college students within the social network. According to the literature review chapter, engaging in identity formation is an essential task for college students, and identities emerge and develop through dynamic interactions between individuals and their social situation. Psychologists often suggest that identity formation follows the classic Marcia style "Commitment-Exploration-Reconsideration" model.

      Existing empirical studies have indicated that the cultural significance of college drinking behavior makes it a highly scripted ritualized behavior, shaping the collective identity of college students. Therefore, as an important part of the situational mechanism describing the influence of the social institutional structure on the internal state of college students, we argue that the cultural significance of drinking behavior will affect college students' identity formation and shape their perception of drinking based on their identity commitment.

      The influence of cultural significance of drinking behavior on identity formation can vary among individuals. The heterogeneity of individual identity statuses suggests that the degree of influence of the social situation on an individual's identity formation process varies, as does the stability of identity statuses among different individuals, while individuals' responses to the social context may also vary with individual differences. Therefore, **we hypothesize that the cultural significance of drinking behavior will influence the identity formation of college students, with effects varying among individuals.**

Specifically, some individuals, strongly influenced by the drinking culture, often closely associate one’s acceptance of drinking behavior with their identity preferences. For instance, embracing drinking may be seen as a manifestation of rebelliousness or an endorsement of perceived maturity and independence, while choosing not to drink may be interpreted as conformity to mainstream social norms or a preference for adhering to established rules.

Conversely, individuals less influenced by the drinking culture may refuse to associate their drinking behavior with any specific identity or value preference.

- **Hypothesis 1.2**: Another essential part of the situational mechanism describing the influence of the social relational structure on the internal state of individuals, as college students are embedded in a friendship network structure. **We hypothesize that the instability of social capital will motivate college students to engage in social integration to maintain or increase the social support they receive from their friendship networks**. As mentioned in the literature review, establishing new social connections and seeking social support are crucial tasks for college students in the new campus social environment.

- **Hypothesis 2**: According to Coleman's diagram, as indicated by Arrow 2, we propose that the internal state of college students, including their individual identity commitment and the need to obtain social capital, will play a role in shaping their friendships and decisions regarding drinking behavior through action formation mechanisms. Specifically,

- **Hypothesis 2.1**: **We hypothesize that college students' identity commitment will influence individual's friendship formation through similarity-based peer selection, manifesting as social inclusion and social exclusion.** The inclusion mechanism implies that college students are more inclined to establish or strengthen friendships with individuals who share similar behaviors and identity, while the exclusivity mechanism implies that college students are inclined to exclude individuals who hold conflicting identities or behaviors. It is important to note that these homophily and exclusivity mechanisms are preferences and non-rational habitual behaviors.

- **Hypothesis 2.2**: **We hypothesize that college students' motives and objectives to establish social connections and seek social support will influence their choices regarding drinking behavior.** The choices made by college students regarding drinking behavior may affect their friendship connections within the social network, ultimately determining the social support they can receive from their friends. In pursuit of the goal of establishing new social connections and seeking social support, college students will engage in relatively rational deliberation by reflecting on their social structure situation to analyze the information they can obtain from the environment to make decisions about drinking behavior that align with their objectives. As mentioned in the literature review, when individuals decide on their drinking behavior for social capital purposes, this is often interpreted as drinking for social motives and conformity motives.

Moreover, as indicated by arrow 5, it is important to note **Hypothesis 2.3**: **The drinking behavior choices and attitudes towards college drinking among individual students, both driven by social capital, along with their similarity-based friendship selections, will collectively contribute to the formation of the friendship network in which they are embedded.** The newly formed social relational structure will, in turn, reshape the behavioral interaction structure among individuals through the situational mechanism represented by arrow 1, highlighting the co-evolutionary process between college drinking behavior and social relational structure.

- **Hypothesis 3**: Based on Coleman's diagram, as indicated by arrow 3, **we hypothesize that the non-linear interaction among college students will result in the emergence of the diffusion of drinking behavior within the social network environment through a bottom-up transformational mechanism.**

Section 4: Using ABM to Test MBE Hypotheses

In the preceding section, we followed the Coleman boat diagram framework to propose six theoretical hypotheses for the target complex social phenomenon. The combination of these six hypotheses constitutes the MBE hypothesis for the target phenomenon. However, it remains uncertain whether the MBE hypothesis provides an effective scientific explanation for the target phenomenon. Therefore, it is essential to test and evaluate the MBE hypotheses, to determine its explanatory validity. The process of testing whether the MBE hypothesis can effectively constitute a candidate generative causal explanation for the target phenomenon is often referred to as a "generative sufficient test" (Epstein, 2007: 36). This necessitates the formalization and implementation of the social mechanisms outlined in the MBE hypothesis to ascertain whether these combinations of social mechanisms can viably and stably reproduce the target social phenomenon.

For this study, potential methodologies for conducting a generative sufficiency test of the MBE hypothesis encompass:

- Identifying a real-world case, specifically a college student friendship network that conforms to the MBE hypothesis's initial conditions. Subsequently, we track, observe, and record longitudinal data from this college student friendship network to determine whether the target social phenomenon emerges in the network over time. However, finding a college student friendship network with a considerable number of individuals and conducting long-term tracking of all individuals in the network to collect data on drinking behavior and relationship networks is difficult and costly.

- Alternatively, we can also conduct a generative sufficiency test on the MBE in the real world through social experiments, but such social experiments are still costly, as we would require large-scale participation of college students over an extended period, ensuring the existence of appropriate friendship networks among participants. As the experiment progresses, we would also need to record the changes in individual attributes, drinking behavior, and friendship relationships of all participants to discern the emergence of the targeted phenomenon, which we consider to be beyond the scope and feasibility of this dissertation. In addition, empirical studies conducted in the real world also face challenges of case-based empirical context dependency.

Aligned with the methodological research gaps identified in Chapter 1, the challenges and the feasibility of conducting real-world empirical research within the social complexity framework, along with the intricacies of collecting and analyzing data, significantly hamper investigations into complex social phenomena within social networks. It thus may be more feasible and efficient to employ alternative research methods to test the MBE hypothesis. Thanks to the rapid development of computational social science over the past two decades, powerful computational tools have been provided, the generative approach based social simulation, particularly Agent-based modeling (ABM), has significant advantages and flexibility in testing the MBE hypothesis. The following section will provide a brief explanation of the ABM method, including what ABM is, why it is used in this study, and how it can be employed.

What is ABM?

ABM is a social simulation method that has rapidly gained prominence in computational social science research over the past two decades. Doran (2000) defines social simulation as a method for examining the functioning of large-scale social phenomena. It involves selecting a specific social research issue and constructing an artificial society within a computer system to systematically explore that issue. Among bottom-up generative social simulation approaches, ABM is one of the most prevalent as it enables a researcher to “create, analyze, and experiment with models composed of agents that interact within an environment”

(Gilbert, 2007) which is considered a powerful computational tool to analyze the micro-macro transition process in the emergence of complex social phenomena (Gilbert, 1996; Sawyer, 2003; Squazzoni, 2010).

Fundamentally, ABM represents a stylized depiction of a set of entities with causal power that interact over time according to given behavioral rules under certain contextual constraints (i.e. social structure). Unlike statistical modeling, in ABM simulation frameworks, variables are replaced by entities with causal power according to micro-theoretical assumptions (i.e. MBE hypotheses) within causal chains (Miller, 2015; Levitt et al., 1999). The simulation result of ABM emerges from the interactions of these entities, which can result in equilibrium points, equilibrium distributions, cycles, randomness, or complex patterns of interaction dynamics (Manzo, 2020). From an Object-Oriented programming perspective, an ABM is a collection of autonomous, interacting computational "objects," which are computational units defined by properties (attributes) and rules of behavior (methods or procedures) (Casini and Manzo, 2016). These objects can be used to model the behavior and interactions of particles, molecules, cells, beliefs, actors, groups, organizations, and more, based on the properties and rules defining each object (ibid).

The concept of “agent” lies at the heart of the ABM paradigm. While there is no universal consensus among researchers on the precise definition of the term 'agent', there are several common features that are typically associated with agents in social simulation from a pragmatic modeling standpoint (Crooks and Heppenstall, 2012):

- Autonomous: An agent is a heterogeneous and self-contained unit with its own internal goals and is self-directed in selecting behaviors (i.e., how an agent decides what to do next) to achieve those goals. It is capable of independently processing information and may exchange this information with other agents in order to make independent decisions in its environment. This heterogeneity distinguishes ABM from standard mathematical models based on differential equations, which generally assume homogeneous representative agents, or no agents at all, for analytic tractability (Squazzoni, 2010).
- Embedded in social structures: An agent exists in an environment that defines the space

in which agents operate, serving to support their interaction with the environment and other agents, such as social networks and social institutions.

- Reactive/Perceptive and incomplete information: Agents could be designed to have an awareness or sense of their surroundings. However, in most practical cases, agents are usually assumed not to be omniscient but to be able to gather non-complete information only from their own local environment.
- Interdependent: Agents interact with each other and/or with their environments over time. The interaction between agents is complicated, nonlinear, discontinuous, or discrete, and the outcomes of individual agents' behaviors are thus interdependent. Flache and Fernandes (2021) note that while autonomous agents control their own internal states, their autonomy is constrained by interdependence. Each agent's actions and possibilities for future actions depend on what happens in the agent's local environment, and these actions in turn have consequences that alter their own environment and that of others. Each agent's ability to achieve its goals thus depends not only on its own actions but also on the actions of other agents.
- Adaptive: Adaptation refers to the capacity of an agent's behavior to evolve in response to its own actions and the conditions of its environment (Skopek, 2023: 151). Some researchers (Duffy, 2006; Grimm et al., 2020) advocate memory and learning are integral facets of an agent's adaptivity, endowing agents with the capability to retain information and glean lessons from past experiences or from the experiences of others. Consequently, agents can be designed to alter their state depending on previous states, permitting agents to adapt through a form of memory or learning.

In practice, ABM modelers run social simulation programs to enable agents to continuously interact with each other in an artificial social environment (in various forms) and observe their long-term consequences at the macro level. This allows macro-outcomes to be viewed diachronically as bottom-up system emergent properties from local interactions (Fararo and Hummon, 2005; Sawyer, 2003). Through this approach, social scientists can analyze the social mechanisms, and micro-interaction processes responsible for the macro complex social phenomena under scrutiny, as well as the diachronic impact of the latter on the former. This facilitates the modeling, observation, replication, and understanding of the self-organizing nature of social patterns, allowing social scientists to address the interdependence structures potentially involved in the "transformation" of the "micro" into the "macro" (Manzo, 2020; Gilbert and Troitzsch, 2005). It particularly provides a computational approach to address the micro-macro transition problem described in the arrow 3 of the Coleman boat diagram.

In summary, from a social epistemological perspective, ABM effectively constructs an artificial social system within a computer program. This artificial system is composed of heterogeneous, adaptive agents that are embedded within designed social structures. The social relational structure within ABM describes the interactions between agents, while the social institutional structure outlines the patterns of these interactions. The construction process of ABM thus implies a computational implementation or instantiation of "structural individualism".

Types of ABM Models

ABM has been applied across various disciplines to investigate a wide range of topics, including physical activity behavior (Yang et al., 2011; Yang, 2013; Baker, 2003; Manzo, 2020), obesity (Widener et al., 2013; Zhang et al., 2015), disease diffusion (Ajelli et al., 2010; Badham et al., 2021), traffic jams (Barthélemy & Carletti, 2017), crime (Malleson, 2012), social inequalities (Manzo, 2013), the diffusion of innovations (Manzo et al., 2018), and opinion dynamics (Flache et al., 2017). Boero and Squazzoni (2005) summarize existing ABM-based social simulation research and list three major types of ABMs commonly used in social science studies:

- "**Case-based models**": These models focus on specific empirical social phenomena or cases with a defined space-time nature. The aim of case-based models is to appreciate realism and complexity rather than achieve generality. They often provide a high level of richness and detail, as they are built with the goal of accuracy, precision, veridicality, and sometimes prediction. To achieve generalizability, case-based models need to be extended to other similar phenomena and abstracted at a higher theoretical level, relating the model to a “typification”.

- "**Typifications**": These models aim to understand the mechanisms operating within a specific class of empirical phenomena that share common properties. The value of typifications lies not in the positive properties of case-based models, such as richness, detail, accuracy, precision, and veridicality, but rather from their pragmatic heuristic and exploratory significance. Railsback and Grimm (2010: 227) refer to this type of ABM as "structurally realistic". Although these models do not achieve the same level of realism as "case-based models", they still include key structural elements (e.g. the structures and processes) of a real system's "internal organization" which produce the system's characteristic properties and behaviors. Consequently, "Typifications" modeling can be seen as a form of pattern-oriented modeling (POM) that aims to reproduce and explore the patterns observed in the real social system (Railsback and Grimm, 2012: 226, 256).[22]

- "**Theoretical abstractions**": These models target general phenomena that do not directly reference specific empirical phenomena or Typifications. The focus of theoretical abstractions is on pure theoretical aims, such as providing new insights and suggestions for theoretical debates or simply demonstrating an idea in a clear manner.

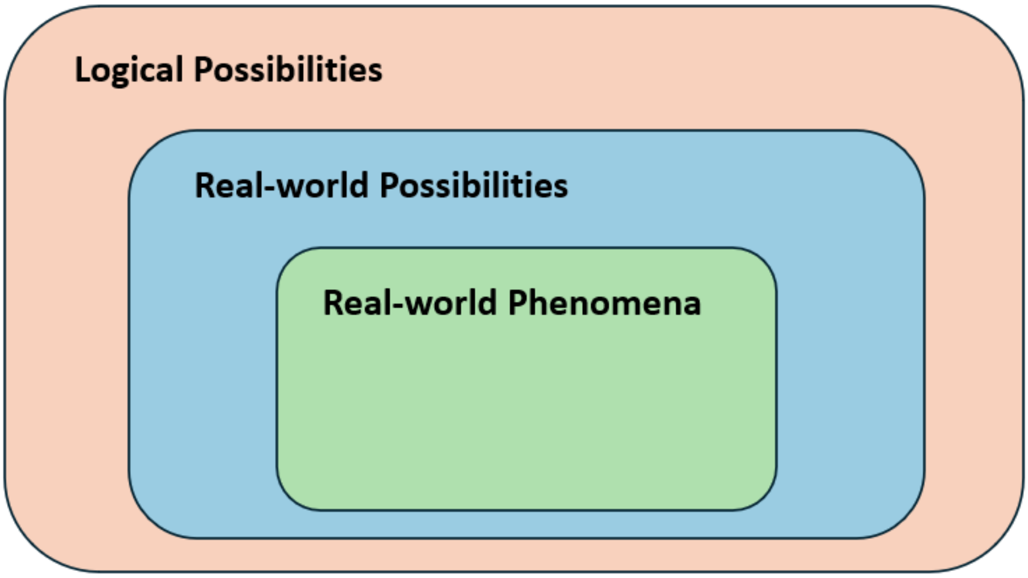
In summary, Šešelja (2022) identifies three types of social simulation models from the perspective of the philosophy of science, each possessing distinct representational properties. These models can represent (1) logical possibilities, (2) real-world possibilities, or (3) real-world phenomena, with each category offering specific explanatory features, empirical realism, and complexity (see Figure 3). Modelers should select the appropriate type of ABM model

[22] The concept of pattern is defined as "anything beyond random variation," such as regularities or signals (Railsback & Grimm, 2012: 228). Patterns are sometimes referred to as "stylized facts," which are broad but not necessarily universal generalizations of empirical observations that describe the essential characteristics of a social phenomenon. If we conceive of a social phenomenon as a visible spectrum, a pattern does not encompass all wavelengths of the spectrum but only one or a few characteristic wavelengths (ibid).

Patterns can be strong or weak: strong patterns offer a robust indication of the characteristics of the social phenomenon and are typically described quantitatively. Conversely, weak patterns are often qualitative and not strictly defined (Grimm & Railsback, 2012; Gallagher et al., 2021).

based on their research objectives.

Figure 3: Different subjects represented by ABMs (Šešelja, 2022)



In this study, we aim to develop "Typifications" ABM for two primary reasons:

- Modeling Subject: The target social phenomenon is not a particular empirical case of alcohol diffusion, but it is also not without direct reference to reality. Instead, as clarified in the Literature Review chapter, the diffusion of drinking behavior in friendship networks among college students is a complex social phenomenon that can be widely observed across different societies, exhibiting some typical social patterns with regularities.

- Modeling Objective: The purpose of employing the ABM approach in this research is to test the generative sufficiency of the MBE hypothesis and evaluate the extent to which this MBE can be regarded as "the best explanation" for the observed target social phenomenon (see following section on abductive reasoning principle), rather than making predictions or conducting purely theoretical research. Consequently, developing a "Typifications" type of ABM model is more conducive to achieving the objective of exploring mechanistic explanations.

ABM and MBE Hypothesis Test

Although ABM is not the sole method for formalizing social mechanisms, it offers distinct advantages over other computational methods, such as nonlinear dynamical systems, statistical models and evolutionary game theory, in the following aspects (Manzo, 2022: 25; Sorensen, 2004: 59): ABM provides greater (1) Flexibility; ABM is not confined to modeling any specific type of entities, properties, activities, interdependence structures, levels of analysis, sequence of activation, or behavioral rule; (2) Granularity; ABM does not impose a priori restrictions on the level of detail at which the elements of social mechanisms can be described; and (3) Generality; ABM can encompass several formalisms, each suited to model specific aspects of the mechanisms under investigation, thus offering a comprehensive approach to complex social phenomena.

These attributes enable ABM to capture not only the effects of theoretical rules, but also the impact of subsequently generated data on agents' behavior in the following time period (Valogianni and Padmanabhan, 2022). In essence, ABM serves as a flexible computational tool for translating, formalizing, and testing theoretical hypotheses about complex social phenomena in a mechanism-based analytical style. It arguably imposes the least substantive constraints on how a model is formulated (Sorensen, 2024: 59).

Manzo (2007) underlines the natural compatibility between the components of MBE and ABM models, as ABM is considered "an adequate infrastructure for the formalization of candidate generative models (i.e., MBE hypotheses)": When developing a set of computational programs to formalize generative hypotheses, we are essentially proposing a series of generative mechanisms. By running the program, we simulate a process resulting from the posited generative mechanisms and identify the social phenomena that these mechanisms can induce. Therefore, ABM can be viewed as a quasi-experimental approach for testing MBE hypotheses, as ABM not only allows us to translate the MBE hypotheses (in form of natural language) we want to test into executable artificial social programs(in form of formal language) for generative testing of MBE, but also gives us almost complete control over all events before and after initiating the simulation (León-Medina, 2017a). This means we have the flexibility to modify any aspect, control for parameters and mechanism components of interest, and generate and analyze any “quasi-empirical data” to determine the roles of interesting components within the MBE mechanisms and ABM models (León-Medina, 2017a). In other words, any precise and consistent formulation of substantive mechanism with a theoretical representation can be implemented within the framework of ABM (transformed into an artificial social scenario involving agents' nonlinear interaction processes) and examined (Sorensen, 2004: 59). Through this, ABM allows researchers to observe how the phenomenon under investigation is generated and how alterations in social mechanisms (such as action logics or relational structures) are likely to change the social outcome.

Using ABM to test and evaluates MBE hypotheses is considered as a "generative research strategy" or "generative approach": if we are able to generate or grow a macro social phenomenon via an ABM, based on mechanism-based theoretical hypotheses of the micro-foundations, then we can consider these MBE hypotheses as sufficient, even if not necessary conditions (limited by the “multi-realizability” of MBE (Sawyer, 2005)) for explaining the generated phenomenon (Squazzoni and Troitzsch, 2006). As noted by Epstein (2006), ABM can assure the "generative sufficiency" of a given MBE hypothesis - "agent-based computational models provide demonstrations that a given micro-specification hypothesis is in fact sufficient to generate a macro social phenomenon of interest" (Manzo, 2014; Epstein, 2006) as ABM provides a formal device to demonstrate that the dependence relationship under scrutiny is deducible by unfolding the postulated (formalized) narrative, meeting the principle of generative sufficiency (Manzo, 2022: 23). Once a candidate micro-specification has been shown to produce a macrostructure of interest through repeated application of a given set of agent-interaction rules, the demonstration that this macrostructure has been 'grown' from that micro-specification then counts as a sufficient condition for the explanation of that macrostructure (Epstein, 1999).

How to Apply ABM to Test MBE Hypotheses?

Employing the ABM approach to test MBE hypotheses typically necessitates adherence to the principles of abductive reasoning. Abduction is an inference approach rooted in logic theory, involving the derivation of a plausible explanatory connection between inputs and outputs, distinct from induction and deduction, which rely on logical inferences to move from inputs to outputs (Valogianni and Padmanabhan, 2022; Lipton, 2017).

In deductive reasoning, if Y is derived by X, then Y is considered a "formal logical consequence" of X. Conversely, in inductive reasoning, if we can infer Y from X, it is quite probable that all similar instances that resemble Y are also inferred by X, without this being the absolute norm. In this sense, deduction is typically viewed as progressing logically from the general to the specific, often involving a "set of axioms and proving consequences that can be derived from assumptions", while induction moves from specific to general, often seen as the "discovery of patterns in empirical data" (David, 2006).

Abductive reasoning allows for inferring Y as a reasonable explanation for X, indicating potential unobserved relationships connecting X and Y, with only some of these relationships inferred by observing the outcome of the X to Y connection (Valogianni and Padmanabhan, 2022). Compared to induction and deduction, abductive reasoning is not a closed, rule-driven form of inference with well-defined procedures but rather an open, conjectural form of inference characterized by incomplete and contestable explanations (Davis, 2018). Abduction reasoning involves a process of evaluating alternative explanations based on available data and then choosing what appears to be "the best one" or "Inference to the Best Explanation" (Valogianni and Padmanabhan, 2022; Lipton, 2017).

As described by Lipton (2004), "we infer the explanations precisely because they would, if true, explain the phenomena. Of course, there is always more than one possible explanation for any phenomenon … so we cannot infer something simply because it is a possible explanation. It must somehow be the best of competing explanations. … Given our data and our background beliefs, we infer what would, if true, provide the best of the competing explanations we can generate of those data … Far from explanation only coming on the scene after the inferential work is done, the core idea of Inference to the Best Explanation is that explanatory considerations are a guide to inference" (Lipton, 2004: 56; Halas, 2011). Furthermore, for Lipton, the best explanation not only offers clarity but also exhibits theoretical elegance, simplicity, and the ability to unify disparate elements (Lipton, 2004: 68)[23].

Given the inherent non-reducibility of emergent properties within complex social systems, the application of deductive and inductive reasoning to tackle these challenges is arduous. Abduction reasoning is thus recognized as a more effective logical method for grappling with the explanations of complex social phenomena. It leverages data and observations to pinpoint plausible explanations that connect observed social outcomes with underlying conditions, following the principle of "Inference to the Best Explanation" for phenomena, holds significance (Ren et al., 2018). Therefore, when dealing with complex social phenomena, abductive reasoning acts as a guiding logical method for employing ABM in social simulation methods.[24]

In simpler terms, adhering to the principle of abduction reasoning in the pursuit of scientific explanations for complex social phenomena implies that we assume there must be one or

[23] The notion of "the Best Explanation" within the purview of abductive reasoning is subject to certain clarifications:

- Given the multi-determinant nature of explanations for complex social phenomena, the equifinality argument- many different paths may exist to the same place, it is common to encounter a multitude of valid explanations. Among these, the one that best conforms to the evaluative criteria of the abductive reasoning principle for "the Best Explanation" may be regarded as such. The designation of "the Best Explanation" is provisional and competitive; should an explanation emerge that more closely aligns with the evaluative criteria, it may supplant the existing candidate.
- In this study, we adopt Lipton's (2004: 68) discourse as the evaluative criteria for "the Best Explanation" under the abductive reasoning principle. The necessary conditions for an explanation to be considered "the Best Explanation" include:
    1. It must be a valid and stable causal explanation that meets the condition of generative sufficiency, being clear and explicit.
    2. It exhibits theoretical elegance and simplicity: While maintaining the effectiveness and generalizability of the explanation, it should include as few unnecessary components as possible to enhance its simplicity. Under the principle of abduction reasoning, higher simplicity and broader applicability are the criteria for identifying "the best one" or making an "Inference to the Best Explanation."

[24] Epstein (2006: 11, 56) highlight that each execution of a generative ABM model to produce results is, in itself, a strict deduction, where the simulation outcome is a formal deductive logical consequence of the model's conditions. However, employing ABM as a research method to explore and test "the best explanation" for a social phenomenon adheres to the principles of abductive reasoning (Miller, 2015).

more social mechanisms responsible for the emergence of the target complex social phenomena under specific conditions. Our task is to identify one or more of these generative mechanisms based on initial conditions, empirical evidence, and observations, that can bridge the gap between the initial conditions and the target social phenomena, leading to the occurrence of the target phenomena (i.e. “antecedent causes from consequents” (Miller, 2015:181)). These mechanisms, which meet the criteria of generative sufficiency, form the candidate mechanism-based explanations under the principle of abduction reasoning.

In the context of ABM approach, abductive reasoning suggests that upon observing an unexplained emergent phenomenon in a social system, it is warranted to construct a corresponding ABM model. If the constructed ABM model successfully reproduces the observed phenomenon, it provides reason to believe that the assumptions of the ABM model are on the right track, constituting a candidate explanation for the target phenomenon (Halas, 2011). An MBE fulfilling the criterion of generative sufficiency attains the fundamental benchmark (minimum standard) set by the abduction reasoning framework for formulating an "Inference to the Best Explanation”. Nevertheless, due to the multifinality limitation inherent in MBEs, supplementary evaluation of this candidate explanation is imperative to ascertain the extent to which it can be convincingly regarded as "the Best Explanation".[25]

Overall, the process of testing the MBE hypothesis could be delineated into two main stages (Vu, et al., 2020; Tuong, 2019),

- “**Redescription**”: A plausible MBE explanation must be able to viably and stably generate the emergence of the target social phenomenon. To confirm the viability of the MBE hypothesis, the ABM modeler is first tasked with transforming and formalizing the MBE hypothesis into an ABM model set within a constructed artificial social system environment. This environment specifies particular initial conditions and interaction rules for social entities, which are directly translated from the MBE hypothesis, at an

[25] Abductive reasoning only produces candidate explanations which are always subject to falsification and revision based on further empirical evidence (Cederman, 2005: 876; Miller, 2015).

appropriate level of empirical realism.[26] Subsequently, through parameter calibration of the ABM model, the objective is to test whether the model can, within its adjustable parameter space, generate emergent outcomes that are comparable to the target social patterns. This evaluation process is recognized as the "face validation" of the model's output (Vu et al., 2020). Additionally, given the uncertainty challenges posed by the multifinality characteristic of ABMs[27], the remaining part of the "generative sufficiency test" involves testing the parameter sensitivity and model uncertainty analysis of the ABM model that has passed "face validation" to assess its ability to stably reproduce the target phenomenon under the current level of empirical realism, known as the "uncertainty quantification".[28]

If the ABM model is able to viably and stably reproduce a known target empirical pattern to be explained, the researcher has provided a computational demonstration that a given microspecification (directly translated from MBE hypothesis) is indeed sufficient to generate the macrostructure of interest (Epstein, 1999). This outcome signifies the completion of the "generative sufficiency" test, and the MBE hypothesis, grounded in the ABM model, forms a candidate (generative) explanation for the target complex social phenomenon (Vu et al., 2020). Conversely, if the ABM model fails to stably generate the outcome to be explained, within its parameter space, the microspecification is not a viable candidate explanation of the phenomenon, and the researcher has demonstrated the falsity or low credibility of the MBE hypothesis (Salgado and Gilbert, 2013). Researchers need to reconstruct an alternative potential causal MBE hypothesis for the target social phenomenon (Railsback and Grimm, 2012: 268).

- "**Retroduction**": This phase involves identifying the fundamental (or indispensable) the

[26] The process of model construction, specifically translating the MBE hypothesis into an ABM model, involves appropriate empirical calibration. This calibration is contingent upon the type of model and the objectives of the modeling, which will be discussed in a subsequent section.

[27] Mutlifinality: The same ABM model could yield diverse outcomes or data in different runs. For instance, due to the stochastic components embedded within ABM models, outcomes may differ in distinct runs even with minimal stochastic variation, reflecting the system's chaotic properties (i.e. uncertainty on model's stochastic elements), Adjusting model parameter values could result in diverse outcomes within the same ABM model (i.e. the model's sensitivity to parameter values).

[28] Appropriate "face validation" and "uncertainty quantification" represents the significant challenges of the ABM simulation methods, which we will discuss in the subsequent section.

indispensable components within the candidate MBE for the emergence of the target social phenomenon. Through the successful completion of the "generative sufficiency" test, the ABM model adequately illustrates that the MBE, as depicted within the model, is capable of generating the envisioned outcomes and furnishing a generative causal rationale for the studied social phenomenon. Such a candidate MBE meets the minimum standard of a “Inference to the Best Explanation within the abduction reasoning principle. Nonetheless, owing to the inherent intricacies (especially the multiple determinants) of ABM, the natural world, and mechanistic explanations, the definitive conciseness, elegance, and explanatory strength of this MBE remain elusive. While it presents a compelling candidate explanatory framework, it may not represent the ultimate optimal choice following the principle of Abduction reasoning.

Specifically, even with a detailed description of initial condition (i.e. entities with causal power, their properties, activities, and interactions) and the causal chain connecting these initial generative conditions to the target outcome as described by the MBE hypothesis, as well as evidence (e.g. pass the "generative sufficiency test") of the generative capacity of this set of micro specifications, the equifinality properties of MBE continue to limit the explanatory power of candidate MBE on the target social phenomena (Valogianni and Padmanabhan, 2022). Equifinality refers to the capacity of different sets of conditions or model representations to yield the same or similar outcomes. This is primarily due to the nature of complex social phenomena and the multiple determinants of social mechanisms. As Vu et al. (2020) stated, many social phenomena may be explained by a multiplicity of mechanism combinations, each of which may pass the generative sufficient test when encoded as an ABM. This compels us to question which MBE serves as the superior explanation and which fundamental (or indispensable) components within the candidate MBE that are pivotal for the emergence of the target social phenomenon (i.e., entities and mechanisms whose absence would preclude the phenomenon’s emergence)?

Therefore, it is vital to reconsider the key components within the ABM model and the original MBE hypothesis to identify and elucidate the essential roles played by these components in the generative process. This process aims to address the central question for all modelers, namely, what must be true about the real system in order to produce the observed pattern (Miller, 2015).

In the phase of "Retroduction", the ABM model provides the flexibility to conduct counterfactual experimentation or adjust parameters or modules in the model as desired to reevaluate and test specific components of interest, as well as compare simulation outputs. Therefore, after the ABM model successfully passed the "generative sufficiency" test, the testing of the MBE hypothesis progresses to the Retroduction phase. Through “Retroduction” analysis, the modelers seek to identify the essential components within the “Redescription” that are crucial for the emergence of the target phenomenon, thereby optimizing the candidate MBE to approach "the Best Explanation" under the principle of abductive reasoning. The counterfactual approach- where X is said to explain Y if Y is contingent upon X in such a manner that the absence of X would preclude the occurrence of Y- is a commonly employed method in ascertaining the indispensable components within the candidate MBE (Bulle and Phan, 2017).

Key Challenges and Strategies for Applying ABM

Designing, developing, calibrating and validating a competent and suitable ABM for testing MBE is a highly challenging task. The following section will outline some of the modeling challenges involved and emphasize key strategies to address these challenges.

Appropriate Level of Model Complexity and Empirical Realism

Due to the abstract nature of the MBE being tested, modelers often have a degree of discretion in determining the appropriate level of model complexity and empirical realism when translating the MBE hypothesis into an ABM model. Finding a balance point can be a challenging task for the modeler. Furthermore, the modeling process is often significantly influenced by the modeler's academic training background, theoretical perspective, personal values, and so on. Therefore, for the same MBE being tested, different modelers often build significantly different ABM models for testing. These various ABM models also exhibit different levels of model complexity and empirical realism. As mentioned earlier, all MBEs have a certain degree of social context dependence, and the same mechanism or combination of mechanisms operating in different social contexts may lead to different outcomes. Instantiating the MBE with ABM models of different levels of model complexity and empirical realism means running the MBE in significantly different levels of social context complexity and empirical realism. This may significantly impact on the results of the mechanism's operation and the conclusions of social simulation research. Therefore, determining an appropriate level of model complexity and empirical realism of the artificial social context is crucial for ABM design. To tackle this challenge, Bruch and Atwell (2015) suggest that modelers should balance the complexity and empirical realism of model design based on the specific objectives of the ABM model.

For the Model Complexity

According to Sun et al. (2016), the degree of the model complexity[29] depends on how detailedly the model structure represents the modelled system and is determined by the number and types of entities with causal power (and their attributes), processes, environment, and interactions within the model.

Determining the appropriate level of model complexity is challenging. Edmonds and Meyer (2017) observe that "with complex social phenomena, it is inevitable that any model is, at best, a very partial picture of what it represents." Social modeling always involves simplifications and approximations, as an artificial society model is an abstraction of the real world and does not encompass all components of the real world (Miller, 2015; Edmonds, 2017). Thus, the appropriate level of model complexity typically depends on the model's generalization goals. Highly complex models include more components, conditions, variables, and parameters,

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[29] Based on our distinction between the concepts of "complex" and "complicated" (In Chapter 1), model complexity is not imposed by modelers but rather emerges from interactions at the individual level, leading to simulated system-level emergent properties (Sun et al., 2016). Even a simple model, which includes only a few components (i.e., low complicatedness), can still produce highly complex behaviors and is thus considered a complex model (ibid). Consequently, a more precise term for what we refer to as model complexity would be model complicatedness. However, to maintain consistency with the prevailing literature, we will continue to use the term model complexity throughout this discussion.

which generally indicate stronger explanatory power. However, an excessive number of variables and components in the model may lead to overfitting problems, limiting the model's generalization capability. Furthermore, overly complex models can become too difficult to understand, explore and assess, which limits the usefulness of the model for improving system understanding (Sun et al., 2016).

Conversely, low complexity models include only the most important aspects or components of the real world, making it easier to study causal dependencies between the given components. A low complexity (high abstraction) model typically has stronger generalization capability but makes it difficult to establish its relation to the real world (Šešelja, 2021). As noted by Boero and Squazzoni (2005), complexity is normally correlated with specificity, and simplicity with generality. For ABM models aimed at testing MBE, structural individualism-based MBE hypotheses encompass all causal powers of interest (and their attributes), the interaction patterns among causal powers, and the causal effects of social structures. Consequently, while modelers retain some degree of discretion regarding aspects such as the number of entities and the time steps of interactions, the complexity of the ABM is largely dictated by the MBE hypothesis.

For Empirical Realism of the Model

The level of empirical realism in an ABM model is determined by empirical calibration. Bruch and Atwell (2015) provide a detailed distinction between highly realistic and lowly realistic models:

- Highly realistic models: The aim of a highly realistic ABM is typically to make policy recommendations and predictions that can be applicable to a particular empirical case (e.g. a real-world phenomenon) (Šešelja, 2022). Researchers need to have confidence that the inferences drawn from the model reflect the actual mechanisms operating in the real world. Highly realistic ABMs allow for potentially greater fidelity between the modeled complex system and the model itself. This fidelity is necessary when analysts need to explore the behavior of a social system under hypothesized conditions for predictive purposes. Highly realistic ABMs ensure that the model predictions are not based on a reduced form account of the social process. Consequently, this fidelity supports the extrapolation of model behavior to real-world system behavior, enabling insights from the model to be used for system understanding and policy comparison (Badham et al., 2018). For example, they serve as virtual "laboratories" for testing the implications of policy interventions or predicting future population dynamics.

- Lowly realistic models: In contrast to highly realistic models, lowly realistic ABMs are not designed to replicate specific real-world situations or predict expected outcomes under alternative policy scenarios. Instead, they represent logical possibilities or real-world possibilities and are considered useful for clarifying or testing new theories or social mechanisms (Bruch and Atwell, 2015). Lowly realistic ABMs offer greater modeling flexibility and a higher level of generalization, enhancing theoretical precision, internal validity, and enabling theoretical elaboration and exploration through computational experimentation (Davis et al., 2007).

When balancing the levels of complexity and realism in a model, it is important to clarify the distinction between the two, as their relationship can be easily confused. Model complexity refers to the number of components included in the model. On the other hand, model realism pertains to the level of empirical validation. It is crucial to note that including more components in the model does not necessarily equate to higher model realism, and vice versa. A model may be relatively simple, with a limited number of components, but those components can be firmly grounded in empirical data. Conversely, complex phenomena may be modeled with only anecdotal evidence (Bruch and Atwell, 2015).

Appropriate Empirical Calibration and Validation

In the process of designing and constructing ABM models, appropriate empirical calibration and validation involve providing the model's conditions and parameters with an empirical knowledge basis, placing the model at an appropriate level of empirical realism. Boero and Squazzon (2005) suggest that empirical knowledge can serve two main purposes in the empirical calibration and validation process: to specify and calibrate model components or parameters at the micro level and to validate simulation results at the macro level. Specifically, Gräbner (2018) identifies three main types of empirical validation for ABMs:

- “Theoretical Realism”: Process validation refers to how well mechanisms represented in the ABMs reflect our empirical knowledge about them (Gräbner, 2018; Šešelja, 2022). This particularly pertains to the extent to which the MBE hypothesis used in designing the model are explicitly grounded on (empirically supported) sociological theories (Manzo, 2022:33).
- “Input Realism”: Input calibration evaluates whether the exogenous inputs for the model are empirically meaningful and suitable for the intended purpose during the model's design and construction phase. This includes the direct incorporation of empirical information from real systems within the ABM’s parameters, distributions, functions, and various substantive components, such as behavioral assumptions ascribed to the agents (Manzo, 2022; Tesfatsion, 2017; Šešelja, 2022; Railsback and Grimm, 2012: 255).
- “Output Realism”: Descriptive and predictive output validation involves determining the extent to which the model's output replicates existing knowledge about the target and whether it can predict its future states (Gräbner, 2018; Šešelja, 2022). This involves using empirical data to test artificial data generated by the ABMs, through intensive analysis and comparison with data on empirical reality. It assesses“the extent to which the model’s outputs are confronted with empirical and/or experimental data”.

It is important to note that, as Skopek (2023: 155-156) notes, data inputs (initial parameters and conditions) and data outputs in ABM typically present as numerical variables. This numerical manifestation can lead to the perception that empirical calibration and validation of an ABM involve a direct quantitative correspondence or comparison between its quantitative inputs or outputs and empirical data. However, the empirical data utilized in an ABM does is not necessarily to quantitative measures. In fact, the data requirements for ABMs are generally flexible, allowing for the representation of both quantitative and qualitative insights through computer programming.

Qualitative data can also be used in various ways within ABM. It may be utilized to guide the modelling of behavioral rules, to define environmental constraints within the simulation context, or empirically validate the model's output. For instance, in the context of pattern-oriented ABM output validation, Railsback and Grimm (2012: 230) emphasize that modelers should first establish qualitative criteria to determine when a target social phenomenon is matched, testing whether the model reproduces specific patterns [30] and exclude inappropriate sub-models. Once the ability of the POM model to qualitatively reproduce specific patterns is confirmed, modelers may proceed with further quantitative output validation if the model is designed to support real-world decision-making. This entails calibrating models to quantitatively align with observations and data by systematically measuring the differences between simulated and observed patterns and assessing model performance (Gallagher et al., 2021; Railsback and Grimm, 2012: 230).

The type and level of required empirical validation depend on the type and purpose of the model:

- The high-fidelity requirements of highly realistic models typically necessitate thorough and comprehensive empirical validation. For instance, the theoretical realism calibration ensures that the model reflects actual mechanisms operating in the world. Modeler also need to use concrete numerical empirical data from real world cases as input for model parameters initializes the simulation environment and allows for input empirical calibration. Finally, validating the model's output with empirical data quantitatively evaluates the overall goodness of fit. In other words, empirical data is used to construct each micro-specification of a given ABM, either when constructing novel models or when examining the robustness of existing ones (Boero and Squazzoni, 2005; Skopek, 2023:154).
- For lowly realistic models, designed to serve an exploratory or testing function instead of a specific empirical target, high-level empirical calibration and validation is generally

[30] For assessing whether the patterns fall within the range of observations or if model results are reflective of system trends, agree with observed patterns can be described as being qualitative ‘consistent’ with empirical knowledge (Gallagher et al., 2021).

unnecessary (Šešelja, 2021; Skopek, 2023:154). Instead of strictly quantitatively comparing the model output to empirical data, researchers should focus on determining whether the low realism can viably and stably reproduce the social pattern of interest qualitatively.

For this study, we aim to construct a "Typifications" type of ABM for test MBE hypotheses on complex social phenomena (i.e., pattern-oriented modeling), rather than examining a specific real-world case for policy recommendation or prediction. Therefore, our "Typifications" type of ABM will have a merely modest level of realism: we will use qualitative empirical knowledge about typical college drinking pattern and social settings, as documented in the literature review chapter. This approach will substitute for empirical data from a specific case of alcohol diffusion among college students, allowing us to conduct empirical calibration and validation of the model's theoretical realism, input realism, and output realism, thereby ensuring that our ABM maintains an appropriate level of empirical relevance to the real world.

Appropriate Behavior and Interaction Rules

An ABM's 'rules' define the autonomous actions that an agent can perform as a function of its state and in response to changes in its local environment. Therefore, rules are formulated to describe discrete, well-defined, individual behaviors that a single agent can enact depending on both its own state and its local environment. Rules link cause-and-effect in a manner enacted by individual agents/entities in the population under consideration. Traditionally, these rules are manually generated by the modeler, often in the form of a fixed set of simple condition-action rules (DeAngelis and Diaz, 2019). Although many simple rule-based (or pseudorandom behavior based) ABM models are capable of creating complex, system-level results, they do not always provide the desired results and have faced some criticism:

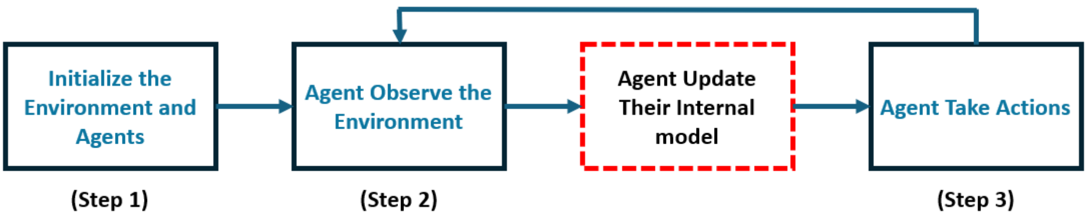
Criticism 1: Subjectivity in rule generation is a significant drawback. The rule-set depends on the modeler's background, expertise, and interpretation of empirical data, expert opinions, and literature. Rule validation in an ABM occurs after simulations are run, and predictions are compared to independent experimental data or a validation dataset. Hence, a common critique of the traditional ABM rule-generation process is the inherent subjectivity that may introduce bias into the rules (Rand, 2006).

<u>Criticism 2</u>: Lack of Adaptive Agents. Humans do not generally just follow simple rules but are reflexive and adaptive agents, people constantly and reflexively adapt to new situations, adopt new behaviors, learn and adapt their behaviours based on its accumulated experiences and are thus constantly changing the very rules of the game (Törnberg, 2017:42; Macal and North, 2005). One of the significant promises of ABM is the ability to have adaptive agents that make decisions in changing environments. In practice, however, few rule-based models make use of an "adaptive mechanism" within the ABM framework.

It is important to clarify that the term "adaptive mechanism" does not refer merely to the capacity of agents to undertake different actions; rather, it pertains to the agents' ability to develop a new strategy for decision-making (Rand, 2006). This involves the agent's ability to learn from their past decisions or the decisions of other agents and improve their decision-making in a continuously changing new social environment (Brearcliffe and Crooks, 2021). Simple rule-based agents are often considered to lack this adaptive capability as they generally cannot learn and remember their own or others' previous decisions to optimize their internal decision model (Brearcliffe and Crooks, 2021).

Rand (2006) uses the following figure 3 to illustrate the operational processes of both adaptive and non-adaptive ABM models. Specifically, the operational process of a typical non-adaptive ABM model can be divided into three steps: (1) initializing the world and a population of agents, (2) each agent observing its world, and (3) each agent taking an action based on the current observations. The model then repeats by returning to step (2). The cycle transforms into an adaptive agent-based model when we introduce a fourth step between (2) and (3), where each agent updates its internal model of the world and determines today's action based on that internal model (Rand, 2006).

Figure 3: Operational Processes of ABM Models



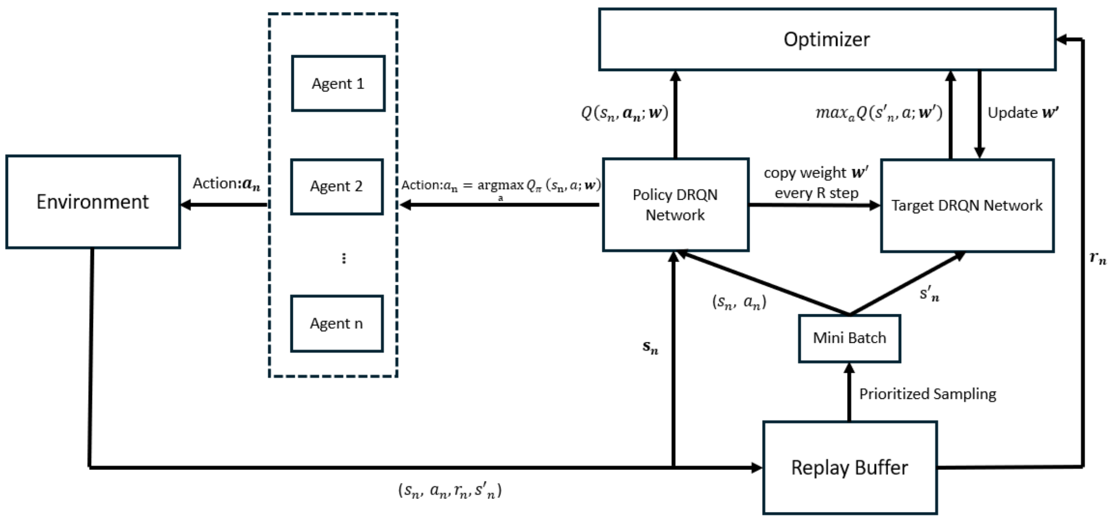
However, endowing agents with adaptive capabilities presents technical challenges, it is intractable when framed mathematically (Bankes et al., 2002). To enable agents to possess adaptability, there is a growing interest in utilizing machine learning (ML) algorithms within ABM, as ML has the potential to transition from simple non-adaptive agents to complex adaptive ones (Brearcliffe and Crooks, 2021; Bankes et al., 2002). Instead of manually generating rules, which may inadvertently introduce biases and be limited by modeler's subjectivity, ML algorithms can objectively learn the rules, parameterizations, and other aspects by examining experimental data or applying fundamental mathematical relationships (ibid). Among various ML approaches, An et al. (2023) highlight that Reinforcement Learning (RL) is a promising tool as RL-enabled agents can "learn" the best behavioral rules from data so that the learned "rules" can maximizes the RL agent's reward (or minimize the penalty) when dealing with other agents and the environment.

RL is a vast field, and covering all types of methods is beyond the scope of this work. We will only provide a brief introduction to the Deep Recurrent Q-Network (DRQN) with prioritized experience replay algorithm, which is applied in this study, to facilitate readers who are unfamiliar with or have little knowledge of reinforcement learning (RL) to gain a general understanding of this algorithm. We will first introduce RL and the basic Deep-Q Networks (DQN) learning algorithm in RL, as DRQN with prioritized experience replay algorithm is an improvement of the DQN algorithm (Hausknecht and Stone, 2015; Schaul et al., 2015), allowing its use for agents that can only obtain partial information about the environment. Additionally, this algorithm allows agents to remember their own or others' experiences to enhance decision-making.

Introduction on RL and DQN [31]

RL involves the learning of control policies for agents that interact with unknown environments. These environments are often formalized as Markov Decision Processes (MDPs), which are described by a 4-tuple (S, A, P, R) In each time step t, an agent interacting with the MDP observes a state $s_t \in S$, and chooses an action at $a_t \in A$, which determines the reward $r_t \sim \mathrm{R}(s_t, a_t)$ and the next state $s_{t+1} \sim \mathrm{P}(s_t, a_t)$. (Mnih et al., 2013; Hausknecht and Stone, 2015; AlMahamid and Grolinger, 2021). A RL model, illustrated by the following figure, depicts the interaction between the agent and the environment in this research:

Figure 4: Reinforcement Learning Overview Diagram (DRQN)



To provide a more specific and accessible explanation of the above figure (Wang, 2020),

1) **State s**: state s describes the current configuration of the game environment. In fully observable model, the agent is able to observe the complete state information, while in a partial observable model, the agent can only observe partial information about the state of the environment.
2) **Action a**: The action a is a set of all possible moves the agent can make.
3) **Policy function π**: The policy function $\pi(a, s) \to [0,1]$ is the strategy that the agent

[31] The DQN algorithm is one of the most fundamental and well-established algorithms within the realm of RL. The Deep Recurrent Q-Network (DRQN) constitutes an advancement built upon the DQN framework. In this section, we provide a very brief summary to the fundamental concepts underlying these algorithms, drawing from existing academic literatures (Mnih et al. 2013; Mnih et al. 2015; Hausknecht and Stone, 2015; Wang, 2020; Van Hasselt et al., 2016).

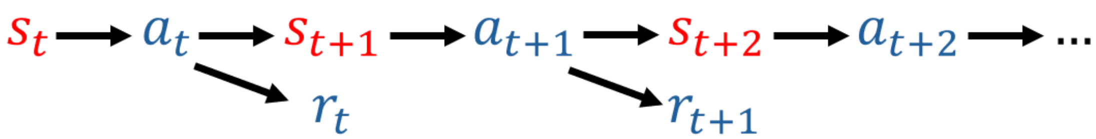
employs to determine the next action a based on the current state s: $\pi(a|s) = P(A = a|S = s)$. Policy function $\boldsymbol{\pi}$ is a probability distribution function which describes the probability of taking action $A = a$ under given state s.

From a given state s, an agent takes actions a and interacts with the environment, which in turn provides the agent with a new state s' and a reward r.

4) **Reward $\boldsymbol{r}$**: Reward r serves as feedback from the game environment, allowing us to evaluate success or failure of the agent's actions a in a given state s.
5) **State transition:** Involves the movement from an old state to a new state: $old\ state \xrightarrow{action} new\ state$; With given state s and action a, the probability of transitioning from state s to state s' is denoted as $p(s'|s,a) = P(S' = s'|S = s, A = a)$. The state transition is determined by the game environment itself.

In the interaction between an agent and the environment, the agent observes state s_t, make action a_t, the environment gives s_{t+1} and agent receives reward r_t. This process is depicted in the following figure (Wang, 2020).

Figure 5: Interaction Process Between Agent and Environment



Each interaction between the agent and the environment generates a sequence of State-Action-Reward-New State (SARS) data.

To facilitate the description of the cumulative rewards obtained by the agent from the environment, RL models typically define the following return functions (Wang, 2020):

6) **Return (aka cumulative future reward):** In RL, agents' goal is to maximize the cumulative future reward or cumulative reward U_t, which is the sum of all rewards received from the environment. The cumulative future reward can be expressed as: $U_t = \sum_{n=0}^{\infty} R_{t+n}$
7) **Discounted return (aka cumulative discounted future reward)**: Since future rewards are

uncertain, immediate rewards R_t are generally valued more than rewards received further in the future. To account for this, a discount rate $\gamma \in [0,1]$ is used to assign less weight to future rewards. The discounted return at time t can be calculated as: $U_t = \sum_{n=0}^{\infty} \gamma^n R_{t+n}$.

8) **Action-Value Function $Q(s, a)$**: The value of taking action a_t in given state s_t according to policy π, is defined as the action-value function $Q_\pi(s_t, a_t)$ which represents the expected return starting from state s_t, taking the action a_t, and thereafter following policy π.

$$Q_\pi(s_t, a_t) = E[U_t | S_t = s_t, A_t = a_t]$$

In simpler terms, given state s, the value of $Q(s, a)$ indicates the desirability of performing a particular action a in a given state s under the policy π. It grades all possible action $a \in A$ in state s_t based on policy π.

9) **Optimal action-value function $Q^*(s, a)$**: Denoting optimal policies by π^*, the maximum action-value function over all policies can thus be written as: $Q^*(s_t, a_t) = \max_{\pi} Q_\pi(s_t, a_t)$. Regardless of the policy function π used, the result of taking a_t at state s_t cannot be better than $Q^*(s_t, a_t)$. The $Q^*(s, a)$ function thus indicates how beneficial it is for an agent to perform action a in given state s_t. In other word, $Q^*(s, a)$ represents the expectation return of performing action a in current state s_t. Obtaining the optimal action-value function $\mathbf{Q}^*$ can greatly assist in controlling and optimizing the agent's behavior. With $\mathbf{Q}^*$, we simply need to choose the action that maximizes the Q^* function as our next action a_t, where $a_t = \operatorname{argmax}_{a} Q_\pi(s_t, a)$. This approach of determining agent behavior by maximizing the $\mathbf{Q}^*$ function is considered a value-based RL method.

DQN is one of the most classical and straightforward value-based RL method: In order to obtain the optimal action-value function $Q^*(s, a)$, DQN utilizes a neural network called the Q-network (as function approximator), denoted as $Q(s, a; \boldsymbol{w})$ to approximate the $Q^*(s, a)$ (Mnih et al., 2013). The Q-network takes the state s as input and output $Q(s, a; \boldsymbol{w})$, which represents the expected return of performing action $a \in A$ under state s, where $\boldsymbol{w}$ is trainable parameters of the neural net. More specifically, $Q(s, a; \boldsymbol{w})$ provides an estimation of the expected return for each action $a \in A$.

To train the Q-network, the classical DQN algorithm typically employs the Temporal Difference (TD) Learning algorithm to optimize the trainable parameter $\mathbf{w}$, aiming to make $Q(s, a; \boldsymbol{w})$ approach the optimal action–value function $\mathbf{Q}^*(\mathbf{s}, \mathbf{a})$. In simple terms, at time t, $Q(s_t, a_t; \boldsymbol{w})$ represents the Q-network's estimation of the expected return obtained by taking action a_t in state s_t.Subsequently, the environment provides a reward $r_t$and updates the state to s_{t+1}.

We thus denote TD target as: $y_t = r_t + \gamma\, max_a Q(s_{t+1}, a; \boldsymbol{w}) = r_t + \gamma\, Q(s_{t+1}, a_{t+1}; \boldsymbol{w})$, where γ is the discount rate. The loss function, known as the TD error, can thus be expressed as: $L_t = \frac{1}{2}(Q(s_t, a_t; \boldsymbol{w}) - y_t)^2$. Gradient descent is then used to update the parameter $\boldsymbol{w}$ of the Q-network:

$$w_{t+1} = w_t - \alpha \cdot \frac{\partial L_t}{\partial w}|_{w=w_t}$$

where α is learning rate.

In summary, DQN utilizes a neural network to approximate the optimal action-value function and make decisions to maximize the agent's return from the game (Wang, 2020). The network is trained using the TD Learning algorithm, with the parameter updates performed through gradient descent.

Table 3: Temporal Difference (TD) learning algorithm to optimize the Q network

1. *Observe state* $S_t = s_t$ *and action* $A_t = a_t$ *(where action* $a_t = \underset{a}{argmax}\, Q(s_t, a; \boldsymbol{w})$*)*
2. *Predict the value:* $q_t = Q(s_t, a_t; \boldsymbol{w}_t)$
3. *Differentiate the value network:* $d_t = \frac{\partial Q(s_t, a_t; w)}{\partial w}|_{w=w_t}$
4. *Environment provides new state* s_{t+1} *and reward* r_t
5. *Compute TD target:* $y_t = r_t + \gamma\, max_a Q(s_{t+1}, a; \boldsymbol{w})$
6. *Apply gradient descent to update parameter:* $w_{t+1} = w_t - \alpha\,(q_t - y_t)\; d_t$

This iteration needs to be repeated until the convergence of the trainable parameter $\boldsymbol{w}$

In terms of neural network structure, the deep Q-network $Q(s, a; \boldsymbol{w})$ typically consists of an input layer, an output layer, and an intermediate fully connected layer (if dealing with image-related tasks, a CNN layer is usually added before the first fully connected layer to extract image information). The DRQN algorithm is a combination of a Recurrent Neural Network (RNN) and a Deep Q-Network, which enables the agent to handle situations where it can only obtain partial observations of the environment. Specifically, an RNN layer (or LSTM, GRU) is added before the first fully connected layer of the original deep Q-network $Q(s, a; \boldsymbol{w})$ to process the agent's partial observations of the environment at multiple time points, allowing for improved estimation of the underlying system state (Hausknecht and Stone, 2015). Additionally, in the training dataset, each State-Action-Reward-New State (SARS) data generated by the agent's interaction with the environment is stored. Experience replay is allowed, and the priority of experiences is set according to the difference in TD error, prioritizing the use of data with larger TD errors for training, thereby enhancing training efficiency and effectiveness.

Summary of RL-based ABM

This section has introduced the application of RL methods to control agents in playing games. RL methods offer an adaptive learning approach for ABM, enabling the agents to develop dynamic rules for optimal behavior based on a predefined structure of rewards and the state of their environment. When applying RL methods to control agents, it is necessary to define what agents can perceive or observe, as well as the available actions. Unlike rule-based ABM, where decision rules governing agent behavior in response to the local environment are explicitly defined, in RL methods, the focus is on determining what agents value in an environment (i.e., the reward function they seek to optimize), as RL-based agents can learn from their own experiences or the experiences of others.

RL methods allow agents to learn how to achieve their goals through interactions with the environment. In situations where constructing rule-based ABM to describe human decision-making processes in a changing environment is challenging, RL methods offer an alternative approach to establishing the ABM.

Using drinking behavior as an example, establishing explicit rules governing adaptive decision-making in a changing environment is difficult. However, in RL-based methods, rewards can be used to understand people's choices and decisions. Our MBE hypothesis suggests that agents' intentions and behaviors are partially based on rational deliberation, with the objective of establishing new social connections and obtaining social support. Furthermore, we assume that agents can obtain partial observations of the environment, including friendship relationships and friends' drinking behavior. The RL method then handles the task of finding the link between observations and optimal actions to achieve the objectives.

When integrating RL methods into an established simulation model, the simulation framework is divided into two phases:

- Training phase: During the training phase, agents iteratively interact with the ABM environment to train a high-performance $Q(s, a; \boldsymbol{w})$. The reinforcement learning outcomes of the agents are stored as decision-making controllers.
- Experimentation phase: Agents with well-trained decision-making controllers can be utilized for modeling purposes and observed, similar to any rule-based ABM.

In this process, RL methods provide ABM with information processing capabilities that enable the exploration of strategies that satisfy the conditions imposed by the interaction rules. In turn, ABM provides RL with access to models of collective behavior that achieve emergence and complexity.

Appropriate Model Output Validation

Output validation is an essential component in establishing the credibility and acceptability of a simulation model, ensuring it fulfills its intended purpose (Collins et al., 2024). Upon completing the construction of an ABM model, the modelers are required to run and test the model to assess its capability to reproduce the target social patterns, particularly evaluating whether: (1) it can viably reproduce the target social patterns and (2) the stability of its capacity to reproduce these patterns.

Current literature indicates that comprehensive model output validation encompasses face validation and uncertainty quantification:

"Face validation" involves a systematic comparison of the model's simulated outcomes with well-defined target social patterns to evaluate to what extent the model's macro-level outcomes can replicate real-world dependency relationships of interest (Manzo, 2022: 57). "Face validation" varies across different types and purposes of ABM models (Edmonds et al., 2017). For the POM ABM model developed in this study, the literature suggests a four-step process for face validation:

Step 1: Utilizing specific datasets (qualitative/quantitative) to precisely defining one or multiple observed social patterns as indicators of the target social phenomena to be replicated (Railsback and Grimm, 2012: 240): without a clearly defined explanandum, no precise cause-effect connection can indeed be established (Casini and Manzo, 2016; Railsback and Grimm, 2012: 234).

Step 2: Defining criteria for pattern-matching to determine whether the model output reproduces each identified pattern. Visual or qualitative criteria, such as visual pattern matching and trends in statistical summary output, are essential for assessing whether the model output falls within the range of observations or reflect pattern trends (Gallagher et al., 2021). Additionally, quantitative criteria could also be used to measure differences between simulated and observed patterns and quantitatively evaluate model goodness-of-fit (Railsback and Grimm, 2012: 234; Gallagher et al., 2021). For example, defining a distance measure function (commonly mean squared error, cross-entropy error) can quantitatively establish an acceptable level of fit criteria for determining what distance between the target pattern and the output data can be deemed acceptable (Gallagher et al., 2021).

Step 3: Calibrating the adjustable parameters and running the established ABM model to generate model output. Modifying adjustable parameter values can alter the relative importance of different processes, thereby influencing the dynamics of the model output. Consequently, identifying a set of plausible parameter values is essential. Depending on the model's purpose, these can range from automated methods like optimization algorithms to more heuristic approaches such as referencing existing literature, consulting with domain experts, employing trial-and-error methods, or leveraging informed estimation (educated guesswork), to ensure that model outputs can reproduce or align with defined empirical patterns (Railsback and Grimm, 2012: 255-257; Lee et al., 2015).

Step 4: Assessing the fitness between the model output and target social patterns based on defined pattern-matching criteria (Casini and Manzo, 2016). If the model output meets the defined pattern-matching criteria, the model passes face validation. Otherwise, the modeler should return to step 3 to recalibrate the model's adjustable parameters within its parameter space and conduct step 4 again to assess the fitness between the model output and target social patterns. This iterative process continues until the model passes face validation. If the model cannot pass face validation within its parameter space, the current MBE hypothesis fails to constitute a candidate MBE. The modeler should reformulate the MBE hypothesis and transform it into a new ABM model.

Passing face validation suggests that the ABM can viably reproduce the intended social pattern. However, to ensure this result is not a mere artifact of the model's stochasticity or a narrow choice of parameters, further analysis of the model's uncertainty is often warranted. This process, known as uncertainty quantification, primarily assesses the stability of the model's capacity to reproduce these patterns, thereby enhancing its credibility. The two most common forms of this analysis are the stochastic uncertainty test and sensitivity analysis (McCulloch et al., 2022; Abreu and Ralha, 2017).

Stochastic uncertainty test involves examining the variability of an ABM's simulated outcomes across repeated simulations under identical parameter settings (Manzo, 2022:63; McCulloch et al., 2022). ABM models often incorporate various stochastic components. For example, agents' attributes are typically initialized based on probability distributions; their behaviors may be determined through pseudo-random sampling; interactions between agents may occur randomly, and the order in which agents are invoked might be randomized. Consequently, a single simulation can be regarded as a specific realization of an unknown stochastic process. As a result, given a set of initial conditions and adjustable parameter values, the model output may vary with each simulation run. Stochastic uncertainty test focuses on quantifying the variability of the ABM's simulated outcomes when the model is executed multiple times under the same parameter settings (Manzo, 2022:66; McCulloch et al., 2022), ensuring that typical results are not merely fortuitous (Alves and Nadalin, 2023).

Sensitivity Analysis is the process of systematically assessing how variations in model parameters affect the model's outputs (Janssen et al., 2019). Its primary objective is to evaluate the robustness of the model's findings, ensuring that the conclusions are not artifacts of a specific parameterization (Alves and Nadalin, 2023). This analysis helps identify the parameters that exert the most significant influence on the outcomes and reveals the conditions under which the model's behavior remains stable or undergoes critical shifts (Šešelja, 2021). Methodologically, sensitivity analysis can be conducted through various techniques, which are often broadly categorized as local methods, such as One-Factor-at-a-Time (OFAT) that assess parameters individually, and global methods, which explore interaction effects across the entire parameter space (Ten Broeke et al., 2016). While comprehensive, conducting a thorough sensitivity analysis can be computationally intensive, particularly for complex models with a large number of parameters, a challenge often discussed in the context of the "curse of dimensionality" (Manzo, 2022:64; Bruch and Atwell, 2015; Lamperti et al., 2018).

Face validation and uncertainty quantification are both important components of the "Redescription" stage to ensure that the ABM model can stably reproduce target social patterns, thereby providing support for the viability and credibility of the MBE hypothesis as a candidate explanation.

Model output validation is widely considered one of the most challenging and time-consuming aspects of the ABM simulation approach. Lamperti et al. (2018) highlight that three computationally expensive steps are involved in ABM validation: running the model, assessing the goodness-of-fit of the model output, and locating parameters of interest. These steps often account for more than half of the time required to calibrate ABMs, even for relatively simple models. Indeed, most POM ABMs utilize many parameters and a relatively large number of time steps, resulting in a "curse of dimensionality" that leads to an exponential number of critical points along the parameter space and impractical computational costs (Lamperti et al., 2018; Perumal and van Zyl, 2020).

In summary, as noted by Casini and Manzo (2016), due to the inherent multifinality and equifinality of MBEs, it remains possible that any ABM, no matter how well calibrated, validated, or tested, may lack external validity. No serious modeler can completely exclude the possibility that the evidence provided by the simulation systematically underdetermines causal inference. However, appropriate and sufficient input empirical calibration and validation are crucial for increasing a researcher's confidence in the external validity of the MBE postulated by the ABM model (Casini and Manzo, 2016).

Summary on Using ABM to Test MBE Hypotheses

We aim to develop a "Typifications" type of RL-based ABM with a moderate level of model complexity and empirical realism, while adhering to the abductive reasoning principle to test the proposed MBE hypotheses. The testing process will be divided into two stages, which will be detailed in Chapter 4 and Chapter 5, respectively:

- Stage 1 (Chapter 4): Successful completion of the “Redescription” of the target social phenomenon is a foundational premise of this study. To achieve this, we will carefully translate and formalize the MBE hypotheses into an RL-based ABM model. We will then run the constructed ABM model for parameter calibration and output validation, aiming to evaluate its capacity to stably reproduce the defined empirical patterns. Models that successfully pass the "generative sufficient test" will advance to the subsequent stage of "Retroduction" analysis.

- Stage 2 (Chapter 5): Following the completion of the Redescription process in Stage 1, the testing of the MBE hypothesis enters the “Retroduction stage.” Through “Retroduction” analysis, we aim to identify indispensable components of the candidate MBE, with a particular focus on the respective roles of social capital and cultural significance of drinking behavior in the emergence of college drinking diffusion.

    (1) Firstly, we will introduce control groups to examine the role of social capital, specifically to determine whether the absence of social capital-driven motivation precludes the target phenomenon, and how social capital-driven motivation operates in individuals’ drinking choices.
    (2) Secondly, we will continue with comparative studies, focusing on the identity homophily and identity exclusivity driven by the cultural significance of drinking behavior, in order to identify its impact on the emergence of alcohol diffusion phenomena.

Ethical Considerations

In accordance with Durham University's Research Ethics policy and guidelines, the adherence to and upholding of ethical standards in any research endeavor is of paramount importance. The empirical research component of this study is entirely predicated on computer simulation experiments and does not involve research activities that encompass human participants.

Chapter 4: ABM Model Design and “Generative Sufficient Test”

Following the principle of abductive reasoning, this chapter aims to translate and formalize the MBE hypotheses proposed in chapter 3 into an RL-based ABM model. This will allow for the conduct of generative sufficient tests on the MBE hypotheses within the artificial social environment defined by ABM model.

To achieve this objective, we have divided this chapter into two sections:

- The first section focuses on the design of an RL-based ABM model. We aim to translate the MBE hypotheses into an RL-based ABM model that simulates the interaction of a large and heterogeneous group of college students' drinking behaviors and the formation of friendship relationships within a college friendship network environment. Given that our model is classified as a POM "typification" ABM model, we will leverage existing qualitative empirical evidence on the typical social psychological characteristics of college students, typical college drinking social contexts, and the mechanisms and features of college students' friendship network formations to build the ABM model on an appropriately empirical ground.

- The second section involves conducting “generative sufficient tests” using the well-designed ABM model, aiming to assess model’s capability to viably and stability reproduce the target social patterns.

Section 1: Design an ABM Model

Drawing from existing empirical research on typical drinking contexts among college students, we will translate the MBE hypotheses into an RL-based ABM model. We will begin by providing a detailed introduction to the design of the ABM model and the rationale behind it. At the conclusion of this section, we will summarize the well-designed ABM model.

Step 1: Initialize Social Network Environment

Based on our MBE hypotheses, all individual college students are embedded within a friendship network on a university campus (with no socially isolated student in the initial network). The typology of this friendship network describes the social relational structure situation of individual college students. Therefore,

- Initial friendship network: We will begin by generating a random Erdős–Rényi network (ER network) as the initial social network environment for college students. The edge probability parameter, p, should be set at a low level (e.g. $p \in (0, 0.2)$) to ensure a low-density initial network environment before interactions begin. The ER network is one of the most commonly used network models for modeling human social networks, particularly when we want the initial network to exhibit complete randomness rather than a specific network structure. This is appropriate for simulating the social relational structure where individual college students are randomly assigned or randomly encounter each other when they first enter the university campus.

  The initial ER network will consist of N nodes, with each node representing an individual college student and the edges representing the friendship relationships between them. The edges will be undirected and weighed. For a college student friendship network, the social network size N should be set at a moderate level, such as $N \in [10, 100]$, as excessively large or small networks are unrealistic for a college student friendship network.

  The initial weight values for all edges will be set to 1, and these values will change as a result of interactions between agents. Higher weight values indicate stronger friendship relationships, and vice versa. A weight value of 0 indicates the absence of a friendship relationship.

- Individual State Attribute: According to the MBE hypotheses, all individual college students possess a certain degree of heterogeneity in their individual attributes, which delineate the current states of these agents. Within the purview of individual state attributes, certain attributes are not autonomously determined by the individual agency but are instead environmentally determined. These non-autonomously determined individual attributes comprise:

- Individual ID: Each individual is recognized as a distinct agent, assigned a unique numerical identifier that remains constant over time and throughout the game process.
- Social support: This attribute describes the social support that the agent receives from their friends in the current network. The method for calculating the social support obtained by individuals will be described later.

Furthermore, there exists a subset of state attributes that are within the purview of the agents' own volition and are amenable to change. These individual attributes, which are subject to the agents' behavioral decisions, are referred to as individual behavioral attributes.

- Individual Behavioral Attributes: According to the MBE hypothesis, all individual college students possess behavioral decision-making autonomy, thereby enabling them to alter their behavioral attributes. Within this ABM model, each agent in the network has two types of behavioral attributes, which, unlike individual state attributes, can be autonomously decided and changed by agents through the decision-making process in the game. They include:

  - Current drinking behavior status of the individual (referred to as Individual Behavioral Attribute 1): College students have the autonomy to decide whether to engage in drinking behavior. Individual Behavioral Attribute 1 describes whether a college student will currently choose to accept drinking, consisting of two states: the individual currently accepts drinking, and the individual currently does not accept/reject drinking.

  - Current identity status of the individual (referred to as Individual Behavioral Attribute 2): The identity status attribute describes the extent to which a college student's identity formation is influenced by the cultural significance of drinking behavior in the social environment. The cultural significance of college drinking behavior makes college drinking behavior as a highly scripted ritualized behavior which links an individual's drinking behavior to their identity. This implies that the acceptance of drinking behavior is suggestive of a preference for an identity characterized by risk-taking, hedonism, and maturity, or a belonging to a collective identity that condones such behavior. Conversely, the refusal to partake in drinking may signify resistance against identifying with these cultural norms and the associated identity constructs. The MBE hypothesis of this study suggests that the cultural significance of drinking behavior may influence the identity formation of individual college students through situational mechanisms, and this influence exhibits heterogeneity among individuals.

Existing empirical studies indicate that the extent to which individual identity is influenced by cultural factors in the environment is the result of the interaction between individuals and the environment. Identity formation is normally believed to follow the Marcia identity formation model (see Literature review chapter): individuals engage in identity exploration, identity reflection, and form new identity commitments. Some college student individuals have relatively unstable current identity commitments making them susceptible to the influence of the cultural structure in the social environment. Conversely, some college students have relatively stable identity commitments and are less influenced by the social environment.

To simplify the model, Individual behavioral attribute 2 describes the extent to which an individual's identity formation is influenced by the cultural significance of drinking behavior and identifies with drinking behavior implying a particular identity preference using a binary classification approach. Therefore, Individual behavioral attribute 2 includes two attribute states:

- Associating drinking behavior with identity implications, where individuals perceive drinking behavior as implying a preference for certain identities (e.g. mature, hedonistic and risk-taking), while refusing to drink implies resistance to the preference for such identities.

- Not Associating drinking behavior with any identity preference.

By combining the two types of individual behavioral attributes, all agents in the social network can be classified into four categories, represented by behavioral states 1-4:

Table 4: Four Types of Agents

	Accept to Drink	***Refuse to Drink***
Associate Drinking with Identity	Committed Drinker (State 1)	Committed Non-Drinker (State 3)
Not Associate Drinking with Any Identity	Modest Drinker (State 2)	Modest Non-Drinker (State 4)

Specifically,

- **State 1**: The agent currently accepts drinking and identifies drinking behavior as implying a specific identity preference. Agents in state 1 strongly favor drinking behavior, as they not only partake in drinking but also identify drinking behavior with the implied identity preference. For mnemonic convenience, State 1 agents are designated as 'committed drinkers.'
- **State 2**: The agent currently accepts drinking but does not identify drinking behavior as implying any specific identity preference. Agents in State 2 moderately favor drinking behavior, as they only accept drinking but do not identify any identity preference implied by drinking behavior. State 2 agents are designated as “modest drinkers”.
- **State 3**: The agent currently refuses to drink but identifies drinking behavior as implying a specific identity preference. Agents in State 3 strongly resist drinking behavior, as they recognize the identity preference implied by drinking behavior but refuse to drink, indicating their resistance to the implied identity preference of drinking behavior. State 3 agents are designated as “committed non-drinkers”.
- **State 4**: The agent currently refuses to drink and does not identify drinking behavior as implying any specific identity preference. Agents in State 4 modestly resist drinking

behavior, as they only resist drinking behavior. State 4 agents are designated as “modest non-drinkers”.

- Initial agents' behavioral states distribution: In the initial social network, the initial proportion distribution of the four different individual behavioral states of agents can be set as an adjustable parameter. For the purpose of generative sufficient testing, all agents' initial behavioral states are set to modest non-drinker, meaning that in the initial college friendship network, all individuals refuse to drink and do not identify any specific identity preference associated with drinking behavior. This setting is primarily based on two reasons: firstly, as interactions between agents have not yet begun in the initial social environment, we assume that the identity formation process of agents has not been influenced by the cultural significance of drinking behavior on campus. Therefore, in the initial network, all agents do not identify any specific identity preference associated with drinking. Secondly, as we aim to observe the dynamic process of the spread of drinking behavior within the college student community, all agents are in a state of refusing to drink in the initial network.[32]

Step 2: Interaction Process

We have configured the initial social network environment and will now proceed to the interaction process among agents in the social network. In each complete social simulation experiment (referred to as a "game"), agents engage in R rounds (or “steps” of the game) of interaction.[33] Each round of interaction consists of four phases: **Phase 1**: Observation, **Phase**

[32] It is important to reiterate that the initial state distribution of agents represents an adjustable parameter, amenable to modification per the dictates of the study's objectives. Although setting all agents' initial states to "modest non-drinker" may conflict with real-world scenarios (such as some students having started drinking before entering college or associating drinking behavior with certain identity preferences) this setup helps us observe how drinking behavior and agents' identification with drinking culture spread within the social network.

[33] R is an adjustable parameter used to describe the number of steps included in each complete simulation experiment. It should be set based on the duration of college student friendship networks in real-life situations and should not be set too large or too small. In simpler terms, after generating an artificial social system, the agents within the system will undergo R rounds of interactions, thereby completing a full simulation experiment. Subsequently, the existing artificial social system will be deleted, and a new one will be instantiated. The novel social system will be then populated with new agents who will then undergo another R rounds of interactions. This process will be repeated iteratively.

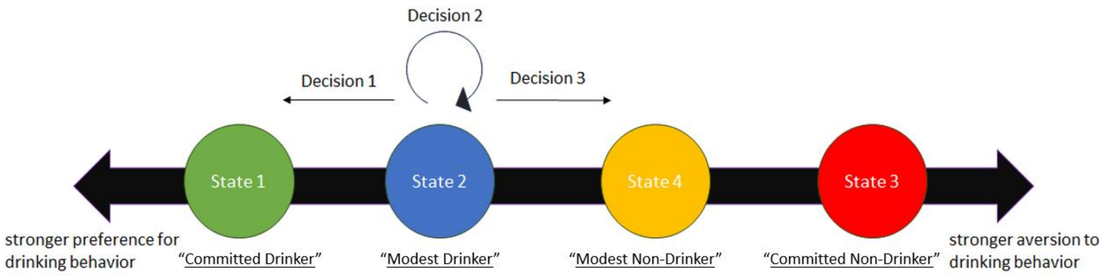
2: Decision-making, **Phase 3**: Interaction and Friendship Update, and **Phase 4**: Recalculation of Social Capital. The following provides a detailed description of these four phases:

- **Phase 1: Observation**. At the beginning of each round of interaction, all agents obtain partial observations of social network information, which they will use for their subsequent decision-making. In a realistic setting, agents are unable to obtain complete information about the complete social environment. Instead, they have limited visibility and can only access local information rather than global information. The observed network information available to agents includes: 1. Agent's own ID, 2. Agent's current behavioral state, 3. Agent's current social support received from its neighboring agents, 4. Weights of the edges connecting the agent to its neighboring nodes, representing the strength of the agent's friendships, and 5. Current behavioral states of all neighboring nodes, representing the behavioral states of the agent's friends.
- **Phase 2: Behavior Decision-Making**. Agents make decisions based on the observational information obtained from the network environment to either change or maintain their current behavioral state. Specifically, the decisions of all agents are controlled by a neural network, referred to as the deep Q-network, trained by DRQN with prioritized experience replay algorithm (see Chapter 3). Agents input their current observations into the deep Q-network, which outputs a tensor. We select the decision represented by the maximum element in the tensor as the decision action for the agent in this round, which will determine the state transition for the agent in this round. The decision action space for the agent includes three elements: Decision 1, Decision 2, and Decision 3. Based on the decisions made by agents, the state of the agent will undergo transformations according to the state transition rules outlined in Table 5.

Table 5: State Transition Rule			
Current State	***Decision 1***	***Decision 2***	***Decision 3***
Committed Drinker (State 1)	Committed Drinker (State 1)	Committed Drinker (State 1)	Modest Drinker (State 2)
Modest Drinker (State 2)	Committed Drinker (State 1)	Modest Drinker (State 2)	Modest Non-Drinker (State 4)
Committed Non-Drinker (State 3)	Modest Non-Drinker (State 4)	Committed Non-Drinker (State 3)	Committed Non-Drinker (State 3)
Modest Non-Drinker (State 4)	Modest Drinker (State 2)	Modest Non-Drinker (State 4)	Committed Non-Drinker (State 3)

To visually illustrate the state transition rules, we can arrange states 1-4 on a line with arrows. The position of each state on the line reflects the degree of preference or aversion towards drinking behavior, with states to the left indicating a greater preference and states to the right indicating a stronger aversion. Agents located at a specific state along the line have three possible decisions: decision 1, transitioning to the state on the left (remaining in the current state if the agent is already in the leftmost state 1); decision 2, remaining in the current state; decision 3, transitioning to the state on the right (remaining in the current state if the agent is already in the rightmost state 3).

Figure 6: State Transition Rule



- **<u>Phase 3: Interaction and Friendship Update</u>.** According to MBE hypothesis, an agent's current drinking behavior and identity commitment will influence the formation of friendship relationships through similarity-based peer selection, in form of homophily (social inclusion) and exclusivity (social exclusion). Therefore, after all agents have made their state transition decisions in the current round of the game, they will interact with all of their first-order and second-order neighbors through pairwise interactions. The friendship relationships between two interacting agents, measured by edge weights, will be influenced by their current states and will change accordingly. The specific interaction rules are presented in the following table 6.

Table 6: Interaction Rules

State	***Committed Drinker (State 1)***	***Modest Drinker (State 2)***	***Committed Non-Drinker (State 3)***	***Modest Non-Drinker (State 4)***
Committed Drinker (State 1)	2a+2b+2c	2a+2b+c	0	0
Modest Drinker (State 2)	2a+2b+c	2a+2b	0	2a
Committed Non-Drinker (State 3)	0	0	2a+2b	2a+2b
Modest Non-Drinker (State 4)	0	2a	2a+2b	2a+2b

Notes:

1. Interaction Contribution: Parameter a

2. Behavioral Homophily Contribution: Parameter b

3. Identity Homophily Contribution: Parameter c

Explanation of interaction rules: Existing Social Network Analysis (SNA) studies, as referenced in the literature review chapter, indicate three common forms of similarity-based peer selection that shape friendship relationships within college student networks: proximity similarity, behavioral similarity, and identity similarity. Therefore, during the process of pairwise interaction between agents, the formation of friendship between any two interacting agents is influenced by these three approaches:

- Friendship enhancement through interaction (proximity similarity): The more frequent the interaction between two agents, the stronger their friendship will be. Therefore, the friendship between two agents is established or strengthened through their interactions. We denote the friendship strength contributed by interaction as adjustable parameter "a".
- Behavioral Homophily: Agents tend to establish or strengthen friendships with others who exhibit the same behaviors. In addition to the friendship strength derived from interaction, the effect of behavioral homophily will contribute additional friendship strength between agents who share the same drinking behavior state (either both drinking or both not drinking). We denote the friendship strength contributed by behavioral homophily as adjustable parameter "b".

- <u>Identity homophily and identity exclusivity</u>: Agents tend to strengthen friendships with other agents if they perceive them as sharing a similar identity. We denote the friendship strength contributed by identity homophily as adjustable parameter "c". At the same time, agents tend to exclude an agent if they perceive that the agent has an identity conflict with themselves. The identity exclusivity between interacting agents will directly sever their friendship relationship.

Using the following parameter combination as an example, we provide a more detailed explanation of the pairwise interaction rules: Contribution parameters to friendship strength:

- Parameter a for friendship strength from interaction: $a = 0.5$
- Parameter b for friendship strength from behavioral homophily: $b = 1$
- Parameter c for friendship strength from identity homophily: $c = 2$

- <u>Modest Drinker ↔ Modest Non-Drinker</u>: In the case of pairwise interaction between modest drinker and modest non-drinker, where the agents have different drinking behavioral attributes (i.e., one accepts drinking and the other refusing drinking) and neither agent identifies with drinking behavior implying identity preference, behavioral homophily and identity homophily do not apply. Therefore, the only approach to strengthen friendship is through an increase in the number of interactions. The contribution parameter (a) to friendship strength from interaction is 0.5. Hence, in each interaction round, each agent will contribute 0.5 units of strength to the friendship, resulting in a total increase of 1 unit of strength in the friendship (described by edge weight) between the two agents.
- <u>(Modest Drinker ↔ Modest Drinker) and (Modest Non-Drinker ↔ Modest Non-Drinker):</u> If two interacting agents have the same drinking behavioral attribute (i.e., both accept or both refuse drinking) and both agents do not identify with drinking behavior implying identity preference, their friendship will not only strengthen due to an increase in the number of interactions but will also be influenced by behavioral homophily. The contribution parameter (b) to friendship strength from behavioral homophily is set to 1. Therefore, in the interaction round, each agent will contribute

1.5 units of strength to the friendship, resulting in a total increase of 3 units of strength in the friendship (described by edge weight) between the two agents.

- Committed Drinker ↔ Modest Drinker: When at least one interacting agent identifies with drinking behavior implying identity preference, we also need to consider the effect of identity homophily on their friendship construction. If both agents drink and one of them identifies with drinking behavior implying identity preference (committed drinker agent), on one hand, the committed drinker agent will exhibit identity homophily towards the modest drinker agent as, from the committed drinker agent's perspective, modest drinker agents accepting the drinking behavior indicates a mature and free identity preference similar to their own identity. Therefore, this one-way identity homophily will contribute an additional strength of 2 units (c = 2) to their friendship. On the other hand, the modest drinker agent will only exhibit behavioral homophily towards the committed drinker agent as, from the modest drinker agent's perspective, the drinking behavior does not imply any identity preference. Hence, in this interaction round, the friendship relationship (edge weight) between the two agents will increase by 5 units of strength.
- Committed Drinker ↔ Committed Drinker: When both interacting agents accept drinking and identify with drinking behavior implying identity preference (Committed Drinker), their friendship will be enhanced by the interaction via the effect of both behavioral homophily and identity homophily. In this case, the friendship relationship (edge weight) between the two agents will increase by 7 units of strength.
- (Committed Drinker ↔ Committed Non-Drinker) and (Committed Drinker ↔ Modest Non-Drinker): When an agent in Committed Drinker interacts with a non-drinking agent (Committed Non-Drinker or Modest Non-Drinker), from the perspective of the Committed Drinker, the rejection of drinking behavior implies a resistance to identity preferences such as maturity and rebellion, conflicting with the Committed Drinker's own identity preference. This leads to the effect of identity exclusivity on their friendship, and the Committed Drinker will serve the friendship with the non-drinking agent (Committed Non-Drinker or Modest Non-Drinker). In other words, the edge weight between them becomes 0, indicating a complete disconnection of their

friendship.

- (Committed Non-Drinker ↔ Committed Non-Drinker) and (Committed Non-Drinker ↔ Modest Non-Drinker): When a pair of non-drinking agents interact, their friendship construction will be influenced by behavioral homophily and the increased interaction frequency, leading to an increase in the friendship relationship (edge weight) between the two agents by three units of strength due to the increased interaction frequency and influence of homophily.

  It is important to note that being in Committed Non-Drinker indicates agent's resistance to the identity preference implied by drinking behavior. However, this resistance does not create a new identity preference when Committed Non-Drinker interact with other non-drinking agents, and their friendship construction is not influenced by identity homophily.

- (Committed Non-Drinker ↔ Committed Drinker) and (Committed Non-Drinker ↔ Modest Drinker): When an agent in Committed Non-Drinker interacts with a drinking agent, from the perspective of the Committed Non-Drinker, the acceptance of drinking behavior implies identity preferences conflicting with the Committed Non-Drinker 's own identity preference, leading to the effect of identity exclusivity on their friendship. The Committed Non-Drinker will sever the friendship with the drinking agent (Committed Drinker or Modest Drinker), resulting in a complete disconnection of their friendship.

- **Phase 4: Recalculation of Social Capital**. After all agents have completed their pairwise interactions with their immediate first-order and second-order neighbors according to the interaction rules in phase 3 and have updated their friendships, the structural typology of the social network, as well as the network positions of the agents, will undergo changes. Consequently, the social support received by each agent will be altered. We need to recalculate the social support received by each agent in the updated social network.

Based on existing research, social capital is commonly categorized into two types, namely bonding capital and bridging capital. In this study, we primarily focus on bonding capital and measure it using the social support that agents receive from their direct friends. Bridging capital is not within the scope of this study (see Literature Review chapter).

To calculate the bonding capital of each agent (i.e., the social support received from friends), we first assume that each agent possesses an equal amount of resources (such as time, emotions, and energy) that can be used to provide social support, meaning that each agent is of equal importance. Agents will allocate these resources to their friends based on the strength of their friendship, which is measured by the edge weights. The bonding capital of each agent is the sum of the resources allocated to the agent by its neighboring nodes (friends).

Specifically, we denote the social network graph as $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ represents the set of nodes and $E \in V \times V.$ represents the set of edges. Each agent has the same total amount of resources, denoted as $R_{v_\mathrm{i}} = 1$ for agent$v_\mathrm{i} \in V$. We regard the set of neighboring nodes of agent v_i as N_{v_i}. Agent v_i will proportionally allocate its resources R_{v_i} to its neighboring nodes based on their friendship strength. For agent v_i's neighboring node v_j, where $v_\mathrm{j} \in N_{v_\mathrm{i}}$, we represent the allocated resource value from agent v_i to agent v_j as R_ij. Thus, $R_\mathrm{ij} = \frac{W_{ij}}{\sum W_i}$, where W_{ij} represents the weight of the edge connecting agent v_i and agent v_j.

After calculating the allocated resource values from each agent v to its neighboring nodes, for agent v_i, the bonding capital or social support: BC_{v_i} is the sum of all resources allocated to agent v_i by its neighboring nodes, denoted as $BC_{v_\mathrm{i}} = \sum_{v_\mathrm{j} \in N_{v_\mathrm{i}}} R_\mathrm{ji}$.

Step 3: Iterating the Interaction Process

The interaction process, which includes four phases: observation, behavior decision-making, interaction and friendship update, and recalculation of social capital, is repeated iteratively. Each complete execution of the four phases in Step 2 is considered as one round/step of interaction in the simulation game. We continuously repeat the interaction process in Step 2 until reaching a total of R rounds of interaction, completing a full game simulation.

ABM Model Design

We have provided a detailed introduction to the ABM model used for testing MBE hypothesis in this study. Below, we summarize the key steps of the model for ease of reference. Given that the decision-making of agents in this ABM should be controlled by a well-trained deep Q-network, the ABM model will be utilized for Simulation Experiments to test MBE hypothesis and for training the deep Q-network. We will provide separate summaries for each.

ABM Model for Simulation Experiments

- Step 1: Initialize social network environment.
    - Phase 1: Generate a weighted undirected ER network with N nodes as the initial social network.
    - Phase 2: Set the weights of all edges in the initial social network to 1.
    - Phase 3: Set the initial behavioral state of all agents in the initial social network to modest non-drinker (Modest Non-Drinker).
    - Phase 4: Calculate and record the initial social support values of all agents.
- Step 2: Interaction process
    - Phase 1: Observation: Traverse all agents, each agent obtains and records local observation information about the current social network environment.
    - Phase 2: Behavioral decision-making: Traverse all agents, each agent input the observed environmental information into the deep Q-network and determine the decision to be made in this round based on the output of the Q-network (the decision space includes {decision1, decision2, decision3}).
    - Phase 3: State transition: Traverse all agents, update the behavioral state of each agent based on the decision made in this round (decision1-decision3) and the current

behavioral state (Committed Drinker to Modest Non-Drinker), following the rule defined by the state transition table (Table 5).

  - Phase 4: Interaction and friendship update: Traverse all agents, each agent sequentially interacts with its first-order and second-order neighbors in pairs. Interaction rule: Based on the current behavioral state of the interacting paired agents, the agent updates the friendship between them following the rule defined by the Interaction Rules Table (Table 6).
  - Phase 5: Recalculation of Social Capital: Traverse all agents, recalculate the social support received by each agent from its first-order neighbors in the updated social network, to record and update each agent's current social support.
- Step 3: Continuously repeat the interaction process in Step 2 until reaching a total of R rounds of interaction.

ABM Model for Neural Network (NN) Training

Before utilizing the above ABM model to test MBE hypotheses, we first train the deep Q-network that controls the agents' decision-making in Step 2 - Phase 2. For this purpose, a neural network training module will be added to the existing ABM model, and the ABM model will be iteratively run to generate training datasets, which will be used to optimize the network parameters of the deep Q-network until the training loss reaches the ideal level.

The ABM model for training the deep Q-network is identical to the ABM model for simulation experiments, except for the addition of a neural network training module (step 2-phase 7):

- Step 1: Initialize social network environment.
  - Phase 1: Generate a weighted undirected ER network with N nodes as the initial social network.
  - Phase 2: Set the weights of all edges in the initial network to 1.
  - Phase 3: Set the initial behavioral state of all agents in the initial network to Modest Non-Drinker (state 4).
  - Phase 4: Calculate and record the initial social support values of all agents.

- Phase 5: Create an empty replay buffer as a training database to store the training dataset.

- Step 2: Interaction process
  - Phase 1: Observation: Traverse all agents, each agent obtains and records local observation information about the current social network environment.
  - Phase 2: Behavioral decision-making: Traverse all agents, each agent input the observed environmental information into the deep Q-network and determine the decision to be made in this round based on the output of the Q-network (the decision space includes {decision1, decision2, decision3}).
  - Phase 3: State transition: Traverse all agents, update the behavioral state of each agent based on the decision made in this round (decision1 to decision3) and the current behavioral state (state 1to state 4), following the rule defined by the state transition table (Table 5).
  - Phase 4: Interaction and friendship update: Traverse all agents, each agent sequentially interacts with its first-order and second-order neighbors in pairs. Interaction rule: Based on the current behavioral state of the interacting paired agents, the agent updates the friendship between them following the rule defined by the Interaction Rules Table (Table 6).
  - Phase 5: Recalculation of Social Capital: Traverse all agents, recalculate the social support received by each agent from its first-order neighbors in the updated social network, to record and update each agent's current social support. This is recorded as the reward obtained by the agent in this round.[34]
  - Phase 6: After completing phases 1 to 5 in Step 2, each agent generates a "State-Action-Reward-New State" (SARS) record for this round. We traverse each agent and store the SARS record for each agent in the experience replay buffer.
  - Phase 7: After every S rounds of the game, randomly sample a batch of SARSdata records with a capacity of T from the experience replay buffer. Each batch contains

[34] According to the MBE hypothesis, the individual's motivation to seek social support will influence their choices in alcohol consumption behavior and identity formation through the action formation mechanism. Therefore, the reward used during the training of the deep Q-network is based on the social support obtained by the agent.

M consecutive time steps of SARS data records from the same agent. The probability of being selected for data extraction is related to the Temporal-Difference (TD) error value of the initial SARS data in the batch. The larger the TD error value, the higher the probability of being selected. Train the deep Q-network using the batch data and update the network parameters using the TD learning algorithm.[35]

- Step 3: Continuously repeat the interaction process in Step 2 until the training error attains a predetermined, satisfactory threshold or the parameters of the neural network exhibit convergence. Save the trained NN parameters for use in social simulation experiments of the ABM model.

Summary on ABM Model Design

In this section, we have translated the MBE hypotheses to be tested into a "Typifications" type of ABM simulation model. This ABM model will contribute to understanding the social outcome that our MBE hypothesis can trigger and allow us to test and evaluate the key components of interest in the MBE hypotheses. In the remaining part of this chapter, we will first utilize this ABM model to complete the generative sufficient test of our MBE hypothesis, following the abductive reasoning principle.

[35] In this ABM model, a single deep Q-network is used as the decision-maker for all agents in the social network. Specifically, in the context of multi-agent reinforcement learning (MARL) in this study, we aim to control the behavior decisions of all heterogeneous agents in the network. Existing MARL research provides various options for control methods, including training-distributed control and distributed training-distributed control. In this ABM model, all agents do not have explicit cooperation or competition relationships, and there is no explicit communication. Each agent only cares about the gains or losses of their own social support. Therefore, the role of all agents as actors can be considered as the same category in reinforcement learning (agents are homogeneous from perspective RL training). For this MARL scenario, homogeneous agents can share the same experiment replay buffer and the same set of parameters (i.e., parameter sharing), which is an effective method (Gupta, et al., 2017).

As Gupta, et al. (2017) pointed out, "If the agents are homogeneous, their policies may be trained more efficiently using parameter sharing. In the parameter sharing approach, we allow all the agents to share the parameters of a single policy. This allows the policy to be trained with the experiences of all agents simultaneously. However, it still allows different behavior between agents because each agent receives different observations, which includes their respective index." In other words, "the control is decentralized but the learning is not." (Gupta et al., 2017).

Therefore, following the work of Gupta et al. (2017), in this study, the deep Q-network that controls the agents' decisions shares the same parameters. The training dataset for the Q-network consists of SARS data from all agents in the game, stored in the same experience replay buffer. We access the training data in the experience replay buffer using prioritized experience replay for training the Q-network. The mentioned parameters S and M are parameters of the neural network training dataset, which will be adjusted during the training of the neural network.

Section 2: Generative Sufficient Test

We qualitatively define the social phenomena to be replicated using three characteristic social patterns. These include:

- Non-drinking students continuously shift towards accepting alcohol consumption.
- The proportion of students accepting alcohol consumption within the friendship network transitions from a minority to a majority.
- The majority status of students accepting alcohol consumption within the friendship network is continuously maintained.

We employ qualitative criteria as the low-bar for pattern-matching to assess whether the model output reproduces the identified empirical patterns. The model output should statistically align with the trends described by the defined social patterns.

Baseline Parameter Setting

We first randomly initialized the parameter settings within the model's adjustable parameter space and ran the ABM model. We then compared the simulation outputs with the defined empirical patterns and calibrated parameter values using a trial-and-error method alongside iterative numerical fine-tuning to match the model output more closely with the defined social patterns. The following parameter combinations were subsequently selected as the calibrated baseline parameter setting (nominal set). Under this calibrated baseline parameter setting, the ABM simulation results are characteristically representative, demonstrating the model's capacity to replicate the target social phenomenon:

- Initial Network Setting Parameters: A weighted undirected ER random network was generated, consisting of 60 nodes (adjustable parameter $N = 60$). All agents on the network were initially modest non-drinkers (state 4). The parameter p for the ER network, representing the probability of forming edges between nodes, was set to 0.1 (adjustable parameter $p = 0.1$), indicating that edges between nodes would form with a probability of 10%. The initial weight value for all edges was set to 1.
- Interaction Rule Parameters: The contribution parameter for interaction, a, is set to 0.5 (adjustable parameter $a = 0.5$). The contribution parameter for behavioral homophily,

b, is set to 0.5 (adjustable parameter $b = 0.5$), and the contribution parameter of identity homophily, c, is set to 0.8 (adjustable parameter $c = 0.8$).

- Reinforcement Learning Parameters: The strength of an agent's "farsightedness," discount rate parameter γ, is set to 0.9. The parameter γ is used in training RL-based neural networks, ranging from 0 to 1, which describes the importance or influence of future expected rewards on an agent's current decision (see chapter 3). A γ value of 1 indicates that future expected rewards and current rewards have equal importance in an agent's current decision, while a value closer to 0 indicates that future rewards have less influence on the current decision, making the agent more shortsighted.
- Agents Iterating Parameters: Each complete simulation experiment consists of 60 rounds of interaction, adjustable parameter $R = 60$.

The ABM model is executed 500 times using the baseline parameter settings to address the uncertainty in model output caused by stochastic elements, resulting in 500 simulations and a total of 30,000 rounds.

Network-Level Simulation Results

Dynamics of the Proportion of Agents in Different Behavior States

We firstly analyzed the dynamics of the proportion of drinkers (i.e., the proportion of all agents in Committed drinker state and modest drinker state in the social network) in the simulation outcome.

- Data Collection: Before the start of each game, we recorded the initial proportion of drinkers in the total population of the network (as all agents in the initial network were in modest non-drinker state, the initial proportion of drinkers in the network was 0). At each step of the game, we calculated and recorded the current proportion of drinkers (i.e., the sum of the number of Committed Drinkers and Modest Drinkers divided by the total population) in the network. Each complete simulation experiment consisting of 60 rounds (steps), therefore provided a sample dataset containing 61 data points. These data points represented repeated measurements of the proportion of drinkers in the network at different game steps throughout the entire game (see table 7 in Appendix A).

- Method: The application of repeated measures analysis of variance (ANOVA) is suitable for analyzing data in which the proportion of drinkers is measured multiple times at different game steps. This statistical method allows for the examination of within-subject effects and the determination of significant differences among the different game steps. Therefore, we employed one-way repeated measures ANOVA to analyze the collected data on the proportion of drinkers. The Greenhouse-Geisser method was used for correction, and a significance level (α) of 0.05 was set. The detailed result of the analysis is presented below.
- Result: Table 8 displays the results of the one-way repeat measures ANOVA conducted on the data of the proportion of drinkers. The analysis revealed significant differences in the proportion of drinkers among different game steps ($F=185.124$, $p<0.001$).

Table 8: Tests of Within-Subjects Effects (the Proportion of Drinking Agents)

Source	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Step	280.575	8.32	33.723	185.124	<0.001
Error(step)	756.287	4151.648	0.182		

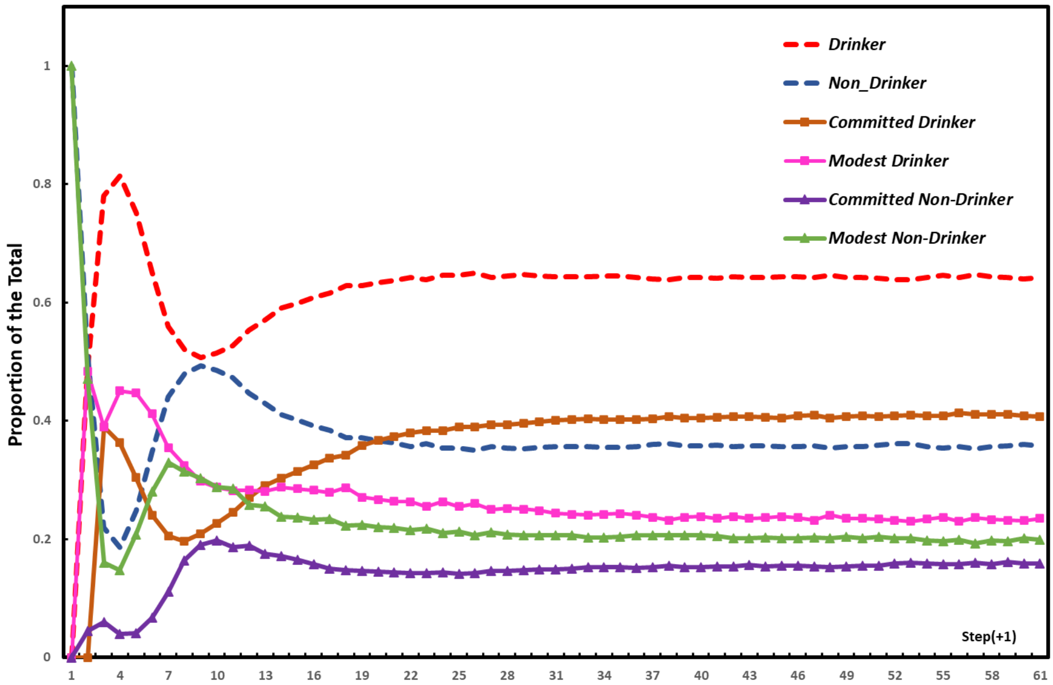
In addition to examining the changes in the proportion of drinkers in the social network, we also utilized the one-way repeated measures ANOVA method to analyze the changes in the proportions of agents in other states relative to the total population.

- Data Collection: At each step of the game, we separately recorded the current proportions of non-drinkers (i.e., the sum of Committed Non-Drinkers and Modest Non-Drinkers divided by the total population), the proportion of Committed Drinkers, the proportion of Modest Drinkers, the proportion of Committed Non-Drinkers, and the proportion of Modest Non-Drinkers in the social network.
- Method: We employed the one-way repeated measures ANOVA analysis with Greenhouse-Geisser correction to analyze the collected data on the changes in the proportions of agents in each state. A significance level (α) of 0.05 was set. The analysis results are presented below.

- Result: Tables 9 to 13 (see Appendix A) present the results of the one-way repeated measures variance analysis conducted on the data of the proportions of each state in the total population. The analysis results indicate that, at a significance level of 0.05, the proportions of all state agents underwent significant changes throughout the game (non-drinkers proportion: $F=185.124$, $p<0.001$; Committed Drinker proportion: $F=221.635$, $p<0.001$; Modest Drinker proportion: $F=168.465$, $p<0.001$; Committed Non-Drinker proportion: $F=53.794$, $p<0.001$; Modest Non-Drinker proportion: $F=454.229$, $p<0.001$).

  Pairwise Comparisons Result: In order to determine the specific trends in the proportions of different states among agents, pairwise comparisons were conducted between the proportions of each behavior type relative to the total population across different game steps. The results of these pairwise comparisons can be found in Tables 14 to 19 (see Appendix A). Figure 7 provides a comprehensive visualization of the estimated proportions of drinkers (Committed Drinker and Modest Drinker), non-drinkers (Committed Non-Drinker and Modest Non-Drinker), as well as the proportions of Committed Drinkers, Modest Drinkers, Committed Non-Drinkers and Modest Non-Drinkers within the total population for each game round. This visual representation offers valuable insights into the results of the pairwise comparisons:

Figure 7: Trends in the Proportion of Agents in Different States



Specifically, the results of the pairwise comparisons reveal the following dynamics:

Table 20: Pairwise Comparison of the Proportional Trends of Agents in Different States

State	*Trend Analysis*	*Legend*
Drinker	The prevalence of drinkers in the initial stages of the game showed a rapid increase, reaching its peak at the 1st step, followed by a decline until reaching a nadir at the 8th step. Subsequently, there was a gradual recovery until the seventeenth step. Beyond this point, the proportion of drinkers remained stable, and no statistically significant changes were observed at a significance level of 0.05 throughout the remaining steps of the game.	
Non-Drinker	A rapid decline in the proportion of non-drinkers during the initial stages of the game, reaching its lowest point at the 3rd step. Subsequently, there was a gradual recovery and a subsequent slow decline, reaching its peak at the 8th step. Beyond the 17th step, the proportion remained stable, with no statistically significant changes observed at a significance level of 0.05. The descending trend in refusal rate became progressively flattened as the game progressed.	
Committed Drinker	A rapid increase in the proportion of committed drinkers, reaching its peak at the 2ed step of the game, followed by a gradual decline until it reached a trough at the 7th step. Subsequently, there was a slow ascent, but the rate of growth became progressively sluggish. From the 27th step onwards, the proportion of committed drinkers remained stable and did not display statistically significant changes at a significance level of 0.05.	
Modest Drinker	A rapid surge in the proportion of modest drinkers during the initial stages of the game. This upward trend reached its peak at the 2ed step, followed by a gradual descent. The decline exhibited some fluctuations, and the rate of decrease progressively slowed down until the 30th step. After that, the proportion of modest drinker individuals remained stable and did not display statistically significant changes at a significance level of 0.05.	
Committed Non-Drinker	After experiencing some fluctuations, there was a rapid increase in the proportion. Subsequently, it reached its peak at the 9th step, followed by a gradual decline and eventually stabilizing. Statistical analysis indicates that there were no significant changes observed after the 26th step at a significance level of 0.05.	
Modest Non-Drinker	at the initial stages of the game, there was a rapid decrease in the proportion, reaching its lowest point in the 3rd step. Subsequently, it gradually started to increase, with a peak observed in the 7th step before a slow decline. The rate of descent gradually decelerated until the 25th step, after which the proportion of modest non-drinker individuals reached a stable state with no significant changes observed at a significance level of 0.05.	

- Summary: The proportions of agents in each state undergo significant changes as the simulation experiment progressed. The proportions of each state typically exhibited significant changes in the initial stages of the game, followed by a gradual stabilization of the magnitude of change. Beyond approximately the 30th step of the game, the proportions of agents in different states no longer significantly changed, maintaining dynamic equilibrium.

During the stable state of the game, the relative proportions of different states within the overall population are as follows: Committed Drinker exhibits the highest proportion, approximately 41%, significantly dominating the distribution. Following it is Modest Drinker, with a respectable proportion of approximately 23%. Modest Non-Drinker also maintains a notable presence, albeit at a lower proportion of approximately 20%. Finally, Committed Non-Drinker demonstrates the lowest proportion within the population, approximately 16%.

The simulation results from the ABM demonstrate the model's effectiveness in reproducing the target social patterns, which are characterized by three main aspects:
On one hand, the ABM model successfully reproduces three main characteristics of the target social phenomenon.

1. Transition in Agent Behavior: As the game progresses, agents continuously transition from a state of refusing to drink to accepting drinking behavior.
2. Shift in Proportions within the Network: The proportion of agents accepting drinking behavior in the network gradually shifts from being a minority to a majority, significantly exceeding the proportion of agents refusing to drink. Specifically, the proportion of drinkers in the social network increases from 0% to approximately 64%, while the proportion of non-drinkers decreases from 100% to approximately 36%. Drinking behavior thus becomes the dominant behavior within the college friendship network.
3. Sustained Majority Status of Drinking Acceptance: After experiencing fluctuations, the proportion of agents accepting drinking behavior in the social network stabilizes at around 64%, maintaining a sustained majority status.

In addition, beyond the reproduction of the target social phenomenon (a low bar), we have observed a continuous expansion of the influence of the ritualistic culture of college drinking on agents, which gradually becomes the majority. Specifically, the proportion of agents who identify with drinking behavior implying identity preference (i.e., all Committed Drinkers and Committed Non-Drinkers) increases from 0% to a stable state of approximately 57%, while the proportion of agents who do not identify with drinking behavior implying any identity preference (i.e., all Modest Drinkers and Modest Non-Drinkers) decreases from 100% to a stable state of approximately 43%.

Dynamics of Expected Social Capital of Agents in Different Behavioral States

We further investigate the dynamics of expected social support (i.e., bonding capital) received by agents in different states in the social network, which may help us understand the reasons for the changes in the proportion of agents in each state.

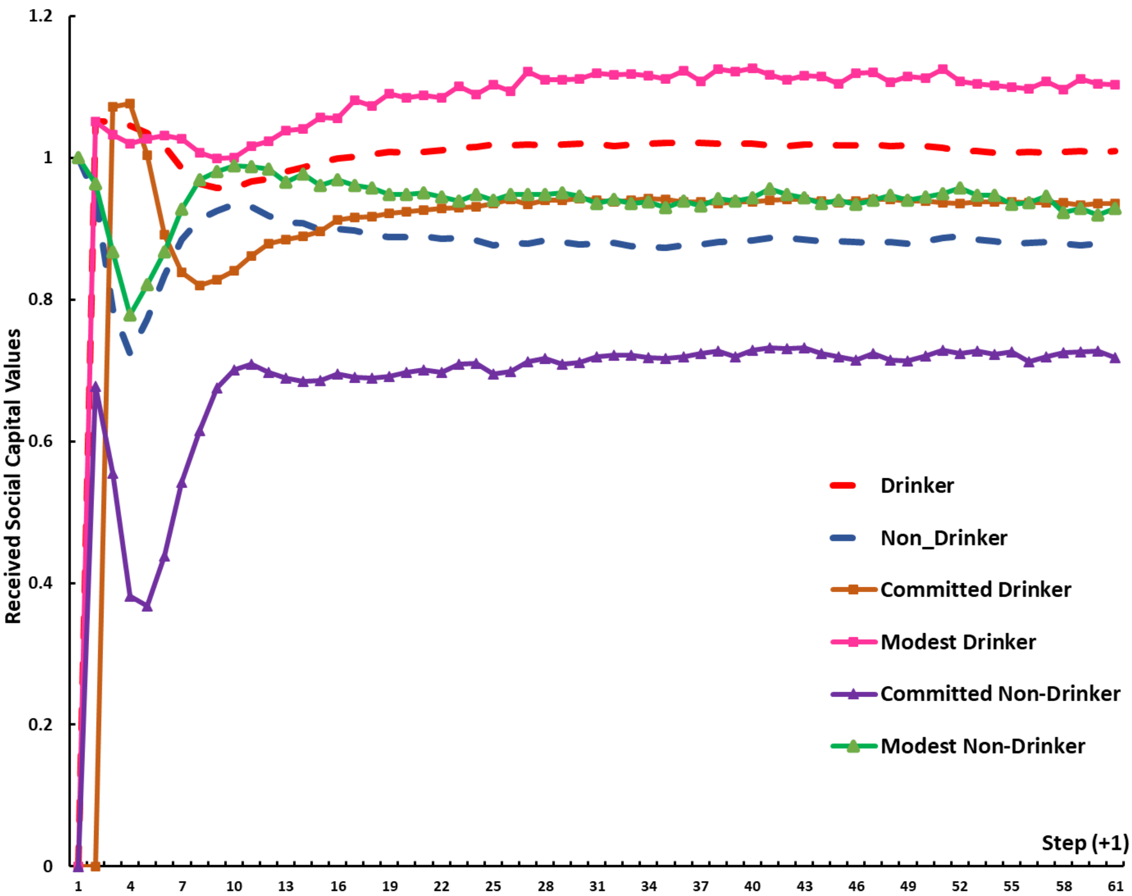
- Data collection: At each round of the game, we recorded the current behavioral state of each agent in the observation phase (step 2-phase 1). At the end of each round of the game, we recorded the social support received by each agent after updating the social support phase (step 2-phase 5). Based on the aforementioned records, we calculated the average received social support for agents in each state in each round of the game, including the average received social support for agents who accepted drinking (Committed Drinker and Modest Drinker), the average received social support for agents who refuse drinking (Committed Non-Drinker and Modest Non-Drinker), and the average received social support for agents in each specific state (Committed Drinker, Modest Drinker, Committed Non-Drinker and Modest Non-Drinker). Since each complete game consisted of 60 rounds, we obtained six repeated measurement samples, each containing 61 data points.
- Method: We used one-way repeated measures ANOVA analysis to separately analyze the average received social capital data for different behavioral states. The Greenhouse-Geisser method was used for correction to account for violations of the sphericity

assumption. The significance level (α) was set at 0.05.

- Result: Tables 21 -26 (see Appendix A) show the results of the one-way repeated measures ANOVA conducted on the expected social capital benefits data for agents in different states. The analysis revealed significant differences in the expected benefits of alcohol consumption across different game steps at a significance level of 0.05 (Drinkers: F=1368.621, p<0.001; Non-drinkers: F=37.708 p<0.001; Committed Drinker: F=848.303, p<0.001; Modest Drinker F=251.677, p<0.001; Committed Non-Drinker: F=113.755, p<0.001; Modest Non-Drinker: F=13.489, p<0.001).

Pairwise Comparison Results: We conducted pairwise comparison analyses on the average social capital returns received by agents in different behavioral states at different game steps. Tables 27 to 32 (see Appendix A) present the results of these analyses. We summarized the evolving trends of expected social capital returns for each type of state in Figure 8:

Figure 8: Trends in Social Capital Values Received by Agents in Different States



Specifically, the pairwise comparisons results reveal the following Table 34:

Table 34: Pairwise Comparison of the Trend in Expected Social Capital Values Received by Agents in Different States

State	***Trend Analysis***	***Legend***
Drinker	The social capital of drinkers initially exhibits a rapid increase in the early stages of the game, reaching its peak at the 3rd step, followed by a slight decline until it reaches a minimum at the 9th step. Subsequently, the social capital of drinkers demonstrates a gradual rise, with no significant changes occurring after the 48th step of the game, suggesting a stabilization of the drinkers' social capital over time.	
Non-Drinker	The social capital of non-drinkers experiences a rapid decline in the early stages of the game, reaching its lowest point at the 3rd step. Subsequently, it begins to rebound and reaches its peak at the 9th step. Following this peak, there is a gradual decline accompanied by minor fluctuations. The social capital of non-drinkers exhibits no significant changes beyond the 16th step of the game at a significance level of 0.05.	
Committed Drinker	Following the introduction of committed drinkers at the 2ed step of the game, the expected social capital returns associated with committed drinkers initially experience a downward trend, reaching a nadir by the 7th step. Subsequently, a gradual recovery is observed, which continues until the 18th step of the game before stabilizing. Subsequent to the 18th step, the expected social capital returns exhibit no significant changes at a significance level of 0.05, indicating an absence of further noteworthy variations.	
Modest Drinker	Following the introduction of modest drinkers at the 1st step of the game, there is a slight decline in the expected social capital returns associated with Modest Drinkers. The decline reaches its lowest point at the ninth step, after which a gradual increase is observed. After the 18th step of the game, no significant changes in the expected social capital returns occur at a significance level of 0.05. The social capital returns then stabilize at a relatively high level, indicating a sustained level of expected social capital benefits.	
Committed Non-Drinker	At the initial stages of the game, there is a significant and rapid decline observed, reaching its lowest point at the 4th step before subsequently recovering. The rate of recovery gradually slows down, eventually leading to minor fluctuations. After the 24th step of the game, the expected social capital returns for committed non-drinkers no longer exhibit significant changes at a significance level of 0.05, indicating a stable trend.	
Modest Non-Drinker	A substantial decrease in the expected returns of social capital up until the 3rd step of the game. Subsequently, a gradual recovery is observed, peaking at the 10th step. However, from that point onwards, the expected social capital for modest non-drinkers undergoes a prolonged period of fluctuation and decline. Eventually, after the 56th step of the game, no significant changes are observed at a significance level of 0.05, indicating a cessation of substantial variations.	
Committed Drinker-- Modest Non-Drinker	Pairwise comparisons indicates that during the stable phase of the game, the average social capital received by Committed Drinker and Modest Non-Drinker does not appear to be significantly different, as indicated by the close alignment of the brown and green lines in Figure 8. To quantify the differences in expected social capital between Committed Drinker and Modest Non-Drinker during the stable phase of the game, we calculated the discrepancy between the anticipated social capital rewards for Committed Drinker and Modest Non-Drinker at each step of the game, using 0 as a reference point for comparison. The outcomes of this comparative analysis are detailed in Table 33 (see Appendix A), illustrating that prior to the 4th step of the game, the expected social capital for Modest Non-Drinker significantly surpassed that of Committed Drinker. However, this disparity gradually diminished over time. Beyond the 6th step, Committed Drinkers exhibited a significantly higher expected social capital compared to Modest Non-Drinker. Nevertheless, after an initial expansion, this difference gradually contracted until reaching a point at the 17th step where the discrepancy between the two agents became statistically insignificant at a significance level of 0.05.	

- <u>Summary</u>: The above analysis indicates that the average social support received by agents in different behavioral states undergoes significant changes as the simulation experiment progresses. The average social support received by agents in each state typically undergoes significant changes in the early stages of the game, followed by a gradual stabilization of variations and entry into a stable phase in the later stages of the game. During this phase, agents in each state no longer undergo significant changes, maintaining equilibrium. In the stable state of the game, the expected social capital returns for each type of agent state are as follows: Modest Drinker demonstrates the highest expected social capital returns, at approximately 1.1, and is the only behavioral state that receives social support above 1, followed by Committed Drinker and Committed Non-Drinker, at approximately 0.93. Modest Non-Drinker exhibits the lowest expected social capital returns, at approximately 0.72. Overall, in the stable phase of the game, the average social capital received by drinkers is approximately 1.01, while the average social capital received by non-drinkers is approximately 0.88, significantly lower than that of drinkers.

Social Motives and Conformity Motives in an Agent's Internal State

In the preceding analysis, we conducted an examination and comparison of the evolution of the proportions of agents in different states and the corresponding social capital returns based on the output of the ABM model's simulation experiments. We have primarily found the following insights:

- Agents who choose to accept drinking behavior (Committed Drinker and Modest Drinker) have higher expected social capital returns compared to agents who refuse drinking behavior (Committed Non-Drinker and Modest Non-Drinker). Correspondingly, the proportion of agents accepting drinking behavior is significantly higher than those who refuse. However, the social capital returns of each state do not strictly correspond to their proportions in the network's total population. During the stable stage of the game, the proportions of each state agent in the total population are ranked as follows: Committed Drinker > Modest Drinker > Modest Non-Drinker > Committed Non-Drinker (refer to Figure 7). However, in terms of the expected social capital returns brought to agents by each state, the ranking of expected social capital returns is as follows: Modest Drinker > Committed Drinker and Modest Non-Drinker > Committed Non-Drinker (refer to Figure 8).
- After experiencing fluctuations in the early stages of the game, the proportions of all state agents and the social capital returns of each state will gradually converge to a stable stage. In this stage, the proportions of agents in each state in the network and their corresponding expected social capital returns remain stable and do not undergo significant changes.

Regarding the aforementioned simulation results:

- On one hand, we believe that the simulation outcome provides evidence supporting the social motives in agents' internal state, where the social motives suggest that agents decide their future actions based on their motivation to obtain higher social support from their friends. The social motives in agents' internal state align with our intuitive expectations, given that the agents' behavioral decisions in the ABM model are controlled by a well-trained deep Q-network, which is driven by achieving higher cumulative rewards measured by social support return. The evidence supporting the social motives includes, for example, the fact that choosing to accept drinking behavior brings higher expected cumulative social capital returns to agents compared to refusing drinking behavior, thereby motivating more agents to choose to accept drinking. Consequently, we observe a rapid increase in the proportion of drinkers in the early stages of the game, indicating the rapid spread of drinking behavior in the friendship network of college students. Furthermore, in the stable stage of each game, the proportion of drinkers in the total population remains stable and significantly higher than that of non-drinkers, and the expected social capital return brought by drinking behavior also remains stable and significantly higher than that of non-drinkers.
- On the other hand, we believe that the output of the simulation also provides evidence supporting the conformity motives in agents' internal state, where the conformity motives suggest that agents are not constantly pursuing higher social capital returns. When agents face the possibility of losing or maintaining their current level of social capital, they make appropriate decisions to minimize social capital loss or avoid it altogether.

Specifically, the following simulation outcomes cannot be explained by agents' social motives:

- Why do not all agents in states with relatively low expected social capital returns will transition to states with higher expected social capital returns under the drive of social motives? What factors lead to the relative balance of the proportions of agents in different states in the face of unbalanced expected social capital returns? For example, despite the significantly higher expected social capital return for choosing to accept drinking compared to choosing to refuse drinking, and the fact that the majority of agents transition from refusing to accepting drinking under the drive of social motives, not all non-drinkers transition to drinkers. In the stable phase of the game, non-drinkers still maintain a proportion of approximately 36% of the total population in the network and remain balanced. This phenomenon parallels real-world experiences, where despite numerous studies indicating that drinking provides more social advantages and conveniences compared to refusing social drinking, it is challenging to explain why non-drinkers do not switch to drinking behavior solely relying on social motives. Similarly, why do Modest Non-Drinkers, with a relatively lower level of expected social capital return, not switch to Modest Drinker, which offers higher expected social capital return? Additionally, despite Committed Non-Drinker having the lowest expected social capital return among all states, in the early stages of the game, a large number of Modest Non-Drinkers transitioned to Committed Non-Drinker instead of Modest Drinker, and the proportion of Committed Non-Drinkers in the total population of the network remains at approximately 16% in the stable phase of the game. This result does not make sense from the perspective of social motives, as from this perspective, Committed Non-Drinkers should be considered a highly socially unfriendly behavioral state.

- The rankings of the proportions of agents in different states on the network do not directly correspond to the rankings of the expected social capital returns for each state. For example, although Modest Drinkers exhibits the highest expected social capital return among all states, its proportion remains significantly lower than that of Committed Drinker, and the majority of agents do not transition to Modest Drinker under the drive of social motives.

The above outcomes of the ABM model cannot be explained by social motives alone and indicate the existence of other behavioral motives in agents' internal states that do not conflict with the agents' pursuit of social support and can balance social motives. In this context, as indicated by existing empirical studies, the conformity motives can serve as a good complementary explanation. For instance, from the perspective of conformity motives, we can interpret the phenomenon where a large number of Modest Non-Drinkers transitioned to Committed Non-Drinker and remained in the state with the lowest expected social capital return as a decision made by agents to minimize or avoid short-term social capital loss. The transition of Modest Non-Drinker agents to the more extreme Committed Non-Drinker can be viewed as a form of warning signals sent to their Modest Non-Drinkers. Specifically, for the Committed Non-Drinkers, by transitioning from Modest Non-Drinker to Committed Non-Drinker, they send warning signals to their Modest Non-Drinker friends to create peer pressure, indicating that if their Modest Non-Drinker friends transition to Modest Drinker, they will immediately lose their friendship and the social support from them. This can potentially prevent current Modest Non-Drinker friends from transitioning to drinking and compel them to choose to stay in the non-drinker group to maintain their existing friendships. By sending warning signals, Committed Non-Drinker agents can prevent more non-drinker neighbors from leaving the abstainer state, thereby avoiding greater social support losses resulting from losing more non-drinker friends, which could be considered a form of conformity motive. As for Modest Non-Drinkers, they are influenced by peer effects from their Committed Non-Drinker neighbors, and some Modest Non-Drinkers also choose to continue refusing drinking driven by conformity motives, in order to avoid the substantial social capital losses that would be incurred if their friendship with Committed Non-Drinkers were severed by transitioning to the drinking state.

From the perspective of ABM model design, the observation of social motives and conformity motives in an agent's internal state is reasonable:

- On one hand, in our ABM model, each agent has the same amount of social resources as a source of social support, which is distributed to all friends based on friendship strength. As a result, the total amount of social capital return in the social network remains constant. For example, in a social network with 60 nodes, if each agent has a total of 1 unit of social support, the sum of social support received from friends by all agents is 60. Therefore, when a portion of agents experience an increase in social capital return, the remaining agents will inevitably face a loss in social capital return, as the total amount of social support is fixed.

- On the other hand, the increase or decrease in social capital return experienced by individuals does not necessarily indicate the type of motives driving their behavior, as individual’s behavior motives are subjective. The key to determining agents' motives is their prediction or expectation of the expected social capital return resulting from their decisions. For instance, if an agent believes that executing a certain decision can lead to a higher social capital return, it indicates the agent’s social motives. Conversely, if executing a certain decision can avoid or minimize social capital loss, it indicates the agent’s conformity motives.

  In this ABM model, agents' predictions or expectations of the social capital return that decisions can bring are reflected in the output of the deep Q-network that controls their decision-making process. A well-trained Q-network can enable agents to make a relatively accurate assessment of the future social capital return of executing certain decisions, thus leading to decisions driven by social motives when faced with opportunities for social capital gains, and decisions driven by conformity motives when facing the risk of social capital loss.

To further analyze the distribution and changes of social motives and conformity motives drives individual behavior in the ABM model simulation outcome, we examined and analyzed the decision-making process of agents, particularly the output results of the deep Q-network for each agent at each step of the game.

- <u>Research Design</u>: In the ABM model, all agents are controlled by a deep Q-network. The agents input their observation into the Q-network, and the Q-network outputs a tensor containing three elements (referred to as Q values), each corresponding to the agent's estimated social capital return from executing three different decisions (decisions 1 to 3) under the current observation.

  For example, in the $t\,th$ round, agent i inputs its observation into the deep Q-network and obtains the output tensor [2,4,1]. This indicates that agent i believes that the future cumulative social capital return for executing decision 1 under the current situation is 2, the future cumulative social capital return for executing decision 2 is 4, and the future cumulative social capital return for executing decision 3 is 1. Based on the output of the Q-network, agent i will choose to execute decision 2, which has the highest future social capital return, thus maintaining the current behavioral state.

Furthermore, if we record the decisions made by agent i in two consecutive rounds, as well as the Q values output by the Q-network, we can determine whether the agent is driven by social motives or conformity motives at that time. For example, if in the t round, agent I inputs the current observation into the Q-network and obtains the output tensor [2,4,3], then agent i will execute decision 2 in this round, as agent i believes that executing decision 2 can bring the highest future social capital return (4) for himself. In the t+1 round, if agent i inputs the new current observation into the Q-network and obtains the output tensor [6,5,2], then agent i will choose to execute decision 1, as he believes that decision 1 can bring a higher future social capital return (6) for himself. Therefore, in this round, agent i is driven by social motives, as he decides his decision in order to pursue a higher social capital return.

On the contrary, if in the t+1 round, the Q-network outputs the tensor [1,2,3], then agent i will choose to execute decision 3, as the Q value corresponding to decision 3 is the highest among the three available decisions. However, all elements in the tensor output in the t+1 round are smaller than the Q value corresponding to the previous round's decision (4). Therefore, at this time, agent i actually believes that regardless of which decision is made, the future social capital return will be worse than the estimated situation in the previous round, and the agent will inevitably face a loss of social capital. Therefore, the decision of the agent in this round can be considered to be driven by conformity motives, as he chooses the decision that minimizes the loss of social capital.

In a more general sense, we defined and recorded the motives under which each agent made decisions in the ABM model using the following method. Firstly, in the t round of the game, we identified the Q-value output by the deep Q-network corresponding to each decision made by an agent. This Q-value represents the agent's estimation of the future social capital return from that decision, and we recorded the highest Q-value as Q_{t1}. In the subsequent $t+1$ round of the game, we again recorded the Q value output by the deep Q-network corresponding to each decision made by an agent, and we recorded the highest Q value as Q_{t2}. When Q_{t2} is greater than Q_{t1}, it indicates that the agent believes that the decision made in this round can achieve a higher expected social capital return and chooses the decision that maximizes the loss. Therefore, in the $t+1$ round, the agent's decision is defined as driven by social motives. On the other hand, when Q_{t2} is smaller than Q_{t1}, it implies that the agent believes that any decision made in this round will result in a loss of future social capital return and chooses the decision that minimizes the loss of social capital. Therefore, in the $t+1$ round, the agent's decision is defined as driven by conformity motives.

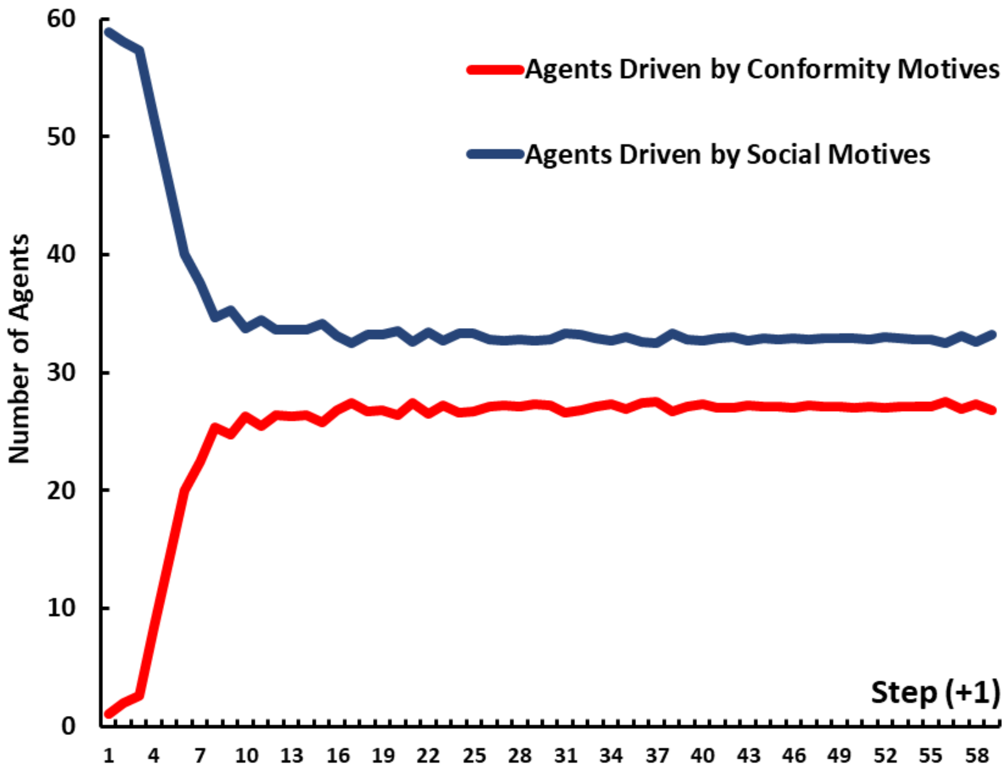
- Data collection: According to the above definition, starting from the third round of the game, we recorded the motives for each decision made by each agent in each round of the game. From this, we can obtain the number of agents driven by social motives (Ns) and the number of agents driven by conformity motives (Nc) in each round. In fact, Ns + Nc = 60. Method: We first analyzed the trend of the number of agents driven by conformity motives (Nc) at different game steps. For this purpose, we conducted a one-way repeated ANOVA on the collected data.
- Result: Table 35 presents the results of this analysis, which demonstrates significant differences in the number of agents driven by conformity motives among different game steps (F=508.698, p<0.001).

Table 35: Tests of Within-Subjects Effects (Proportion of Conformity Motivate)

Source	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Step	1416848.029	38.868	36453.035	508.698	<0.001
Error(step)	1389835.704	19395	71.659		

Pairwise Comparisons Result: To identify specific trends in the changes of the number of agents driven by conformity motives, pairwise comparisons were conducted for the number of agents driven by conformity motives at different game steps. The results of the pairwise comparisons are presented in Table 36 (see Appendix A). Additionally, a visual representation summarizing the evolving trends of the number of agents driven by conformity motives and social motives is provided in Figure 9:

Figure 9: Trends in the Number of Agents Driven by Conformity and Social Motives



The pairwise comparisons reveal that the number of agents driven by conformity motives starts at a relatively low level during the initial steps of the game but rapidly increases significantly as the game progresses. It gradually stabilizes and shows no significant variation below the 0.05 significance level from the 32nd step onwards. By the final step of the game (step 60), the average number of agents driven by conformity motives is observed to be 26.8, accounting for approximately 44.67% of the total population. Consequently, agents driven by social motives account for approximately 55.33% of the total population. This result indicates that social motives initially dominated agents' behavioral motives in the early steps of the game, possibly due to low friendship strength and a higher number of remaining game steps. We hypothesize that the weaker friendship relationships provided agents with greater flexibility to pursue mid- to long-term expected social capital return. As the loss of cutting off friendships with current friends is relatively small, making it easier for agents to establish new friendships, particularly for those transitioning to Committed Drinker, who can easily establish stronger friendships based on identity homophily.

However, as the game progresses, the strength of existing friendships increases, and severing these relationships leads to significant losses, prompting agents to become more conservative and place greater importance on the attitudes of existing friends, resulting in a gradual increase in conformity motives. In the mid to late stages of the game, the proportions of agents driven by social motives and conformity motives stabilize.

- Summary: The analysis above helps answer our research question: *How does social capital contribute to the emergence of the spread of drinking behavior in friendship network of college students?* Our original MBE hypothesis indicates that *the instability of social capital will motivate college students to engage in social integration to maintain or increase the social support they receive from their friendship networks through situational mechanisms.* Our ABM simulation results show that agents' motivation to seek social support can be further decomposed into two types of motivations:
    - Social motivation: When there is an opportunity to obtain higher social support, agents' decisions will be focused on achieving higher social support benefits.
    - Conformity motivation: When the loss of social support is unavoidable, agents' decisions will be focused on minimizing or avoiding the loss of social support.

  Social motives initially dominate the agents' behavioral motivations in the early stages of the game but gradually decrease in proportion and stabilize. On the other hand, the proportion of agents driven by conformity motives gradually increases and stabilizes.

Community Structure in the Social Network

- The Concept and Calculation of Modularity: Modularity is a concept and metric used to evaluate the presence and strength of community structures within social networks. It measures the extent to which nodes within the same community are more densely connected to each other compared to nodes in different communities. Modularity is a valuable tool for evaluating the effectiveness of community detection algorithms and understanding the organization and functional relationships within social networks.

In this study, we utilized the Girvan-Newman method to calculate the modularity of a social network. The Girvan-Newman community detection method is a widely employed algorithm in social network analysis (SNA). It is based on the concept of edge betweenness centrality, which quantifies the number of shortest paths passing through each edge in the network. The Girvan-Newman method progressively removes edges with the highest edge betweenness centrality, gradually breaking down the network into smaller connected components. The resulting connected components represent the communities within the network. By iteratively removing edges with high betweenness centrality, the algorithm effectively identifies and separates communities in a hierarchical manner.

To calculate the modularity of a network using the Girvan-Newman method, the following steps are followed. Firstly, the algorithm starts with the original network and computes the edge betweenness centrality for all edges. Then, it removes the edge with the highest betweenness centrality and recalculates the edge betweenness centrality for the remaining edges. This process is repeated until all edges are removed, resulting in a hierarchical clustering of the network. Finally, the modularity of the network is computed by comparing the clustering obtained from the Girvan-Newman method with the expected random clustering. The modularity value ranges from -1 to 1, with a higher value indicating a stronger community structure.

- <u>Data Collection</u>: Using the Girvan-Newman method, we computed and recorded the modularity value of the initial network. Furthermore, at each step of the game, we recorded the modularity value of the current network, resulting in a dataset comprising 61 modularity records.
- <u>Data Analysis</u>: To understand the trend of modularity changes in a game session, we conducted one-way repeated measures ANOVA on the collected data. The Greenhouse-Geisser method was employed for correction, with a significant level of $p=0.05$.

- Result: The specific results of the analysis are presented in Table 37, which displays the outcomes of the one-way repeated measures ANOVA conducted on the modularity data. The results indicate significant differences in the modularity levels of the network at different game steps (F=62.269, p<0.001).

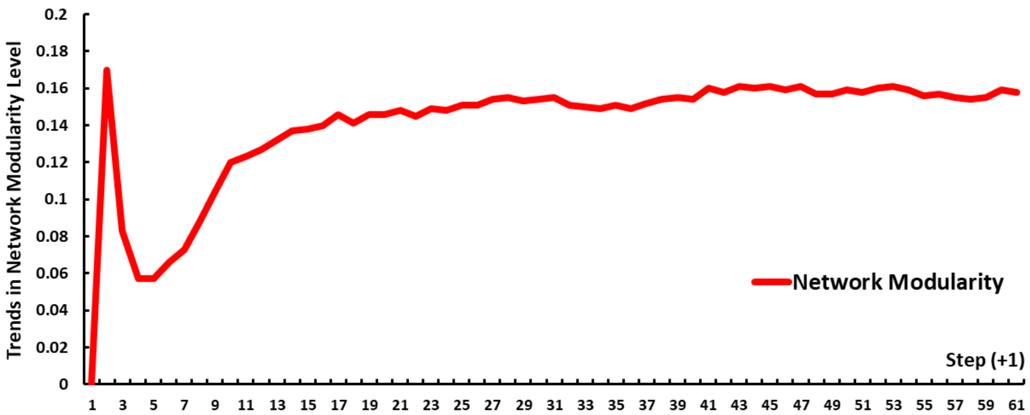
Table 37: Tests of Within-Subjects Effects (Modularity)

Source	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Step	31.264	9.808	3.187	62.269	<0.001
Error (Step)	250.536	4894.32	0.051		

***. The mean difference is significant at the 0.05 level.**

Pairwise Comparison Result: The pairwise comparison results of the network's modularity levels at two different game steps are presented in Table 38 (see Appendix). Additionally, we have compiled data illustrating the changes in network modularity levels throughout the game and depicted it in Figure 10. This visual representation provides a clearer understanding of the evolving trends in modularity as the game progresses.

Figure 10: Trends in Network Modularity Level



The results indicate that due to the use of an ER random network as the initial network, the modularity of the network starts at a low level in the beginning of the game. Analysis of the network's modularity level reveals a significant increase, with the peak observed at the first step of the game coinciding with the emergence of distinct clusters of agents categorized as drinkers and non-drinkers. Subsequently, a significant decline in the modularity value is observed, reaching its lowest point at the fifth step. Following this decrease, the modularity value gradually rises until the 21st step of the game. However, beyond this point, no statistically significant changes in the modularity level of the network are found at a significant level of 0.05.

Individual-level simulation outcomes

The MBE hypothesis suggests that college students' motives and objectives in establishing social connections and seeking social support will influence their choices regarding drinking behavior through action formation mechanisms. Specifically, previous analyses indicate that, on one hand, an agent's social motives drive them to make decisions that they perceive will yield the highest social capital return. On the other hand, an agent's conformity motives drive them to make decisions that can avoid or minimize potential social capital loss. Building upon this, we also aim to understand whether agents, driven by social and conformity motives, exhibit significant behavioral strategies through action formation mechanisms. Therefore, the following research is designed to analyze individual-level simulation outcomes.

Predicting Agent Behavior Strategies

In our ABM model, the decision-making process of agents is controlled by a well-trained deep Q-network. However, due to the limited interpretability of neural networks, directly understanding and recording the specific strategies employed by agents when making decisions is challenging. To overcome this challenge, we propose using several typical behavioral strategies to predict agent behavior and measure the accuracy of these predictions. By evaluating the accuracy of predictions, we can indirectly gain insights into the behavior strategies of agents.

We define three classic behavioral strategies widely reported in existing empirical research in college drinking behavior (see Literature Review chapter):

Table 39: Three Classic Behavioral Strategies

Type	***Behavioral Rule***
Conformity	The agent observes the current states of all its neighbors and selects the mainstream behavior of all neighbors as the action it will take next. If none of the agent's neighbors exhibit a mainstream behavior, the agent will maintain its current behavior.
Imitate Best Friend	The agent observes the current action of its best neighbor (the neighbor with the highest edge weight) and adopts it as the action it will take next. If the agent has multiple best friends, it randomly selects one of the best neighbors to imitate their behavior.
Imitate Most Popular Friend	The agent observes the behavior of the neighbor with the highest social capital among its neighbors and adopts it as the action it will take next.

- Data collection: the data recording of the predicted results for each behavioral strategy: Before each game step, we iterate through each $Agent_i$ in the network and record the states that $Agent_i$ would take according to the three classic behavioral strategies mentioned above. We record these predicted states as e_{i1}, e_{i2}, and e_{i3} After recording the predicted states for all agents under the three behavioral strategies, we proceed with the normal game execution and record the actual states taken by each agent under the control of the neural network, denoted as a_i. After the current game step, we compare ai withe_{i1}, e_{i2}, and e_{i3} If a behavioral strategy's prediction is correct, we count one correct frequency for that specific behavioral strategy. Upon completing the game, we obtain the number of correct predictions for each behavioral strategy in this game. For $Agent_i$, we obtain a list$[n_{i1}, n_{i2}, n_{i3}]$, where n_{i1}, n_{i2} and n_{i3}correspond to the number of correct predictions for the Conformity, Best Friend Imitation, and Highest Social Capital Imitation strategies, respectively, in this game. We compare these three sets of data with the expected correct frequency of 25 (60 * 5/12 = 25) obtained by completely random guessing to evaluate the effectiveness of these behavioral strategies in predicting agent behavior.
- Method: Independent sample t-tests are conducted to compare the number of correct predictions obtained from the behavioral strategies with the expected number of correct predictions from random guessing over 25 trials.
- Results: The results of the T-tests are presented in Table 40.

Table 40: t-test result

Strategy Type	*Mean*	*t*	*Sig. (2-tailed)*	*Mean Difference (Test Value = 25)*
Conformity (N = 30000)	32.16	128.474	<0.001	7.156
Imitate Best Friend (N = 30000)	30.17	92.756	<0.001	5.166
Imitate Most Popular Friend (N = 30000)	21.72	-60.117	<0.001	-3.28

. The mean difference is significant at the 0.05 level.

The t-test results indicate that both Conformity (t=128.474, p<0.001) and Best Friend Imitation (t=92.8756 p<0.001) significantly outperform completely random guessing in predicting agent decisions at a significant level of 0.05. This suggests that using the Conformity and Best Friend Imitation strategies can predict agent behavior to some extent, although their accuracy is not high, with means values of 32.16 and 30.17, respectively. However, the t-test results (t = -60.117, p < 0.001) showed that the strategy of imitating the state with the highest social capital among friends yielded significantly lower accuracy in predicting agent states compared to random guessing. This indicates that agents are unlikely to prefer imitating the state of the friend with the highest social capital.

- Summary: The analysis above provides an in-depth exploration of the research question: How do the internal states of individual college students influence their behavior and interactions? Our original MBE hypothesis suggests that college students' motives and objectives to establish social connections and seek social support will influence their choices regarding drinking behavior through action formation mechanisms. The ABM simulation results show that agents, driven by social motives and conformity motives, exhibit a certain degree of strategic tendencies and regularities in their decision-making, particularly with the Conformity and Best Friend Imitation strategies being able to predict agent behavior to some extent. However, due to the low accuracy of predictions, using a single strategy to predict agent decision-making is highly inefficient. Therefore, we conclude that under the control of the deep-Q network, agents' decision-making does not exhibit a singular behavioral strategy, and cannot be described by a single or simple behavioral strategy. It is necessary to further analyze the behavioral preferences of agents in different network positions in subsequent analyses.

Summary

During the "Redescription" process (generative sufficient test), we ran the ABM model and conducted an analysis of the simulation outcomes, leading to the following three main conclusions:

- Firstly, the most significant finding is that the ABM model successfully reproduce the target social phenomena, specifically the diffusion of drinking behavior within a social network. This indicates that the MBE hypotheses have passed the "generative sufficient" test and formed a candidate mechanism-based explanation for the target social phenomenon.

  The initial network in our study was a low-density ER network with all included agents initially in a modest non-drinker state. The simulation results of the ABM model showed that as the game progressed, a large number of agents who originally refused to drink shifted to accept drinking behavior. The proportion of drinkers within the social network increased from 0% to a stable level of approximately 64%, while the proportion of non-drinkers decreased from 100% to approximately 36%. Drinking behavior spread within the friendship network of college students and became the dominant behavior. Moreover, as the game progressed, the majority status of drinkers in the network remained stable, with the proportion of drinkers stabilizing at about 64% in the later stages of the game. These simulation results meet the low bar for our ABM model to reproduce the target social phenomenon.

  Additionally, the proportion of agents who identify with drinking behavior implying identity preference (i.e., Committed Drinker and Committed Non-Drinker agents) also increased from 0% to a stable level of approximately 57%, while the proportion of agents who do not identify with drinking behavior implying any identity preference (i.e., all Modest Drinker and Modest Non-Drinker agents) decreased from 100% to a stable level of approximately 43%. The cultural significance of drinking behavior, which indicates the identity implication of drinking behavior, was also significantly widely accepted and became mainstream culture.

  Furthermore, as the game progressed, the density and friendship strength (edge weight) of the friendship network significantly increased, forming a certain degree of community structure. These simulation outcomes align with our target social phenomenon, indicating that the ABM model can effectively reproduce the target phenomenon.

- Secondly, through the analysis of the decision-making process of agents, we found evidence supporting the social motives and conformity motives of agents' internal states. Our original MBE hypothesis suggests that college students' internal states are influenced by social capital within the social network via situational mechanisms, and individuals are assumed to seek social support from their friends. The simulation output results of the ABM model indicate that the pursuit of social capital by agents can manifest as two types of behavioral motives: social motives (agents make decisions that they perceive will yield the highest social capital return) and conformity motives (agents make decisions that can avoid or minimize potential social capital loss).
- Finally, through the analysis of agents' behavioral strategies, we found that the decision-making of agents driven by social capital exhibits a certain strategic regularity but does not show a singular behavioral strategy tendency. The behavior of agents cannot be explained by a few typical singular behavioral strategies.

In summary, we have translated the MBE hypotheses into a RL-based ABM model and successfully "redescribed" the target social phenomenon. This achievement signifies that the MBE hypotheses constitute a candidate explanation for the target social phenomenon, as evidenced by passing the generative sufficient test. In the following chapter, we will proceed to the "Retroduction" stage, which involves exploring and analyzing the roles played by two Explanans, namely social capital and the cultural significance of drinking behavior, in the emergence of Explanandum (the target social phenomena).

Chapter 5: "Retroduction" Analysis

The purpose of the "Retroduction" analysis is to identify the components in the ABM model that are fundamentally responsible for the emergence of the target social phenomenon (i.e., entities and mechanisms whose absence would prevent the phenomenon from occurring) and to further ascertain the role of these indispensable components in reproducing the target social phenomena. By doing so, we aim to optimize the candidate MBE by eliminating non-essential components for reproducing the target social phenomenon or clarifying the roles of indispensable components within the candidate MBE, thereby approaching "Inference to the Best Explanation" under the principle of abductive reasoning. In this study, our focus is on two components that constitute our explanatory interests in the candidate MBE, namely social capital and the cultural significance of drinking behavior. To evaluate the contributions of these two components in the "redescription" process, this chapter on "retroduction" will be divided into two sections. The first section will concentrate on the role of social capital in reproducing the target phenomenon. In the second section, we will examine the role of the cultural significance of drinking behavior in reproducing the target phenomenon.

Section 1: The Role of Social Capital

In order to assess the role of social capital in reproducing the social phenomenon of the diffusion of drinking behavior in social networks, we will examine it from both a network-level and an individual-level perspective.

- Firstly, at the network-level, we will investigate whether the absence of social capital influence would preclude the emergence of the target social phenomenon, thereby determining whether social capital is fundamentally constitutive to the phenomenon.
- Secondly, at the individual-level, we will explore the differences in decision-making among agents located in different positions within the network under the influence of social capital.

To achieve the first objective of studying the role of social capital in reproducing the target social phenomenon, we will conduct two contrasting experimental studies.

Firstly, a comparison will be made between the simulation model that considers the influence of social capital and the simulation models that exclude the influence of social capital. This control experiment aims to evaluate whether excluding the influence of social capital would preclude the target social phenomenon.

Secondly, a comparison will be made under varying levels of importance placed on future social capital. This experimental comparison aims to assess whether there are differences in the impact of long-term/short-term social capital on reproducing the target social phenomenon.

In the following sections, we will present the designs and results analysis of these two contrast experiments separately.

Comparative Experiment: Social Capital vs. No Social Capital

Due to the flexibility of ABM model programming, it enables us to conduct counterfactual inference in existing ABM artificial social environments. In this section, we will introduce counterfactual control groups that exclude the influence of social capital on agents in the social network and compare the simulation results of these counterfactual control groups with the simulation results of the experimental group that considers the situational influence of social capital on agents. This comparison aims to evaluate the dynamics of the proportions of agents in different states after excluding the situational influence of social capital, particularly focusing on the diffusion of drinking behavior in the social network, and to assess the role of social capital in reproducing target social phenomena. Specifically, the simulation research design is as follows:

- Social Capital Driven Group (considering the situational influence of social capital on the agents): We consider a simulation experiment where agents are influenced by social capital through the situational mechanism as the experimental group. This group uses the base parameter setting from Chapter 4, and agents' decision-making in the ABM model is controlled by a deep Q-network, enabling decisions based on social motives and conformity motives as indicated in Chapter 4. We will then conduct 200 complete simulation games and record the network-level simulation outcomes.

- Non-Social Capital Driven Groups (excluding the situational influence of social capital on the agents): We introduce five different types of Non-Social Capital Driven experimental groups where agents are not influenced by social capital through the situational mechanism. To exclude the situational influence of social capital on agents, we redesign the decision-making module of agents in these experimental groups, removing control by the trained deep Q-network. Instead, in these experimental groups, we use several typical simple rule-based approaches to control agent's decision-making. Apart from the decision-making module, these Non-Social Capital Driven experimental groups remain consistent with the Social Capital Driven experimental group. The decision-making modules for agents in each Non-Social Capital Driven group are as follows[36]:
    - Random Walk Group: Agents have a 100% probability of making random decisions, essentially engaging in random walks across the various behavior states.
    - Static Group: Agents have a 99% probability of maintaining their current state and a 1% probability of making a random decision.
    - Conformity Group: Agents have a 99% probability of adopting a conformity strategy[37] in decision-making and a 1% probability of making a random decision.
    - Imitate Best Friend Group: Agents have a 99% probability of imitating their best friend's state[38] and a 1% probability of making a random decision.
    - Imitate Most Popular Friend Group: Agents have a 99% probability of adopting the state of their neighbor with the highest social capital [39] and a 1% probability of

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[36] Given that within the initial social network, all agents are initialized to the state of "modest non-drinker", if the influence of social capital on the internal state of the agents is excluded and the behavioral decisions of the agents are made to strictly adhere to "Static Rule," "Conformity Rule," "Imitate Best Friend Rule," or "Imitate Most Popular Friend Rule," then the distribution of behavioral states among the agents within the social network will remain unchanged, as no agent will transition from Modest Non-Drinker state to any other state. Drawing on the stochastic disturbances present in the real world and also to imbue the experimental groups with greater randomness, we have introduced a 1% decision-making randomness in the aforementioned "experimental groups."

[37] Conformity strategy: The agent observes the current states of all its neighbors and selects the mainstream behavior of all neighbors as the action it will take next. If none of the agent's neighbors exhibit a mainstream behavior, the agent will maintain its current behavior.

[38] Best Friend Imitation: The agent observes the current action of its best neighbor (the neighbor with the highest edge weight) and adopts it as the action it will take next. If the agent has multiple best friends, it randomly selects one of the best neighbors to imitate their behavior.

[39] Highest Social Capital Imitation: The agent observes the behavior of the neighbor with the highest social capital among its neighbors and adopts it as the action it will take next.

making a random decision[40].

Each experimental group conducted 200 complete simulation games under the specified decision-making rules and recorded the simulation outcomes. Next, we will compare the simulation results of the social capital driven experimental group (Social Capital Driven Group) with five Non-social capital driven experimental groups.

Dynamics of Drinking Behavior in Different Groups

- Data Collection: In all simulation experiments of experimental groups, we recorded the proportion of agents accept drinking behavior at each step of the game. Each game consisted of 60 steps, resulting in a sample dataset of 61 data points. These data points represent repeated measurements of the proportion of drinkers at different game steps. We completed a total of 1200 games, resulting in the collection of 1200 datasets, each containing 61 data points representing the proportion of drinkers at different steps (step 0, step 1, ..., step 60) along with the corresponding network ID and network type. The collected data, along with repeated observations, are presented in Table 41 (see Appendix A).
- Method: We will use a two-way repeated measures ANOVA to analyze the collected data on the proportion of drinkers. This method allows us to assess the impact of game steps on changes in the proportion of drinkers, as well as the differential effects of different groups on these changes, and the interaction effects between group categories and game steps. The Greenhouse-Geisser method will be used for correction purposes, maintaining a significance level (α) of 0.05.
- Result: The results of the two-way repeat measures ANOVA analysis are shown in Table 42:

Table 42: the two-way repeated measures ANOVA analysis [41]:

[41] Regarding annotation a, there were significant differences in the proportion of drinkers between the current step and the proportion of drinkers 10 steps prior within subjects, at a significance level of 0.05. Regarding annotation b, there were significant differences in the proportion of drinkers between the current step for the control group and the proportion of drinkers at the corresponding step for the social capital driven group, at a significance level of 0.05.

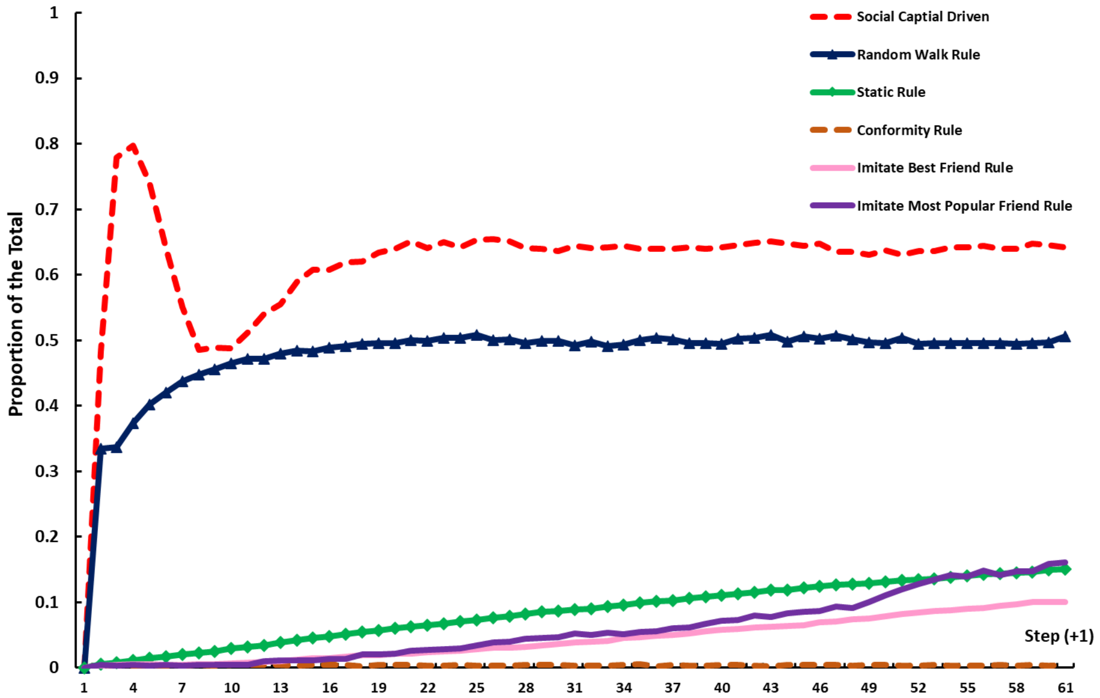
	T0	T1	T10	T20	T30	T40	T50	T60	F	P
Social Capital Driven (n=200)	0±0	0.48±0.07a	0.51±0.26a	0.65±0.19a	0.64±0.18	0.63±0.32	0.63±0.17	0.64±0.17	1696.684	<0.001
Random Walk (n=200)	0±0	0.33±0.06a,b	0.47±0.06a,b	0.5±0.07a,b	0.49±0.06b	0.5±0.07b	0.5±0.07b	0.51±0.06b	4.633	<0.001
Static (n=200)	0±0	0±0.01b	0.03±0.02a,b	0.06±0.03a,b	0.09±0.04a,b	0.31±0.06a,b	0.13±0.05a,b	0.15±0.05a,b	12.144	<0.001
Conformity3 (n=200)	0±0	0±0.01b	0±0.01b	0±0.01b	0±0.01b	0.02±0.02b	0±0.01b	0±0.01b	0.089	1
Imitate Best Friend (n=200)	0±0	0±0.01b	0.01±0.02b	0.02±0.04b	0.04±0.06a,b	0.52±0.14a,b	0.08±0.09a,b	0.1±0.11a,b	1.622	0.002
Imitate Most Popular Friend (n=200)	0±0	0±0.01b	0±0.02b	0.03±0.13a,b	0.05±0.21a,b	0.39±0.47a,b	0.12±0.3a,b	0.16±0.35a,b	3.329	<0.001
F	.	6083.012	1008.991	1632.759	1061.281	871.75	581.527	458.536		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		
F_step= 211.096, p<0.001; F_type=2241.372, p<0.001; F_(step*type)=49.896, p<0.001;										

The analysis results revealed significant main effects for step (F_{step}= 211.096, p < 0.001), indicating significant differences in the proportion of agents accepting alcohol in the social network across different game steps. Specifically, in terms of group comparisons, we found that except for Conformity Group (F= 0.089, p = 1), the proportion of drinkers in each group varied significantly as the game steps progressed. The main effect of type was also significant (F_{type} = 2241.372, p < 0.001), indicating significant differences in the proportion of drinkers in the network among the different groups. Furthermore, the significant interaction effect of step*type ($F_{step*type} = 49.896, \text{p} < 0.001$) suggests that the trends of proportion of drinkers in each group varied significantly as the game progressed.

Pairwise comparisons result: In the pairwise comparisons, the proportion of drinkers in the Social Capital Driven Group was significantly higher than the proportion of drinkers in all control groups at all time points. The simulation results of the Social Capital Driven Group indicate a significantly higher proportion of drinkers in the stable phase compared to non-drinkers, suggesting that drinking behavior is the dominant behavior in the network. In contrast, the simulation results of all control groups show either a non-significant increase in the proportion of drinkers (such as the Conformity Group) or a significant increase in the proportion of drinking agents but still significantly lower than the proportion of non-drinkers (such as the Static, Imitate Best Friend, Imitate Most Popular Friend Groups), or a proportion of drinking agents that is comparable to the proportion of non-drinkers without significant differences (such as the Random Walk Group). Therefore, the simulation outcomes of control groups fail to reproduce the target social phenomenon.

Moreover, the experimental group exhibited a trend of initially increasing, followed by a decline and subsequent increase, gradually converging into a stable state in terms of within-group changes in the proportion of drinkers. In contrast, the changes in the proportion of drinkers in the control groups show monotonicity. The evolving trends of the proportion of drinkers for each type of network are summarized in Figure 11, providing a more comprehensive and intuitive understanding of the dynamic evolution and trends associated with different network types as the game progresses.

Figure 11: Trends in the Proportion of Drinkers in the Network Driven by Different Decision-Making Rules



Summary: Comparison of Including and Excluding the Influence of Social Capital

In the aforementioned simulation experiment, we compared the simulation outcomes of the social capital-driven experimental group, which includes the situational influence of social capital on individuals, with the non-social capital-driven experimental group, which excludes the influence of social capital. The simulation outcomes indicates that for our candidate MBE, the presence of social capital in the Explanandum constitutes fundamental components to reproduce target social phenomena, as the absence of social capital would prevent the Explanans phenomenon from occurring.

Compared to all Non-Social Capital Driven groups, only the simulation result of Social Capital Driven Group meets the low bar for passing the “generative sufficient test”: (1) agents continuously transition from a state of refusing to drink to accepting drinking behavior. (2) the proportion of agents accepting drinking behavior in the network gradually shifts from being a minority to a majority, and (3) the proportion of agents accepting drinking behavior in the social network stabilizes at around 64%, significantly higher than the proportion of agents refusing drinking behavior (approximately 36%).

Conversely, in all Non-Social Capital-Driven Groups, the proportion of agents accepting drinking behavior is not significantly higher than the proportion of agents refusing drinking behavior. The proportion of agents accepting drinking behavior in the social network does not reach or maintain a majority position, thus failing to meet the low bar for passing the "generative sufficiency test." Consequently, upon excluding the situational influence of social capital on individuals from the candidate MBE, the simulation results indicate that the diffusion of drinking behavior within the social network cannot occur.

Therefore, the aforementioned "Retroduction" analysis indicates that the situational influence of social capital on individuals' internal states is an indispensable fundamental component within the candidate MBE for reproducing the target phenomenon; the absence of social capital would prevent the occurrence of the target social phenomenon.

Comparative Experiment: Long-Term Social Capital vs. Short-Term Social Capital

In the aforementioned comparative experiment, we compared the simulation outcomes of ABM models that include and excludes the influence of social capital on agents. We found that social capital is an indispensable component in our candidate MBE.

In the ABM model that includes the influence of social capital, social capital affects individuals' internal states through situational mechanisms, driving them with social motives and conformity motives in the decision-making process. Specifically, the deep Q-network that determines agent decision-making optimizes social capital return as the goal, where social capital return refers to the agent's estimation of accumulating social capital in the future. Since being driven by social capital is an indispensable component for reproducing target social phenomena in the candidate MBE, the next question is, at what level of emphasis on future social capital returns should the reproduction of target phenomena occur? To address this question, in this section, we further compare the changes in the proportions of agents in different states driven by long-term social capital and short-term social capital in the social network.

- Simulation Study Design: In the social capital-driven model, agents' decision-making processes are controlled by a well-trained deep Q-network to optimize their social capital return. As delineated in Chapters 4, the training of the deep Q-network is conducted through iterative runs of the ABM model with an added neural network training module, allowing agents to continuously play games, accumulate game experience, and learn from a large amount of experience stored in the replay buffer. During the training process, we need to define the reward feedback signals that agents receive from the social environment, namely the social capital return that agents receive.

  In this ABM model, by modulating the parameter γ value, ranging from 0 to 1, we can control the deep Q-network to make decisions that are more favorable for short-term or long-term social capital return, as the parameter γ describes the importance of future expected rewards on the agent's current decision.

  Specifically, a parameter γ value of 1 indicates that future expected rewards and current rewards are equally important in the agent's current decision-making, while a γ value of 0 implies that future rewards have no impact on the current decision-making, with the agent only considering current rewards. A higher parameter γ value, closer to 1, suggests that the agent is more influenced by long-term social capital during the training process, whereas a lower parameter γ value, closer to 0, indicates that the agent is more influenced by short-term social capital.

To analyze the changes in the proportions of agents in different states driven by long-term social capital and short-term social capital, we trained the deep Q-networks at three different parameter values samples:

- Low importance of long-term social capital: $\gamma_1 = 0.7$
- Moderate importance of long-term social capital: $\gamma_2 = 0.8$
- High importance of long-term social capital: $\gamma_3 = 0.9$

We ran the ABM models with these three different deep Q-networks trained under three different γ levels, completing 500 full simulations at each level, totaling 1500 simulations. Network-level data were recorded for comparison purposes.

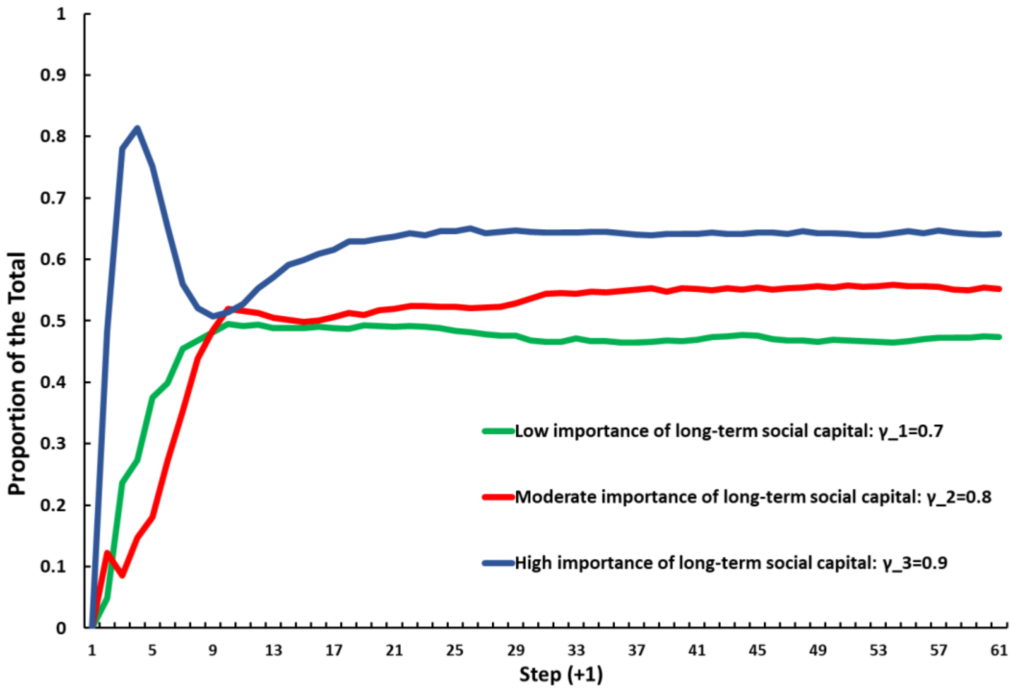
Dynamics of Drinking Behavior in Different Gamma Levels

- Data Collection: We recorded the proportion of agents in the social network who accepted drinking at each step of every simulation game. A total of 1500 simulation games were conducted, with each data set consisting of 61 data points, as presented in Table 43 (see Appendix A).
- Method: A two-factor repeated measures analysis of variance (ANOVA) was conducted on the collected data to compare the differences in the evolution of drinking rates within the network across different gamma levels.
- Results: Table 44 (see Appendix A) displays the results of the analysis. The results of the two-way repeated measures ANOVA on the trend of changes in the proportion of drinkers within the network are as follows: The main effect of Step is significant ($F_{step} = 417.54, p < 0.001$), indicating significant differences in the average proportion of drinkers across different game steps. Post-hoc tests revealed significant variations in the average proportion of drinkers across the $\gamma_3 = 0.9$ group ($F = 1459.905, p < 0.001$), the $\gamma_2 = 0.8$ group ($F = 151.16, p < 0.001$), and the $\gamma_1 = 0.7$ group (F=162.894, p<0.001), indicating significant changes in the proportion of drinkers within each group over time. The main effect of Type is also significant ($F_{gamma} = 196.706, p < 0.001$),

indicating significant differences in the average proportion of drinkers between different groups. Furthermore, the interaction effect between Step and Type is significant ($F_{step*gamma} = 91.322, p < 0.001$), suggesting significant differences in the trend of changes in the proportion of drinkers within different gamma levels with respect to game steps.

<u>Pairwise Comparisons Result</u>:

Figure 12: Trends in the Proportion of Drinkers in the Network Driven by Different Importance of Long-Term Social Capital



Specifically,

- In the $\gamma_3 = 0.9$ group, the proportion of agents accepting drinking behavior exhibited an initial increase, followed by a decrease, then a gradual rebound, and eventually converged to a stable state. During the stable stage, the proportion of agents accepting drinking behavior (approximately 64%) was significantly higher than the proportion of agents refusing drinking, with the agents accepting drinking behavior maintaining a majority position in the network. Thus, under $\gamma_3 = 0.9$, simulation result meets the low bar for reproducing the target social phenomenon and pass the “generative sufficient” test.

- In the $\gamma_2 = 0.8$ group, the proportion of agents accepting drinking behavior continuously increased and gradually converged to a stable state. During the stable stage, the proportion of agents accepting drinking behavior (approximately 55%) was significantly higher than the proportion of agents refusing drinking, with the agents accepting drinking behavior maintaining a majority position in the network. Thus, under $\gamma_2 = 0.8$, simulation results also meet the low bar of reproducing the target social phenomenon and passing the "generative sufficiency test."
- In the $\gamma_1 = 0.7$ group, the proportion of agents accepting drinking behavior showed a continuous increase, followed by a slight decline, and gradually converged to a stable state. During the stable stage, the proportion of agents accepting drinking behavior (approximately 47%) was significantly lower than the proportion of agents who refuse to drink, with the agents accepting drinking behavior remaining in a minority position in the network. Thus, under $\gamma_1 = 0.7$, the simulation results fail to meet the low bar for reproducing the target social phenomenon and do not pass the "generative sufficiency test."

Dynamics of Agents in Various States in Different Gamma Levels

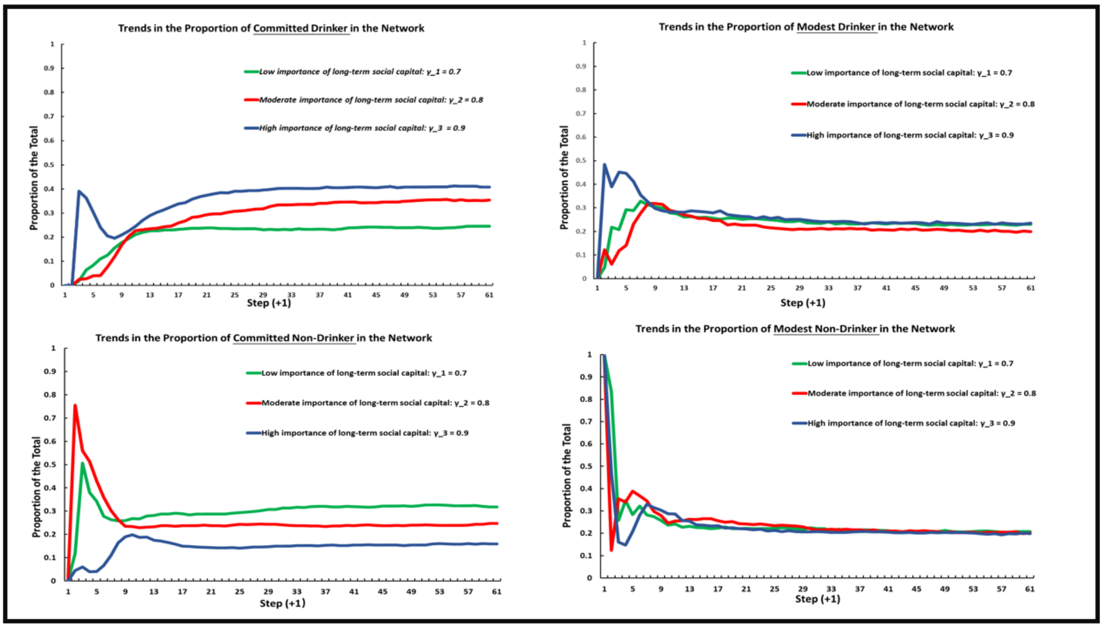
We analyzed the trends in the proportion of agents in four distinct states under the three different gamma levels through two-factor repeated measures analysis of variance (ANOVA). Given that these statistical analyses employ the same methodology as the section preceding this, to avoid redundancy in description, we have summarized all the results of the Two-factor repeated measures ANOVAs in Table 45.

Table 45: Two-factor repeated measures ANOVA results

	Committed Drinker	*Modest Drinker*	*Committed Non-Drinker*	*Modest Non-Drinker*
Main Effect of Step	*F_step= 548.893, p<0.001*	*F_step= 180.429, p < 0.001*	*F_step= 180.429, p < 0.001*	*F_step = 23.372, p < 0.001*
Gamma_1 = 0.7	*F=40.894, p<0.001*	*F = 146.635, p < 0.001*	*F = 146.635, p < 0.001*	*F = 297.235, p < 0.001*
Gamma_2 = 0.8	*F=66.098, p<0.001*	*F = 110.482, p < 0.001*	*F = 110.482, p < 0.001*	*F = 2491.004, p < 0.001*
Gamma_3 = 0.9	*F=591.053, p<0.001*	*F = 1212.245, p < 0.001*	*F = 1212.245, p < 0.001*	*F = 591.053, p < 0.001*
Main Effect of Gamma	*F_gamma= 242.716, p<0.001*	*F_gamma= 46.214, p < 0.001*	*F_gamma= 46.214, p < 0.001*	*F_gamma = 233.36, p < 0.001*
Interaction Effect of (Step * Gamma)	*F_(step*gamma)= 50.286, p<0.001*	*F_(step*gamma)= 69.992, p < 0.001*	*F_(step*gamma)= 69.992, p < 0.001*	*F_(step*gamma) = 132.288, p < 0.001*

Pairwise Comparisons Result: the following figures delineate the trends in the proportion of agents in four distinct states within the network, driven by three varying levels of the importance of long-term social capital (for detailed Pairwise comparisons result, refer to Tables 46-49 in Appendix A).

Figure 13-16:



Summary: Comparison of Long-Term and Short-Term Social Capital

In summary, we compared the simulation outputs of ABM models under different levels of emphasis on future social capital return. The simulation outcomes demonstrate that an appropriate emphasis on future social capital return is essential to reproduce the target phenomena.

- For the High importance of long-term social capital (gamma=0.9) group, where agents prioritize future social capital return, the simulation results meet the low bar of "generative sufficient" test. The simulation results show successfully reproduces of the diffusion of drinking behavior (with approximately 64% of agents accepting drinking in the stable state) and the prevalence of drinking culture (with approximately 57% of agents identifying drinking behavior with identity implications). In this context, both drinking behavior and the acceptance of college drinking cultural significance are dominant behaviors.

- In the Moderate importance of long-term social capital (gamma =0.8) group, where agents show modest emphasis on long-term social capital return, the simulation results also meet the low bar of "generative sufficient" test. The simulation results show successfully reproduces the diffusion of drinking behavior (with approximately 55% of agents accepting drinking in the stable state) and the prevalence of drinking culture (with approximately 59% of agents associating drinking behavior with identity implications). However, the proportion of drinkers significantly decreases compared to the gamma=0.9 group.
- For the Low importance of long-term social capital (gamma=0.7) group, where agents prioritize short-term social capital return, the simulation results fail to meet the low bar of "generative sufficient" test. The simulation results fail to reproduce the diffusion of drinking behavior (with approximately 47% of agents accepting drinking in the stable state) and the prevalence of drinking culture (with approximately 57% of agents assciate drinking behavior with identity implications).
- Across the three different gamma levels, we observed that higher gamma values (indicating greater emphasis on long-term social capital benefits) result in a higher proportion of agents accepting drinking behavior in the social network, with more agents transitioning to the state of accepting drinking in the initial stages of the game. As the gamma value decreases to 0.7, the phenomenon of drinking behavior dominance disappears.

Therefore, to accurately reproduce the target social phenomena, agents must maintain an appropriate level of emphasis on long-term social capital return. When agents excessively prioritize short-term social capital return, the diffusion of drinking behavior disappears. In such cases, we fail to reproduce the target phenomenon.

Individual Decision Differences under the Influence of Social Capital

In the previous research, we analyzed the role of social capital in reproducing target social phenomena. We conducted controlled experiments to compare simulation models that include and exclude the influence of social capital, as well as simulations driven by short-term and long-term social capital, to assess the differences in simulation outcomes. The results of the controlled studies indicate that social capital, as an explanatory factor in candidate MBE, is a fundamental component in reproducing phenomena. it is essential for agents to maintain a focus on long-term social capital return to produce the desired outcomes.

With these key conclusions, the next question arises: under the influence of social capital, what are the characteristics of individual-level decision-making behavior?

Specifically, in our candidate MBE, the mechanism through which social capital affects Explanans can be decomposed following Coleman's boat diagram into:

- Situational mechanism: Social capital, as an institutional structure (indicating a structure of potential social resource flow relationships among college students within college friendship network), can influence the objectives and motives of individual college students. Our ABM model simulation results in Chapter 4 suggest that social capital shapes individual social motives and conformity motives through the situational mechanism.
- Action formation mechanism: The social and conformity motives of college students will drive their decision-making in drinking behavior. Our previous ABM simulation results indicate that agents exhibit certain regularities in their decision-making during this process but cannot be explained by three common single behavioral strategies. To clarify this mechanism, the focus of this section is on the behavioral decision preferences of

individuals under the influence of social capital.

- ○ Transformational mechanism: Individual decision-making behavior under the influence of social capital, along with the preference for friendship relationships influenced by another explanatory factor in the candidate MBE (the cultural significance of drinking behavior), contribute to the nonlinear interactions among individuals, ultimately resulting in the emergence of the target social phenomena.

In this section, we focus on the decision-making preferences of agents in the action formation mechanism under the influence of social capital. We aim to further investigate how agents, at an individual level, undergo state changes under the influence of social capital. Specifically, we seek to understand how agents make behavioral decisions under different social situations driven by social capital.

- Simulation Study Design: We conducted simulation experiments using the base parameter setting from Chapter 4, where the ABM model incorporated the influence of social capital on agents, with agents emphasizing long-term social capital return (parameter gamma=0.9). The complete simulation consisted of 500 simulation games (Game sequence number No.0 to No. 499), and for each simulation game, we recorded the following social situation information for each agent in the social network at each round of the game: (1) Game sequence number, (2) Agent ID, (3) Current state of the agent, (4) State the agent is transitioning to, (5) Current social capital of the agent, (6) Number of friends the agent currently has, (7) Proportion of the agent's current "Committed Drinker" neighbors to their total number of friends, (8) Proportion of the agent's current "Modest Drinker" neighbors to their total number of friends, (9) Proportion of the agent's current "Committed Non-Drinker" neighbors to their total number of friends, (10) Proportion of the agent's current "Modest Non-Drinker" neighbors to their total number of friends.
- Data Collection: We conducted a total of 500 complete simulation games, with each simulation game consisting of 60 rounds. As a result, we collected a total of 1,800,000 agent-level data records, with each data record containing the ten social situation

information points for each agent as mentioned above.

Behavioral State Transition of Modest Non-Drinkers

Our main focus is on the behavioral decisions of “Modest Non-Drinker”, as the drinking behavioral choices of modest non-drinkers directly impact the diffusion of drinking behavior within the social network. As outlined in the State Transition Rule (Table 5) in Chapter 4, modest non-drinkers can undergo one of three transitions: they may choose to accept drinking behavior (transitioning to the "Modest Drinker" state), continue to refuse drinking behavior (remaining in the "Modest Non-Drinker" state), or opt to strongly oppose drinking behavior (transitioning to the "Committed Non-Drinker" state). Therefore, we first analyze the decision-making of modest non-drinkers in different social situations under the situational influence of social capital.

- Method: We aim to evaluate how social situation factors influence the decision-making of modest non-drinkers. The agent's state transition choice from modest non-drinker is taken as the dependent variable, which includes three types: transitioning to modest drinker state, transitioning to committed non-drinker state and staying in modest non-drinker state. Four social situation factors are considered as independent variables: the current social capital of the agent (referred to as social capital), the current number of friends of the agent (referred to as number of friends), the average friendship strength of the agent with their neighbors (referred to as Average friendship strength), and the proportion of “modest drinker” neighbors to the total number of friends (referred to as “modest drinker” friend proportion). We utilized multinomial logistic regression to analyze the relationship between the independent variables and the dependent variable.
- Results: The results of the logistic regression analysis are presented in Table 49 and Table 50. Table 49 shows the results of the univariate analysis, where all four independent variables were found to be statistically significant at a p-value of 0.05. Hence, all four variables were included in the subsequent multivariable model.

Table 49: Univariable Logistic Regression

Variable	Modest Non-Drinker to Modest Non-Drinker (N=130988)				Modest Non-Drinker to Committed Drinker (N=32390)			
	B	*p-value*	*Exp(B)*	*95% CI*	*B*	*p-value*	*Exp(B)*	*95% CI*
Social capital	0.767	<0.001	2.154	2.097-2.213	0.26	<0.001	1.297	1.247-1.349
Number of friends	0.022	<0.001	1.022	1.021-1.023	0.001	<0.001	1.037	1.036-1.038
Average friendship strength	0.045	<0.001	1.046	1.045-1.047	0.015	<0.001	1.016	1.014-1.017
Modest Drinker friend proportion	-1.339	<0.001	0.262	0.252-0.273	-0.095	0.002	0.91	0.858-0.965

*The reference category is Modest Non-Drinker to Modest Drinker *(N=84287)*

Table 50 presents the results of the multivariable analysis:

Table 50: Multivariable Stepwise Logistic Regression

Variable	Modest Non-Drinker to Modest Non-Drinker (N=130988)					Modest Non-Drinker to Committed Drinker (N=32390)				
	B	*std. B*	*p-value*	*Exp(B)*	*95% CI*	*B*	*std. B*	*p-value*	*Exp(B)*	*95% CI*
Social capital	0.248	0.083	<0.001	1.281	1.243-1.32	-0.103	-0.035	<0.001	0.902	0.861-0.945
Number of friends	0.016	0.217	<0.001	1.016	1.015-1.017	0.039	0.538	<0.001	1.04	1.039-1.041
Average friendship strength	0.039	0.627	<0.001	1.039	1.038-1.04	0.005	0.078	<0.001	1.005	1.003-1.006
Modest Drinker friend proportion	-1.177	-0.26	<0.001	0.308	0.295-0.322	-0.222	-0.049	0.002	0.801	0.753-0.853

*The reference category is Modest Non-Drinker to Modest Drinker (N=84287)

The results of the multivariable logistic regression analysis revealed that the full model, incorporating all four independent variables, was statistically significant ($\chi 2 = 27529.416, df = 8, N = 247665, p < .001$). This indicates that the state transition types of modest non-drinker agents were associated with the four independent variables: Social capital of the agent, Number of friends of the agent, Average friendship strength of the agent, and modest drinker friend proportion of the agent. More detailed regression analysis results are presented in Table 50, which includes two sets of logistic regression data separately for the transitions from "modest non-drinker" to "modest non-drinker" and from "modest non-drinker" to "committed non-drinker". The transition from "modest non-drinker" to "modest drinker" serves as the reference category, with all coefficients set to 0. The analysis results provide a summary of the raw score multivariable logistic regression coefficients, standardized regression coefficients, p-values, odds ratios [$Exp\,(B)$], and the corresponding 95% confidence intervals.

- "Modest Non-Drinker" to "Nodest Non-Drinker": The findings indicate that all four variables - Social capital ($B = 0.248, p < 0.001$), Number of friends ($B = 0.016, p < 0.001$), Average friendship strength ($B = 0.039, p < 0.001$), and modest drinker friend proportion ($B = -1.177, p < 0.001$) - significantly influence the decision of "modest non-drinker" agents to remain in "modest non-drinker" state compared to transitioning from modest non-drinker to modest drinker (Modest Non-Drinker to Modest Drinker, as reference category). Among these variables, social capital ($OR = 1.281$), Number of friends ($OR = 1.016$), and Average friendship strength (OR=1.039) have a positive effect. This implies that for modest non-drinkers, each unit increase in social capital, number of friends, or average friendship strength respectively increases the probability of staying in Modest Non-Drinker by 28.1%, 1.6%, and 3.9%. Considering the different measurement scales of these variables, the variable with the most significant positive impact on the decision is Average friendship strength ($std\ B\ =\ 0.627$), followed by Number of friends ($std\ B\ =\ 0.217$), and then Social capital ($std\ B\ =\ 0.083$). Conversely, modest drinker friend proportion ($OR\ =\ 0.308$) has a negative influence on the selection of modest non-drinkers. With each unit increase in modest non-drinker's modest drinker friend proportion, the probability of remaining in modest non-drinker decreases by 69.2% compared to transitioning to modest drinker.

- <u>"Modest Non-Drinker" to "Committed Non-Drinker"</u>: The findings indicate that, in comparison to modest non-drinker transitioning from "modest non-drinker" state to "modest drinker" state (Modest Non-Drinker to Modest Drinker, as the reference category), all four variables - Social capital ($B = -0.103, p < 0.001$), Number of friends ($B = 0.039, p < 0.001$), Average friendship strength ($B = 0.005, p < 0.001$), and "modest drinker" friend proportion ($B = -0.222, p = 0.002$) - significantly impact the decision of modest non-drinkers to transition to committed non-drinker state. Among these variables, Number of friends ($OR = 1.04$) and Average friendship strength ($OR = 1.005$) have a positive effect. This means that for modest non-drinkers, each increase in the number of friends or a unit increase in average friendship strength respectively increases the probability of transitioning to Committed Non-Drinker by 4% and 0.5% when compared to transitioning to modest drinker state. Taking into account the different measurement units of these two variables, the standardized B values suggest that Average friendship strength ($std\ B\ =\ 0.039$) has the most significant positive impact on the decision, followed by Number of friends ($std\ B\ =\ 0.005$). Conversely, Social capital

($OR = 0.902$) and modest drinker friend proportion ($OR = 0.801$) have a negative influence on the decision of modest non-drinkers. This means that for modest non-drinkers, ach unit increase in social capital, or "modest drinker" friend proportion decreases the probability of transitioning to committed non-drinker, compared to transitioning to modest drinker, by 9.8% and 19.9% respectively.

In summary, the data analysis results of the simulation outcomes reveal differences in the behavioral decisions of modest non-drinkers in different social situations. It is observed that the majority of modest non-drinkers (52.9%) who have higher levels of friend support (social capital) tend to remain in "modest non-drinker" state. As the support from friends decreases (i.e., lower social capital), modest non-drinkers are more likely to transition towards accepting drinking behavior (i.e., transitioning to modest drinker state, accounting for 34% of cases). Besides social capital, other factors such as having fewer friends, lower average friendship strength, and a higher proportion of "modest drinker" friends also increase the likelihood of modest non-drinkers transitioning towards accepting drinking behavior. Notably, the influence of the independent variables, Number of friends and Average friendship strength, on agents' decisions varies across different stages of the game. In the early stages, when both the Number of friends and Average friendship strength are relatively low, modest non-drinkers are more inclined towards transitioning to accepting drinking behavior. However, in the later stages, as the number of friends and the strength of friendships increase through interactions, modest non-drinkers with higher Number of friends and Average friendship strength are more likely to reject drinking behavior. Therefore, a significant number of modest non-drinkers transition towards accepting drinking behavior in the early stages of the game, while in the later stages, they are more likely to refuse to accept drinking behavior and remain in "modest non-drinker" state.

Behavioral State Transition of Modest Drinkers

We are also interested in the behavioral decision-making of modest drinkers, as the behavioral decision of modest drinkers also significantly impacts the diffusion of drinking behavior in social networks. As outlined in the State Transition Rule (Table 5) in Chapter 4, modest drinkers can undergo one of three transitions: Modest Drinkers may choose to refuse drinking behavior (transition to “Modest Non-Drinker” state), continue to accept drinking behavior (remain in “Modest Drinker” state), or adopt a more proactive attitude towards drinker behavior (transition to “Committed Drinker” state). Therefore, we also analyze the decision-making of modest drinkers in different social situations under the situational influence of social capital.

- Method: We aim to evaluate how social situation factors influence the decision-making of modest drinkers. The agent's state transition choice from “modest drinker” state is taken as the dependent variable. The dependent variable is a categorical variable, which includes three types, i.e. transitions from “modest drinker” state to “committed drinker” state, transitions from “modest drinker” state to “modest non-drinker” state, and transitions from “modest drinker” state to “modest drinker” state. Four social situation factors are considered as independent variables: (1) the agent's current social capital (referred to as social capital), (2) the number of friends the agent currently has (referred to as number of friends), (3) the average friendship strength between the agent and their neighbors (referred to as Average friendship strength), (4) the proportion of “Modest Non-Drinker” neighbors to the total number of friends the agent currently has (referred to as “Modest Non-Drinker” friend proportion). We also utilized multinomial logistic regression to analyze the relationship between the independent variables and the dependent variable.
- Results: The results of the univariate analysis are presented in Table 51. All four independent variables were found to be statistically significant at a p-value of 0.05. Therefore, all four variables were included in the multivariable model.

Table 51: Univariable Logistic Regression

Variable	Modest Drinker to Committed Drinker (N=58392)				Modest Drinker to Modest Drinker (N=148664)			
	B	*p-value*	*Exp(B)*	*95% CI*	*B*	*p-value*	*Exp(B)*	*95% CI*
Social capital	-0.962	<0.001	0.382	0.37-0.395	0.674	<0.001	1.963	1.916-2.01
Number of friends	-0.03	<0.001	0.97	0.969-0.972	0.018	<0.001	1.018	1.016-1.019
Average friendship strength	-0.047	<0.001	0.954	0.953-0.956	0.016	<0.001	1.016	1.016-1.017
Modest Non-Drinker friend proportion	0.855	<0.001	2.352	2.195-2.52	-1.794	<0.001	0.166	0.156-0.177

**The reference category is Modest Drinker to Modest Non-Drinker (N=72916)*

Table 52 presents the results of the multivariable analysis:

Table 52: Multivariable stepwise Logistic regression

Variable	Modest Drinker to Committed Drinker (N=58392)					Modest Drinker to Modest Drinker (N=148664)				
	B	*std. B*	*p-value*	*Exp(B)*	*95% CI*	*B*	*std. B*	*p-value*	*Exp(B)*	*95% CI*
Social capital	-0.366	-0.145	<0.001	0.694	0.666-0.723	0.661	0.263	<0.001	1.936	1.881-1.993
Number of friends	-0.031	-0.253	<0.001	0.97	0.968-0.971	0.01	0.086	<0.001	1.01	1.009-1.012
Average friendship strength	-0.035	-0.518	<0.001	0.966	0.965-0.967	0.004	0.065	<0.001	1.004	1.004-1.005
Modest Non-Drinker friend proport	0.013	0.002	0.738	1.013	0.938-1.094	-1.729	-0.255	0.002	0.178	0.166-0.19

**The reference category is* Modest Drinker to Modest Non-Drinker *(N=72916)*

The results of the multivariable logistic regression analysis indicate that the full model, which includes all four independent variables, was statistically significant ($\chi2 = 31414.814, df = 8,\ N = 279972, p < 0.001$). This suggests that the state transition types of modest drinkers were associated with the four independent variables: Social capital of the agent, Number of friends of the agent, Average friendship strength of the agent, and “modest non-drinker” friend proportion of the agent. Detailed results of the logistic regression analysis are presented in Table 52, which includes two sets of logistic data for the transitions from “modest drinker” state to “committed drinker” state and “modest drinker” to “modest non-drinker”, with the latter as the reference category. The table provides raw score multivariable logistic regression coefficients, standardized regression coefficients, p-values, and odds ratios ($Exp\ (B)$) with a 95% confidence interval, offering a comprehensive summary of the statistical analysis.

- “Modest Drinker” to “Committed Drinker”: The analysis result reveal that, compared to modest drinker state transitioning to modest non-drinker state, three out of the four variables significantly influence the modest drinkers’ decision to transition to committed drinker state. Specifically, Social capital ($B = -0.366, p < 0.001$), Number of friends ($B = -0.031, p < 0.001$), and Average friendship strength ($B = -0.035, p < 0.001$) show significant effects. However, the variable “modest non-drinker” friend proportion ($B = 0.013, p = 0.738$) does not exhibit statistical significance at the 0.05 level implying that the proportion of “modest non-drinker” friends among the total friends does not differ significantly between modest drinker transitioning to committed drinker state and those transitioning to modest non-drinker state.

Analyzing the significant independent variables influencing modest drinkers' transition types, it is observed that social capital ($OR = 0.694$), Number of friends ($OR = 0.97$), and Average friendship strength ($OR = 0.966$) have negative effects. Each unit increase in social capital, number of friends, or average friendship strength leads to a respective decrease of 30.6%, 3%, and 3.4% in the probability of transitioning from modest drinker to committed drinker state. Standardized coefficients ($std\ B$) suggest that Average friendship strength ($std\ B = -0.518$) has the greatest negative impact on agents' transition types, followed by Number of friends ($std\ B = -0.253$), and social capital ($std\ B = -0.145$).

- <u>"Modest Drinker" to "Modest Drinker":</u> the analysis results indicate that, compared to modest drinkers transitioning to modest non-drinker state, all four variables - Social capital ($B = 0.661, p < 0.001$), Number of friends ($B = 0.018, p < 0.001$), Average friendship strength (B=0.016, p<0.001), and "modest non-drinker" friend proportion ($B = -1.794, p < 0.001$) - significantly influence whether modest drinkers remain in modest drinker state. Specifically, three out of the four variables, Social capital ($OR = 1.936$), Number of friends ($OR = 1.01$), and Average friendship strength ($OR = 1.004$) have positive effects. his means that for modest drinkers, with Each increase in the number of friends or average friendship strength results in a higher probability of remaining in modest drinker state, with increases of 93.6%, 1%, and 0.4% respectively, compared to transitioning to modest non-drinker state.

  Standardized coefficients reveal that social capital ($std\ B = 0.263$) has the most positive impact, followed by Number of friends ($std\ B = 0.086$), and Average friendship strength ($std\ B = 0.016$). Conversely, "modest non-drinker" friend proportion ($OR = 0.166$) has a negative affect the choice of modest drinkers This means that with each increase in one unit of "modest non-drinker" friend proportion, the probability of modest drinkers remaining in modest drinker state, compared to transitioning to modest non-drinker state, decreases by 83.4%.

In summary, the data analysis results show differences in the behavioral decisions of modest drinkers in various social situations under the driven of social capital. In the early stages of the game, modest drinkers with lower levels of Number of friends and Average friendship strength are more inclined (20.9%) to transition to committed drinker state. As the game progresses, the Number of friends and Average friendship strength increase, modest drinkers with higher levels of friend support and a lower proportion of "modest non-drinker" friends (53.1%) are more likely to remain in modest drinker state. On the other hand, modest drinkers with moderate levels of social capital, Number of friends, and Average friendship strength, and a higher level of "modest non-drinker" friends (26%), are more inclined to transition from modest drinker state to modest non-drinker state, i.e., towards refusal of drinking behavior. In conclusion, the data analysis reveals that the level of friend support, indicated by the Number of friends and Average friendship strength, plays a significant role in determining whether modest drinkers transition to committed drinker state or modest non-drinker state. Additionally, the presence of "modest non-drinker" friends and the level of social capital also impacts the decision-making process of modest drinkers.

Summary: Variations in Behavioral Decision-Making of Individuals Under the Influence of Social Capital

In the preceding multivariable logistic regression analysis, we investigated the impact of social situational factors on the state transition types of Modest Drinkers and Modest Non-Drinkers to ascertain under what social situations agents are more likely to transition towards accepting or maintaining drinking behavior under the driven of social capital motives. The key findings are outlined as follows:

- For modest non-drinkers, the likelihood of transitioning to the modest drinker state is increases when they have fewer friends, weaker average friendship strength, receive less social support from friends, and have a higher proportion of friends who are drinkers, as opposed to remaining in "modest non-drinker" state. Additionally, modest non-drinkers are more likely to transition to "modest drinker" state during the early steps of the game. This tendency can be attributed to the lower number of friends and weaker average friendship strength among agents in the initial game phases, which may result in a relatively smaller loss of social capital from

"Committed Non-Drinkers" for modest non-drinkers who transition to “modest drinker” state.

- For modest drinkers, they are more likely to maintain the state of “modest drinker” when they have a larger number of friends, stronger average friendship strength, receive more social support from friends, and have a higher proportion of friends who are drinkers.

When modest drinkers have fewer friends, weaker average friendship strength, and receive less social support from friends, they are more likely to transition towards the more radical committed drinker state. Due to the generally lower number of friends and weaker average friendship strength among agents in the early stages of the game, modest drinkers who initially accept drinking behavior are more likely to transitioning towards “committed drinkers” state, where they both accept drinking behavior and endorse drinking behavior implying identity preference. In contrast, in the later stages of the game, agents typically have a higher number of friends and stronger average friendship strength. Therefore, modest drinkers who initially accept drinking behavior are more likely to choose to remain in “modest drinkers” state.

Summary: The Role of Social Capital in Candidate MBE

In this section, we tested and evaluated the role of social capital as the Explanandum in our candidate MBE in reproducing the target social phenomena.

- Firstly, by contrasting experiments that include and exclude the influence of social capital on agents, we found that social capital is a fundamental component in the candidate MBE for producing the target phenomena. When we excluded the impact of social capital on agents, the ABM model fails to reproduce the target phenomena.
- Secondly, through experiments comparing agents' decision-making driven by long-term social capital returns and short-term social capital returns, we found that agents' appropriate focus on long-term social capital returns is fundamental to reproduce the target phenomena. Overemphasizing short-term social capital returns can lead to the failure of reproducing the diffusion of drinking behavior in the social network.

- Finally, we further analyzed the behavioral decision-making preferences of modest non-drinkers and modest drinkers in different social situations under the influence of social capital (via action formation mechanism). We found that modest non-drinkers are more likely to transition to "modest drinking" state when they have fewer friends in the social network, weaker average friendship strength, receive less social support from friends, and have a higher proportion of friends who are drinkers. Additionally, modest drinkers are more likely to remain in the "modest drinker" state when they have a higher number of friends, stronger average friendship strength, receive more social support from friends, and have a higher proportion of friends who are drinkers.

Section 2: The Role of Cultural Significance of Drinking Behavior

After assessing the role of social capital in reproducing target social phenomena, this section focuses on examining the role of the cultural significance of drinking behavior in reproducing the target phenomenon. The cultural significance of drinking behavior serves as another Explanandum in our candidate MBE, and its role in the social mechanisms of the Explanans can be decomposed following Coleman's boat diagram:

- Situational Mechanism: The cultural significance of drinking behavior, as an institutional structure within the social environment, influences the internal state of college students. This includes the formation of identity and attitudes towards drinking culture, i.e. whether drinking behavior implying identity preferences.
- Action Formation Mechanism: The identity preferences of college students will influence their choices in forming friendships through identity homophily and identity exclusivity. Identity homophily suggests that individuals tend to establish stronger friendships with those who are perceived to share similar identity preferences. Identity exclusivity, on the other hand, indicates that individuals tend to sever friendships with those perceived to have conflicting identities during interactions.
- Transformational Mechanism: The cultural significance of drinking behavior further shapes the formation of friendships, influencing the distribution of social support in the

social network. The dynamics of social support distribution, along with social motives and conformity motives shaped by another Explanandum (social capital), trigger nonlinear interactions among individuals, ultimately leading to the emergence of the target social phenomenon.

To evaluate the role of the cultural significance of drinking behavior in reproducing the target social phenomena within the candidate MBE, we will primarily analyze how identity homophily and identity exclusivity in the action formation mechanism impact the reproduction of the target phenomenon.

The Impact of Identity Homophily on Friendship Construction

In order to investigate the influence of identity homophily on the diffusion of drinking behavior within the network, we conducted simulations at various levels of identity homophily. Within our ABM model, the level of identity homophily is quantified by the adjustable parameter "c". Altering the values of parameter " c " enabled us to assess the differences in the simulation outcomes of the ABM models at different levels of identity homophily. Specifically, we ran ABM models at parameter " c " value samples of 1.2, 1.6, 1.8, 1.9, 1.95, 2.05, 2.1, 2.25, 2.4, 3, and 4, For each level of parameter " c ", we conducted 500 simulation experiments as control tests, resulting in a total of 5500 simulation runs.

- Data Collection: Prior to each simulation run, we recorded the initial proportion of drinkers within the total population of the network. Throughout each game iteration, we calculated and documented the current proportion of drinkers in the network. Each game comprised 60 steps, generating a dataset of 61 data points. These data points represent repeated measurements of the proportion of drinkers at different stages of the game. In total, we conducted 5500 games, resulting in the collection of 5500 datasets, each consisting of 61 data points indicating the proportion of drinkers at various steps (step 0, step 1, ..., step 60), along with the corresponding network ID and the current level of parameter " c ", totaling 335,500 data points.
- Method: To analyze the fluctuations in the proportion of drinkers within the social

network at different levels of identity homophily, we performed a two-factor repeated measures analysis of variance (ANOVA) on the gathered data. This statistical analysis enabled us to evaluate the significance of the primary factors and their interactions in relation to the observed changes in drinking rates.

- Results: The results of the two-factor repeated measures ANOVA analysis are presented in Table 53.

Table 53: Results of the two-factor repeated measures ANOVA analysis

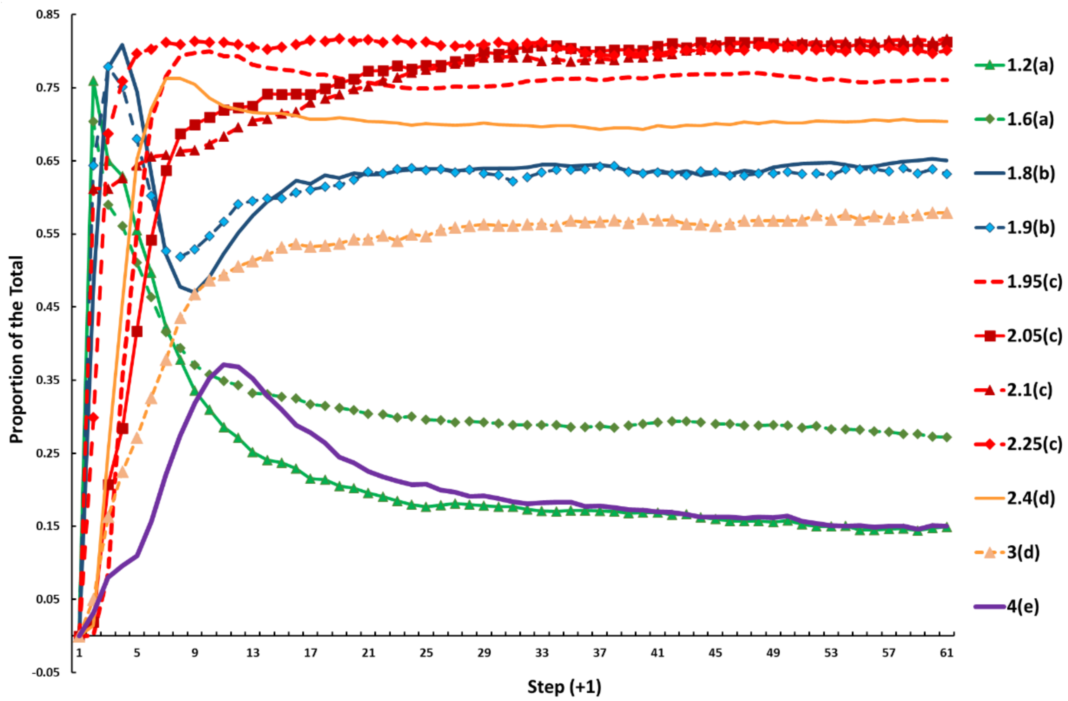
Identity Homophily level	*T0*	*T1*	*T10*	*T20*	*T30*	*T40*	*T50*	*T60*	*F*	*P*
1.2 (n=500)	0±0	0.76±0.05	0.29±0.21	0.2±0.15	0.18±0.14	0.17±0.14	0.15±0.13	0.15±0.12	2316.88	<0.001
1.6 (n=500)	0±0	0.7±0.06	0.35±0.29	0.3±0.28	0.29±0.28	0.29±0.28	0.29±0.27	0.27±0.27	2003.54	<0.001
1.8 (n=500)	0±0	0.48±0.07	0.52±0.25	0.63±0.2	0.64±0.18	0.64±0.18	0.65±0.18	0.65±0.18	1408.28	<0.001
1.9 (n=500)	0±0	0.64±0.06	0.57±0.22	0.64±0.17	0.62±0.15	0.63±0.15	0.63±0.14	0.63±0.14	1972.13	<0.001
1.95 (n=500)	0±0	0±0	0.79±0.19	0.76±0.21	0.76±0.21	0.77±0.21	0.76±0.21	0.76±0.21	334.329	<0.001
2.05 (n=500)	0±0	0.02±0.02	0.72±0.2	0.77±0.17	0.8±0.14	0.81±0.14	0.81±0.13	0.81±0.14	341.854	<0.001
2.1 (n=500)	0±0	0.61±0.06	0.68±0.23	0.75±0.22	0.79±0.18	0.79±0.19	0.81±0.17	0.82±0.17	1782.66	<0.001
2.25 (n=500)	0±0	0.3±0.06	0.81±0.17	0.82±0.15	0.81±0.15	0.8±0.16	0.8±0.15	0.8±0.15	1010.06	<0.001
2.4 (n=500)	0±0	0.01±0.02	0.72±0.21	0.7±0.2	0.7±0.19	0.7±0.21	0.7±0.21	0.7±0.21	361.957	<0.001
3 (n=500)	0±0	0.05±0.03	0.49±0.23	0.54±0.2	0.56±0.18	0.57±0.18	0.57±0.18	0.58±0.18	173.141	<0.001
4 (n=500)	0±0	0.03±0.02	0.37±0.29	0.23±0.19	0.18±0.17	0.17±0.16	0.16±0.15	0.15±0.15	37.762	<0.001
F	.	26868.26	294.993	597.103	783.751	808.635	909.016	949.287		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

*F_step = 1798.159, p<0.001; F_homophily =1368.592, p<0.001; F_(step*homophily)=231.298, p<0.001*

The analysis results indicate a significant main effect of Step ($F_{step} = 1798.159, p < 0.001$), signifying notable variations in the average proportion of drinkers across different game steps. Post-hoc tests further revealed significant differences in the average proportion of drinkers among various identity homophily levels, including $c = 1.2$ group ($F = 2316.875, p < 0.001$), $c = 1.6$ group ($F = 2003.54, p < 0.001$), $c = 1.8$ group ($F = 1408.28, p < 0.001$), $c = 1.9$ group ($F = 1972.13, p < 0.001$), $c = 2.05$ group ($F = 341.854, p < 0.001$), $c = 2.1$ group ($F = 1782.661, p < 0.001$), $c = 2.25$ group ($F = 1010.062, p < 0.001$), $c = 2.4$ group ($F = 361.957, p < 0.001$), $c = 3$ group ($F = 173.141, p < 0.001$), $c = 3.5$ group ($F = 3105.086, p < 0.001$), and $c = 4$ group ($F = 37.762, p < 0.001$), indicating significant changes in the proportion of drinkers within each group over time. Moreover, the main effect of identity homophily level is also significant ($F_{homophily} = 1368.5921, p < 0.001$), demonstrating significant differences in the average proportion of drinkers among different identity homophily levels. The interaction effect between Step and identity homophily level is also significant ($F_{step*homophily} = 231.298, p < 0.001$), indicating that the trends in the proportion of drinkers within various identity homophily levels exhibit significant differences across game steps.

Pairwise comparisons Results: Figure 17 visually represents fluctuations in the proportion of drinking agents to total agents within each group under different levels of identity homophily.

Figure 17: Variation in the Proportion of Drinkers at Different Levels of Identity Homophily



The analysis reveals distinct patterns in the proportion of drinkers across varying levels of identity homophily, which are summarized in Table 54 below:

Table 54: Trend Analysis on Pairwise comparisons Results

Homophily Level	Trend Analysis	Legend
Low Level: c= 1.2, 1.6	The proportion of drinkers initially rises rapidly in the early game stages, peaks, and then declines swiftly, eventually stabilizing with no significant fluctuations. In this stable state, the proportion of drinkers remains relatively low, significantly below that of non-drinkers. For instance, with parameter c = 1.2, drinkers make up around 15% of the population, while with parameter c = 1.6, this figure increases to approximately 27%.	1.2(a) 1.6(a)
Moderate Level: c= 1.8, 1.9	The proportion of drinkers exhibits a similar rapid increase in the early game stages, followed by a slight decline post-peak, before rising again and stabilizing without significant changes. In the stable state, the proportion of drinkers remains moderate but notably higher than non-drinkers. For example, with parameter c = 1.8, drinkers constitute about 65% of the population, and with parameter c = 1.9, this proportion is around 63%.	1.8(b) 1.9(b)
Slightly High Level: c= 1.95, 2.05, 2.1,2.25	The proportion of drinkers continues to rise rapidly in the early game stages, stabilizes without significant fluctuations, and remains at a high level in the stable state, significantly surpassing non-drinkers. For instance, with parameter c = 1.95, drinkers represent approximately 76% of the population, increasing to about 81% with parameter c = 2.05, 82% with parameter c = 2.1, and 80% with parameter c = 2.25.	1.95(c) 2.05(c) 2.1(c) 2.25(c)
High Level: c= 2.4, 3	The proportion of drinkers rapidly increases in the early game stages and continues to rise steadily, stabilizing without notable changes. In the stable state, the proportion of drinkers decreases compared to scenarios with lower identity homophily levels, yet remains significantly higher than non-drinkers. For example, with parameter c = 2.4, drinkers make up around 70% of the population, and with parameter c = 3, this proportion decreases to approximately 58%.	2.4(d) 3(d)
Extramely High Level: c= 4	The proportion of drinkers experiences a rapid increase in the early game stages, peaks, declines swiftly, and stabilizes with no further significant changes. In this stable state, the proportion of drinkers remains relatively low, significantly below that of non-drinkers, with drinkers representing approximately 15% of the population.	4(e)

- **Summary:** The simulation results of ABM models indicate that an appropriate level of identity homophily is necessary to reproduce the target phenomenon, and both excessively high and low levels of identity homophily are detrimental to reproducing the target social phenomena.
    - When identity homophily is low (e.g., parameter c = 1.1, 1.6), the proportion of drinkers in the network stabilizes at a lower level, significantly lower than the proportion of non-drinking agents. In this scenario, a low level of identity homophily implies that agents are not able to establish stronger friendships in a shorter time by transitioning to "committed drinker" state and thus gaining higher social support through identity homophily. This deprives committed drinkers of social advantages and reduces the attractiveness of accepting drinking behavior for agents.
    - As the level of identity homophily increases (e.g. parameter c = 1.8, 1.9), the proportion of drinkers in the steady state fluctuates and gradually increases. When the identity homophily level reaches a higher level (e.g. parameter c = 1.95, 2.05,

2.1, 2.25), the proportion of drinkers in the steady state gradually converges and stabilizes at around 80%.

- Continuing to rise to very high levels (e.g. parameter c = 2.4, 3), the proportion of drinkers in the steady state gradually decreases and ultimately falls below the proportion of non-drinkers. In this scenario, excessively high levels of identity homophily result in the friendship strength among committed drinkers being much stronger than their relationships with modest drinkers. This leads "committed drinkers" to allocate more social resources to "committed drinker" friends instead of modest drinkers, depriving modest drinkers of social advantages and reducing the attractiveness of accepting drinking behavior for agents.

The Impact of Identity Exclusivity on Friendship Construction

To assess the influence of identity exclusivity on the diffusion phenomena of drinking behavior in social networks, we will conduct a controlled experiment to compare the differences in simulation outcomes when considering the impact of identity exclusivity on agents' friendship construction versus excluding the consideration of identity exclusivity.

In our previous studies, our original ABM incorporated the influence of identity exclusivity on agents' friendship construction, where agents in "committed drinker" state and "committed non-drinker" state were both affected by identity exclusivity and would sever their friendships with those they perceived as conflicting with their own identity. The flexibility of ABM modeling allows us to adjust this identity exclusivity mechanism accordingly. Specifically, we will use the original ABM model as the experimental group and introduce two additional sets of ABM models with different identity exclusivity modules as control groups. Therefore, we have three groups of ABM models with different identity exclusivity patterns:

- **"Both Committed Drinker and Committed Non-Drinker" group**: Agents in both "Committed Drinker" state and "Committed Non-Drinker" state are affected by identity exclusivity in the formation of their friendships. In this group, due to identity conflicts, committed drinkers will sever ties with Non-Drinkers (i.e., immediately ending friendships with Non-Drinkers). Furthermore, Committed Non-Drinker will also serve ties with Drinker (i.e., immediately ending friendships with drinkers).

- **"Only Committed Drinker" group**: Only agents in "Committed Drinker" state would be affected by identity exclusivity in the formation of their friendships. In this group, only Committed Drinker will sever ties with Non-Drinkers (i.e., immediately terminating friendships with Non-Drinkers).
- **"None" group**: No agents are influenced by identity exclusivity in the formation of their friendships. In this group, we completely exclude the impact of identity exclusivity on agents, meaning that no matter what the state of the agents, they will not sever ties with any other agents within the network.

We will conduct 500 simulations for each ABM model with different identity exclusivity modules, totaling 1500 simulation experiments.

Dynamics of the Proportion of Drinkers in Different Identity Exclusivity Groups

We begin by comparing the changes in the proportion of drinkers as the game progresses in different identity exclusivity groups.

- Data Collection: At each game step, we calculated and recorded the current proportion of drinkers in the network. Each game comprised 60 steps, resulting in a dataset of 61 data points. These data points represent repeated measurements of the proportion of drinkers at various game steps. In total, we conducted 1500 games, leading to the collection of 1500 datasets, each containing 61 data points representing the proportion of drinkers at each game steps (step 0, step 1, ..., step 60) alongside the corresponding network ID and current identity exclusivity type, resulting in a total of 91,500 data points.
- Methodology: We will employ a two-way repeated measures ANOVA to analyze the collected data concerning the proportion of drinkers. This approach will enable us to evaluate the impact of game steps on changes in the proportion of drinkers, as well as the distinct effects of various exclusivity mechanisms on these changes, while also considering the interaction effects between group categories and game steps. The Greenhouse-Geisser method will be utilized for corrections, maintaining a significant

level (α) of 0.05.

- Results: Table 55 presents the outcomes of the two-way repeated measures analysis of variance (ANOVA) regarding the trend of changes in the proportion of drinkers within the network.

Table 55: Two-factor repeated measures ANOVA results

	T0	T1	T10	T20	T30	T40	T50	T60	F	P
Both Committed Drinker and Committed Non-Drinker(n=500)	0±0	0.48±0.07a,c	0.52±0.25a,c	0.63±0.2a,c	0.64±0.18c	0.64±0.18c	0.65±0.18c	0.65±0.18c	1517.55	<0.001
Committed Drinker (n=500)	0±0	0.28±0.06a,b	0.78±0.22a,b	0.84±0.18a,b	0.87±0.14a,b	0.88±0.13b	0.89±0.12b	0.89±0.12b	1016.3	<0.001
None (n=500)	0±0	0±0.01a,b,c	0.09±0.12a,b,c	0.08±0.12b,c	0.06±0.1b,c	0.04±0.07b,c	0.04±0.07b,c	0.03±0.06b,c	5.262	<0.001
F	.	10473.113	1454.101	2733.383	4124.201a	5130.312a	5444.179	5879.702		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

*F_step=641.572, p<0.001; F_type=9966.213, p< 0.001; F_(step*type)=318.014, p<0.001.*

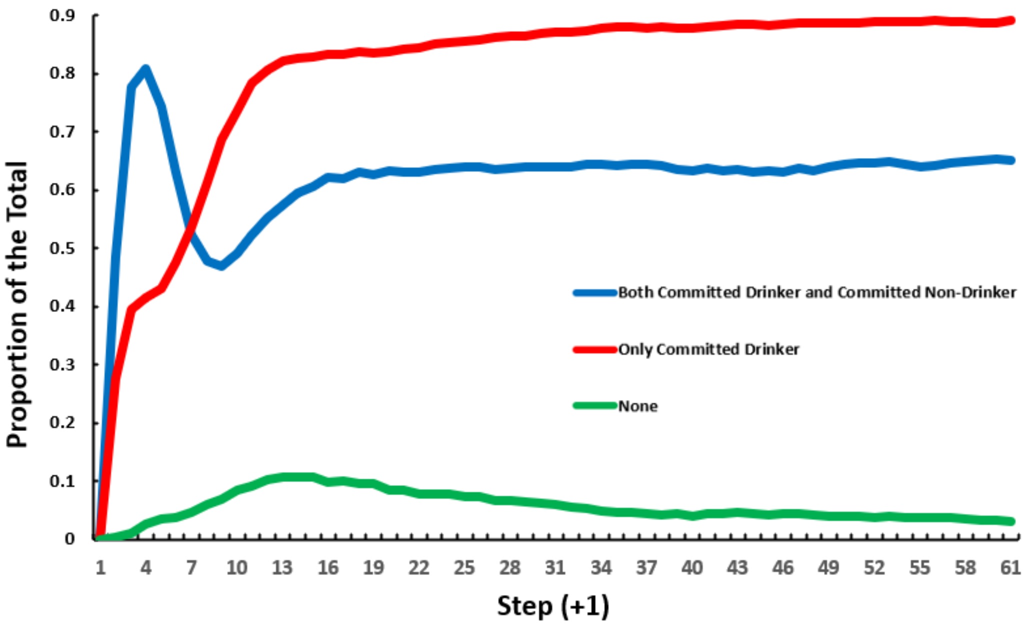
The main effect of Step is significant (F_{step}= 641.572, p < 0.001), indicating substantial differences in the average proportion of drinkers across different game steps. Specifically, the post-hoc tests revealed that the average proportion of drinkers significantly varies across "Both Committed Drinker and Committed Non-Drinker" group (F=1517.548, p<0.001), "Only Committed Drinker" group (F=1016.297, p<0.001), "None" group (F=5.262, p<0.001) indicating that the proportion of drinkers within each group significantly changes over time.

Moreover, the main effect of identity exclusivity type is significant (F_{type} =9966.213, p<0.001), indicating notable differences in the average proportion of drinkers across different identity exclusivity groups. Furthermore, the interaction effect between step and group is also significant ($F_{step*type} = 318.014$, p<0.001), suggesting distinct trend in the changes of the proportion of drinkers within different networks characterized by distinct types of identity exclusivity across various game steps.

Pairwise comparisons: Figure 18 illustrates the dynamics of the proportion of drinkers across three distinct types of identity exclusivity:

Figure 18: the dynamics of the proportion of drinkers under three different identity

exclusivity mechanisms:



Pairwise comparisons indicate that within the " Both Committed Drinker and Committed Non-Drinker " group, the proportion of drinkers initially increased, reaching its peak at step 3, followed by a subsequent decrease until reaching its lowest point at step 8. Subsequently, there was a gradual rebound, albeit with a diminishing rate of increase, and no significant changes were observed after step 23. In the " Only Committed Drinker " group, the proportion of individuals engaging in drinking showed a continuous and gradual increase, eventually reaching a stable state. No significant changes were observed after step 34. Within the "None" group, the proportion of individuals engaging in drinking also displayed a continuous increase, peaking at a considerably lower level by step 11, followed by a decline. Gradually, the proportion converged to a stable state with no significant changes observed after approximately step 36.

- Summary: The comparative analysis of changes in the proportion of drinkers within social networks reveals significant variations across three distinct ABM models with different identity exclusivity modules. Comparing the simulation outcomes of the three groups in the stable stage of the game:

- In the " Both Committed Drinker and Committed Non-Drinker " groups, after incorporating identity exclusivity between drinkers and non-drinkers, the simulation results showed a modest level of drinkers (approximately 65% of agents accepting drinking) and a modest level of non-drinkers (approximately 35% of agents refusing drinking). This group's simulation result reproduces the diffusion of drinking behavior in social networks.
- When excluding identity exclusivity of non-drinkers towards drinkers and retaining identity exclusivity of drinkers towards non-drinkers in the “Only Committed Drinker” group, the simulation results showed the highest proportion of drinkers (approximately 89% of agents accepting drinking) and the lowest proportion of non-drinkers (approximately 11% of agents refusing drinking). This group's simulation result reproduces the target phenomenon, with the proportion of drinkers at the stable stage significantly higher than the "both" group and the proportion of non-drinkers significantly lower than the “Both Committed Drinker and Committed Non-Drinker” group. It is evident that the identity exclusivity of committed non-drinkers towards drinkers helps increase the proportion of non-drinkers in the network.
- Continuing to exclude the identity exclusivity of drinkers towards non-drinkers, thus completely excluding the influence of identity exclusivity on friendship construction for all agents, the "None" group's simulation results showed the lowest proportion of drinkers (approximately 3% of agents accepting drinking) and the highest proportion of non-drinkers (approximately 97% of agents refuse drinking). This group's simulation result fails to reproduce the target phenomenon, indicating that the identity exclusivity of drinkers towards non-drinkers is a fundamental component in producing the target social phenomenon. Excluding the identity exclusivity of drinkers towards non-drinkers will prevent the emergence of the target social phenomenon.

Dynamics of the Proportion of Different State Agents in Different Identity Exclusivity Groups

We also analyzed the trends in the proportion of agents in different states under three different social exclusion mechanisms using two-factor repeated measures analysis of variance (ANOVA). Given that these two-factor repeated measures ANOVAs employ the same statistical method as the analyses presented previously, to prevent redundancy in the narrative, we present the results of all two-factor repeated measures ANOVA analyses in Table 56:

Table 56: Two-factor repeated measures ANOVA results

	Committed Drinker	***Modest Drinker***	***Committed Non-Drinker***	***Modest Non-Drinker***
Main Effect of Step	$F_{step}= 966.364, p < 0.001$	$F_{step}= 301.073, p < 0.001$	$F_{step}= 260.453, p < 0.001$	$F_{step}= 1848.452, p < 0.001$
"Both Committed Drinker and Committed Non-Drinker" Group	$F=565.963, p<0.001$	$=1068.425, p<0.001$	$F=44.302, p<0.001$	$F=2101.989, p<0.001$
"Only Committed Drinker" Group	$F=392.654, p<0.001$	$F=510.619, p<0.001$	$F=110.82, p<0.001$	$F=1674.14, p<0.001$
"None" Group	$F=0.108, p=1$	$F=5.717, p<0.001$	$F=4855.252, p<0.001$	$F=2791.132, p<0.001$
Main Effect of Type	$F_{type} =5464.263, p<0.001$	$F_{type} =1537.198, p<0.001$	$F_{type} =7937.977, p<0.001$	$F_{type} =335.648, p<0.001$
Interaction Effect of (Step * Type)	$F_{(step*type)}=382.586, p<0.001$	$F_{(step*type)}=105.394, p<0.001$	$F_{(step*type)}=225.833, p<0.001$	$F_{(step*type)}=215.063, p<0.001$

For Pairwise comparisons, the subsequent figures illustrate the trends in the proportion of agents in four distinct states under the three different social exclusion mechanisms (for detailed statistical analysis results, refer to Tables 57- 60 in Appendix A).

Figures 19-22 illustrate the trends in different state agents under various social exclusion mechanisms:

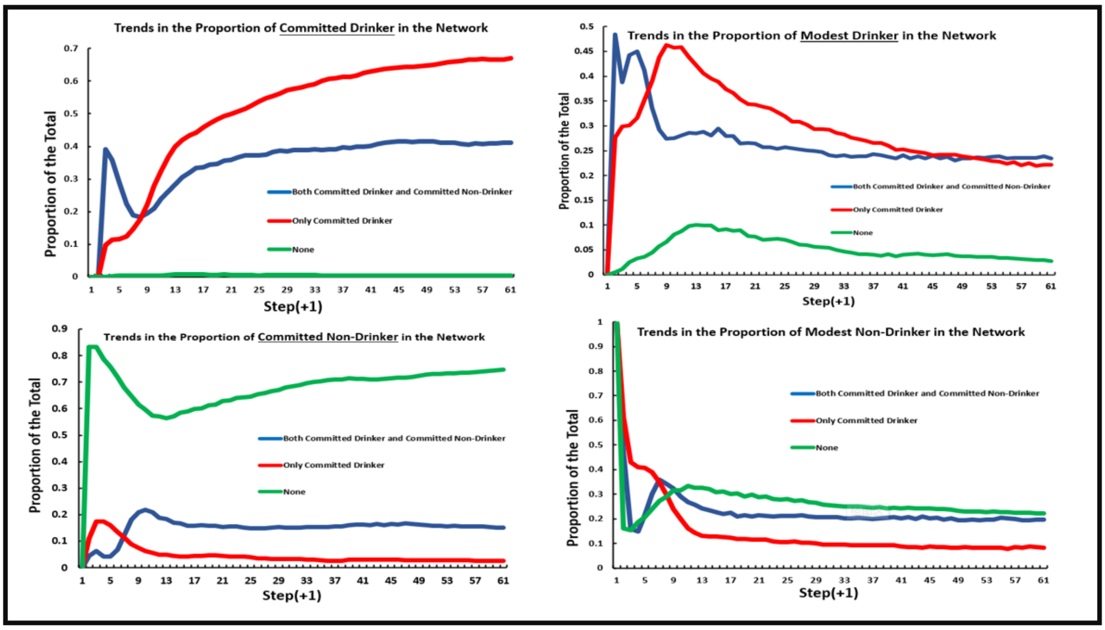


Table 61 below presents the simulation analysis results of agents in four different states under three distinct social exclusivity mechanisms:

Table 61:

State	*Result Analysis*
Committed Drinker	When the ABM model incorporates mutual identity exclusivity, the simulation results of the "Both Committed Drinker and Committed Non-Drinker" group showed a modest level of committed drinker proportion (approximately 41% of total agents). When the ABM model includes unidirectional identity exclusivity of drinkers towards non-drinkers, the simulation results of the "Only Committed Drinker" group revealed a high level of committed drinker proportion (approximately 67% of total agents). When the ABM model excludes the influence of identity exclusivity on agents, the simulation results of the "None" group showed the lowest level of committed drinker proportion, with the proportion of committed drinkers not exhibiting significant changes compared to 0% at a significance level of p = 0.05.
Modest Drinker	When the ABM model includes mutual identity exclusivity, the simulation results of the "Both Committed Drinker and Committed Non-Drinker" group showed a modest level of modest drinkers proportion (approximately 24% of total agents). When the ABM model incorporates unidirectional identity exclusivity of drinkers towards non-drinkers, the simulation results of the "Only Committed Drinker" group revealed a modest proportion of modest drinkers (approximately 22% of total agents). When the ABM model excludes the influence of identity exclusivity on agents, the simulation results of the "None" group displayed the lowest level of modest drinker proportion (approximately 3% of total agents). In the stable stage, the simulation results of both the "Both Committed Drinker and Committed Non-Drinker" group and the "Only Committed Drinker" group showed similar proportions of modest drinkers, significantly higher than the "None" group.
Committed Non-Drinker	When the ABM model includes mutual identity exclusivity, the simulation results of the "Both Committed Drinker and Committed Non-Drinker" group showed a modest level of committed non-drinker proportion (approximately 15% of total agents). When the ABM model incorporates unidirectional identity exclusivity of drinkers towards non-drinkers, the simulation results of the "Only Committed Drinker" group revealed the lowest proportion of committed non-drinkers (approximately 3% of total agents). When the ABM model excludes the influence of identity exclusivity on agents, the simulation results of the "None" group displayed the highest level of committed non-drinker proportion (approximately 74% of total agents).
Modest Non-Drinker	When the ABM model includes mutual identity exclusivity, the simulation results of the "Both Committed Drinker and Committed Non-Drinker" group showed a modest level of modest non-drinker proportion (approximately 20% of total agents). When the ABM model incorporates unidirectional identity exclusivity of drinkers towards non-drinkers, the simulation results of the "Only Committed Drinker" group revealed a modest level of modest non-drinker proportion (approximately 22% of total agents). When the ABM model excludes the influence of identity exclusivity on agents, the simulation results of the "None" group displayed a lower level of modest non-drinker proportion (approximately 8% of total agents). In the stable stage, the simulation results of both the "Both Committed Drinker and Committed Non-Drinker" group and the "Only Committed Drinker" group showed similar proportions of Modest Non-Drinkers, significantly higher than the "None" group.

Summary of Identity Exclusivity

The comparative research analysis above indicates that in an ABM model, the identity exclusivity of drinkers towards non-drinkers is indispensable for reproducing the diffusion phenomenon of drinking behavior. In our simulation results:

- In the "Both Committed Drinker and Committed Non-Drinker" groups with mutual identity exclusivity, the simulation results show a modest level of drinker proportion (approximately 65%) and a modest level of non-drinker (approximately 35%).
- The "Only Committed Drinker" groups exclude the unidirectional identity exclusivity of non-drinkers towards drinkers, retaining only the unidirectional identity exclusivity of

drinkers towards non-drinkers. The simulation results show the highest level of drinker proportion (approximately 89%), with committed drinkers accounting for about 67% of the drinkers. On the one hand, the proportion of non-drinkers reaches the lowest level (approximately 11%), with committed non-drinkers at a very low proportion of about 2.5%. In this case, as committed non-drinkers do not exclude drinkers in the network, they provide social support to both non-drinkers and drinkers, depriving committed non-drinkers of peer pressure on modest non-drinkers. On the other hand, drinkers maintain their unidirectional identity exclusivity towards non-drinkers, enhancing cohesion among drinkers in the network. As seen in Figure 18, the proportion of drinkers in the “Only Committed Drinker” group shows a monotonic increase without any decline.

- In the "None" groups where identity exclusivity is completely excluded from the ABM model, the simulation results show the lowest proportion of Drinker (approximately 3%) and the highest proportion of Non-Drinkers (approximately 97%). In this case, as drinkers lose their identity exclusivity towards non-drinkers, they allocate social support to both drinker and non-drinker friends, depriving drinking behavior of its social advantage. Consequently, drinking behavior cannot spread in the friendship network where all agents start as committed non-drinkers.

Therefore, our simulation results indicate that the unidirectional identity exclusivity of drinkers towards non-drinkers enhances cohesion within the drinking agents. Excluding this unidirectional identity exclusivity of drinkers towards non-drinkers will prevent the emergence of the target social phenomenon.

Summary

In this chapter, we conducted a "Retroduction" analysis of candidate MBEs that passed the generative sufficient test to evaluate the fundamental components in reproducing the target social phenomenon. Specifically, we utilized the ABM model to conduct a series of controlled simulation experiments to evaluate the roles of two Explanans components in candidate MBEs: social capital and cultural significance of drinking behavior in reproducing the Explanandum social phenomena, and whether excluding the impact of these Explanans components on individuals would prevent the emergence of the target phenomenon.

First, we evaluated the role of social capital in reproducing the target social phenomena:

- We compared the simulation outputs of models that include the influence of social capital on individual decision-making and those that exclude this influence: Utilizing common college student drinking behavior strategies found in existing empirical research, such as conformity strategies, imitating the best friend strategy, or imitating the friend with the highest social capital strategy, or employing random behavior strategies to control the decision-making of agents in a social simulation model, the model's simulation results are unable to meet the minimum criteria for reproducing the target social phenomenon and fail to pass the generative sufficient test. The results indicate that the influence of social capital on individuals' decision-making constitutes a fundamental component in reproducing the target social phenomena, as the absence of social capital would preclude the emergence of the phenomenon.
- We compared the simulation outcomes under different levels of emphasis on future social capital returns in the ABM model. The results show that emphasizing long-term social capital returns is necessary to reproduce the target phenomena, as an excessive emphasis on short-term returns would prevent the emergence of the diffusion of drinking behavior.
- We investigated the impact of social situational factors on the state transition types of individuals driven by social capital motives. The simulation results show that individuals who currently reject drinking are more likely to transition to accepting drinking behavior if they have fewer friends, weaker average friendship strength, receive less social support from friends, and have a higher proportion of friends who are drinkers. On the other hand, individuals who currently accept drinking are more likely to maintain drinking behavior if they have a larger number of friends, stronger average friendship strength, receive more social support from friends, and have a higher proportion of friends who are also drinkers.

We also evaluated the role of the cultural significance of drinking behavior in reproducing the target social phenomena:

- We conducted controlled experiments to compare the differences in the proportion of drinking agents in simulation outcomes at different levels of identity homophily. The results indicate that an appropriate level of identity homophily is necessary to reproduce the target phenomenon, with excessively high or low levels being detrimental.

- We compared the simulation outcomes when considering the impact of identity exclusivity on agents' friendship construction versus excluding the influence of identity exclusivity. The results show that the unidirectional identity exclusivity of drinkers towards non-drinkers is necessary to reproduce the Explanandum phenomenon as it enhances cohesion within the drinking agents. Excluding this identity exclusivity prevents the emergence of the target social phenomenon.

Based on the 'Retroduction' analysis of the ABM social simulation results, we have updated the original MBE hypothesis to a more plausible version that better aligns with the 'best explanation' standard under the abductive reasoning principle, addressing the substantive research questions of this study:

- Situational Mechanisms (Macro to Micro): Social capital and the cultural significance of drinking behavior within the social network will influence the internal state of individual students through situational mechanisms. Specifically,
  - The cultural significance of drinking behavior will influence the identity formation of college students, and this effect may vary among individuals.

  - Social capital motivates college students to build strong social connections and seek social support by utilizing alcohol consumption as an effective tool for social integration. The influence of social capital is reflected in two types of drinking motives as part of the individual's internal state: social motives and conformity motives.
- Action Formation Mechanisms (Micro - Micro): The internal state of college students, including their identity and drinking motives driven by social capital, will play a role in shaping their friendships formation and drinking behavior through action formation mechanisms. Specifically,
  - College students' identity preferences will influence individual's friendship choices and

the formation of friendships through similarity-based peer selection, manifested as identity similarity-based social homophily and social exclusivity.

  - College students' motives and objectives to establish social connections and seeking social support will influence their choices regarding drinking behavior. Specifically, modest agents who refuse alcohol initially are more likely to transition to accept drinking behavior if they receive less social support. Conversely, modest drinking students with a larger number of friends, stronger average friendship strength, more social support, and a higher proportion of friends who drink are more likely to continue accepting drinking behavior.

- Transformational Mechanism (Micro to Macro): The pursuit of social capital by individual students and their preference for similarity-based peer selection led to the co-evolution of college students' drinking behavior dynamics and friendship dynamics. This non-linear interaction ultimately results in the emergence of the diffusion of college drinking behavior within the friendship network through a bottom-up transformational mechanism.

We believe that the aforementioned MBE constitutes a good "inference to the best explanation" under the abductive reasoning principle, temporarily bridging the Explanans of interest with the Explanandum, until a more concise and efficient explanation is proposed. This updated MBE effectively addresses our substantive research questions posed.

Chapter 6: Discussion

This chapter will examine how simulation study, based on the constructed pattern-oriented ABM model, contributes to making causal statements about the emergence of targeted social phenomena in the real world. To this end, we will clarify the following key points: (I) The current academic debate on the real-world applicability of social simulation studies and our stance on this issue; (II) The real-world applicability of the findings from this simulation study; and (III) The potential policy implications arising from our results.

Real-World Applicability of Social Simulation Research

To begin with, it is essential to clarify the extent to which social simulation research can be utilized for causal explanations of real-world social phenomena or case. Existing literature indicates that there is ongoing academic debate regarding the extent to which and under what conditions ABMs can contribute to causal inference in the real-world contexts (Manzo, 2022:3).

On one hand, some researchers, such as O'Sullivan and Perry (2013: 14–15), Törnberg (2019), and Morgan and Winship (2015: 341) express skepticism about the causal inference derived from ABM-based research, arguing that it is impossible to ascertain how a simulated mechanism will behave in the real world. For instance, Diez Roux (2015: 101) asserts that utilizing the tools of complex systems involves constructing an artificial world based on prior knowledge or intuition, within which researchers can test hypotheses regarding causal relationships. However, he emphasizes that in such simulation models, it is not feasible to ascertain whether X actually causes Y in the real world, as the simulated environment is a construct of the researcher. Instead, the focus is on exploring the potential effects of variations in X on Y within the parameters established by the model. In reality, we deal with observable phenomena and seek to make inferences about counterfactual scenarios—what outcomes we would have observed under different circumstances. Conversely, within a simulation model, all scenarios are inherently counterfactual since they are deliberately generated by the researcher.

This raises significant concerns about the validity of using ABM outcomes to draw causal inferences applicable to real-world situations (Törnberg, 2019: 13). For instance, Morgan and Winship (2015: 341) propose the specific role for ABMs in social science research “[t]he computational model can generate hypotheses for empirical testing, but it cannot “bear the burden of proof”. In summary, the critics suggest that any ABM, at its best, can only represent a form of logical possibility, making it difficult to assess concrete connections between the model's findings and real-world phenomena.

On the other hand, advocates of the ABM approach challenge the perspective that ABMs function merely as "thought experiments" and instead highlight their practical applicability in real-world causal inference. Manzo (2022: 57) argues that ABMs are capable of generating data and arguments that support both generative and dependence real-world causal claims. Specifically, from a production perspective on causation, ABMs provide a well-defined generative mechanism that illustrates causal chains through a multi-level dynamic system of interacting components, thereby elucidating the "why" and "how" behind the observed effects or outcomes related to the cause of interest. In terms of a dependence perspective on causation, the manipulation of specific elements within the ABM enables researchers to explore "what-if" scenarios, facilitating the establishment of counterfactual relationships between the mechanisms of the model and the real-world phenomena it seeks to explain.

Moreover, for ABMs to produce data and arguments pertinent to causal inference beyond the model (into the real world), Manzo (2022: 57, 70) emphasizes the importance of appropriate empirical calibration and validation to ensure theoretical, input, and output realism. He notes that an ABM, in principle, can integrate theoretical realism with both input and output realism through empirical calibration and validation. This combination transforms an ABM into a "mimicking device," enabling modelers to leverage the insights generated by the ABM regarding the interplay of factors across different analytical levels, which in turn facilitates inferences about those mechanisms in the real world. According to Manzo (2022: 70), an ABM that maximizes empirical calibration and validation, along with systematic reliability assessments, is well-positioned to support causal assertions about real-world connections across various analytical levels through a synthesis of data obtained from empirical calibration and validation processes and arguments grounded in reliability analysis. Casini and Manzo (2016) conclude that the integration of theoretical/input realism, empirical calibration and validation allows ABMs to produce generative knowledge that is causally relevant, as the relationships established within the numerical realm of the model can be mapped, in terms of both inputs and outputs, onto their real-world counterparts.

Simultaneously, Manzo (2022: 45) emphasizes that low levels of 'realism' (a lack of empirical calibration and validation) may hinder an ABM's ability to contribute to causal inference. Particularly, ABMs that adhere to a "Keep It Simple and Stupid" philosophy are frequently regarded as mere "tools to think with" (O'Sullivan and Perry, 2013: 14-15) or "intuition engines" (Manzo, 2022: 36), which undermines their potential to substantiate claims about real-world mechanisms (Manzo, 2022: 40).

The ongoing academic debate regarding the real-world applicability of ABM simulation extends beyond the confines of this study. Given that this research has developed a "Typifications" POM ABM model with a moderate level of realism, we cautiously adopt the view that generating "Inferences to the Best Explanation" regarding target real-world patterns is the primary purpose of such simulations (Halas, 2011). Although the findings derived from simulations of the POM ABM model with moderate realism are limited in their capacity for causal inference regarding real-world cases - meaning it cannot be proven that the model is actually at work in a specific real-world case (i.e., representing actual empirical processes) (Casini and Manzo, 2016)- nor can they be directly applied to real-world case explanations or predictions. However, a POM ABM model that has undergone thorough empirical calibration (both theoretical and empirical) and validation still supports a credible "causal adequacy" of a social mechanism in generating real-world social patterns. This mechanism describes a set of conditions sufficient to regularly produce specific real-world social patterns, representing plausible real-world possibilities. According to Šešelja (2022), our POM ABM model provides causal how-possibly explanations (HPEs)[42] of real-world phenomena, which encompass accounts of possible ways in which phenomena can occur. These HPEs indicate that, under certain conditions, the emergence of targeted social patterns is causally plausible in real-world contexts.

Real-World Applicability of This Study

Based on the aforementioned clarification regarding the real-world applicability of the POM ABM model in this study, we first summarize the conditions underpinning this ABM. Since the MBE tested by our simulation study constitutes a type of HPE, suggesting that the emergence of the target real-world social phenomenon is causally possible (generatively sufficient) under the hypothetical conditions embedded within the ABM model. Furthermore, through the process of “retroduction” analysis, these conditions are shown to be indispensable in the mechanism-based causal chain. Consequently, our simulation study provides an HPE of the target social pattern in the real world and offers "the best explanation" inference for the emergence of the target social pattern under given conditions (at least temporarily, until a more compelling model is proposed).

The conditions embedded within our POM ABM model have been qualitatively calibrated using empirical evidence based on the typical college drinking patterns indicated by existing literature. Therefore, these conditions are grounded in robust real-world theories and empirical facts. Following the epistemological framework of structural individualism, the conditions within the ABM can be categorized into two types: conditions on social structure and conditions on structure-embedded individuals.

- **Conditions on Social Structure**

  The social structure exerts a causal effect on the emergence of emergent properties

[42] Šešelja (2022) highlights that the types of real-world explanations generated by ABMs representing real-world cases and real-world possibilities differ significantly. ABMs of the "real-world case" type produce "how-actually explanations (HAEs)," which articulate propositions in the form of: 'p because q and initial conditions c,' where the specific conditions are known and verified to apply to a particular empirical target. In contrast, ABMs of the "real-world possibilities" type generate "how-possibly explanations (HPEs)," which convey propositions in the form of: 'It is causally possible that: p because q and initial conditions c.' Here, while the conditions are known, it may be uncertain whether they apply to a specific empirical target, or it is known that they do not apply to that particular target.

within social systems. Our ABM model incorporates three primary conditions on social structure:

(1) **Embedded Friendship Networks**: All college students are embedded within friendship networks. These networks, as relational structures, shape, enable, and constrain the options available for individual interactions (as discussed in Chapter 3). Unlike other forms of social relationships, friendships heavily rely on the continuous initiation, maintenance, or enhancement of relational ties (Ezzy, 1998; Pahl, 2000; Buhrmester, 1985; Rawlins, 1992). Consequently, friendship networks are not static but typically undergo dynamic changes over time.

(2) **Social Capital**: This refers to the resources embedded within the friendship networks of college students. The distribution of social capital outlines a structure of potential resource flow relationships among college students (Zhao et al., 2020; Burt, 2004; Lin, 2017).

(3) **College Drinking Culture**: As a social institutional structure, it transforms college drinking behavior into a highly ritualized activity, a social performance or practice characterized by its own set of assumptions, traditions, and routines (Tan, 2012; Workman, 2001; Supski et al., 2017). This condition is based on a solid foundation of empirical facts with extensive supporting evidence (Supski et al., 2017; Tan, 2012). College students are embedded within this cultural institutional structure, where drinking behaivor is societally constructed as a form of risk-taking, pursuit of "hedonistic" pleasure, a rite of passage, and an affirmation of one's social or collective identity (Calnan and Davoren, 2022; Tan, 2012). Within this cultural structre, all participating students play roles in social performance and rituals.

- **<u>Conditions on Structured Individuals</u>**

  College students represent entities with causal power, where emergent properties of social systems emerge from the interactions among these structured entities. The influence of social structure on individual actions and interactions is not direct but is primarily mediated through relatively rational reflexive deliberations and unconscious habits (Caluzzi et al., 2021). Our ABM incorporates three critical conditions regarding the internal states and behaviors of individual college students:

(1) **Behavioral Decision-Making Driven by Social Capital:** Within the college environment, social support predominantly originates from friendship networks (Arifuddin et al., 2022; Bagwell & Bukowski, 2018; Laursen & Veenstra, 2021). This support provides essential instrumental, emotional, informational, and companionship resources that are crucial for psychosocial adjustment and success during college (Grant-Vallone et al., 2003; Friedlander et al., 2007; Nikhila et al., 2016; Khan et al., 2014; Harakeh & Vollebergh, 2012; Laghi et al., 2012). Developing new social support systems, especially through fostering robust friendship relationships, is a critical and challenging task for college students, driving their behavior through a decision-making process founded on relatively rational reflective deliberations (Pesola et al., 2015; Borsari, 2007; Lewis et al., 2008; Baumeister & Leary, 1995; Laninga-Wijnen et al., 2021).

(2) **Influence of College Drinking Culture on Identity Formation:** This condition is grounded on the Erikson-Marcia identity status model, which asserts that identity emerges and develops through dynamic interactions between individuals and their social contexts (Klimstra et al., 2009). Through interactions with their surroundings, individuals continuously reassess their current identities, determining whether to explore new identity commitments or maintain existing ones. The maintenance of identity commitment represents a form of dynamic stability shaped by environmental interactions. Notably, identity formation exhibits significant heterogeneity among college students: while some may experience decreased self-certainty and heightened identity confusion, a substantial number exhibit stability in their identity processes (Branje et al., 2021). Alcohol, as a symbolic and integrative element within college drinking culture, plays a role in the formation of individual and social identities among students. Participation in drinking during social activities can serve as a boundary marker that signifies an individual's identity and delineates group membership (e.g., “we drink, therefore we are”) (Monaco et al., 2020; Tempelman, 1999; Tan, 2012).

(3) **Social Relational Structure Shaping Friendship Formation**: Based on social network

theory, our ABM model posits two relational mechanisms to describe the dynamics of friendships among structured individuals: Reciprocity and similarity-based peer selection.

a. **Reciprocity**: Individuals tend to prefer those who reciprocate their feelings, leading to friendships often being bidirectional relationships (Montoya & Insko, 2008).
b. **Similarity-Based Peer Selection**: Recognized as a fundamental organizing principle of friendship dynamics (McPherson et al., 2001; Berten and Van Rossem, 2015), which includes:
   - **Proximity Similarity**: Frequent and regular interactions promote the initiation and maintenance of friendships, with affinities often arising from sustained exposure and visibility.
   - **Behavior Similarity:** Individuals prefer forming stronger friendships with those sharing similar behaviors or experiences (Boman et al., 2013; Way & Greene, 2006; MacLean, 2016; Van Duijn, 2023).This preference for similar peers is often accompanied by an aversion to individuals who exhibit differences (Laursen and Veenstra, 2021). Behavioral heterogeneity may lead to negative thoughts and conflicts, undermining friendship stability and contributing to social exclusion (Laninga-Wijnen and Veenstra, 2021; Knecht et al., 2011).
   - **Identity Similarity**: Shared identities, a sense of belonging, and aligned value preferences enhance compatibility and diminish social exclusion, thereby fostering stronger friendships, and vice versa (Van Duijn, 2023; Asikainen et al., 2020; Laursen & Veenstra, 2021).

Under the aforementioned conditions, our simulation study reveals two key points:

1. The behavioral decision-making process driven by social capital may lead college students to perceive participation in social drinking as an effective means of enhancing social integration, consequently contributing to the diffusion of drinking behaviors within

friendship networks. Specifically, an individual's social capital (social support) is not static; rather, it is contingent upon the individual's position within the network and the structure (typology) of that network. However, the positioning of individuals and the structure of the network are determined endogenously and evolve as the network forms and changes, rendering an individual’s social capital inherently unstable (Alaa et al., 2017).

The context-dependent and unstable nature of social capital can influence college students' alcohol consumption in two primary ways: (1) Acquiring or maintaining adequate social support from friendship networks can be challenging, as it often necessitates ongoing efforts toward social integration and investment in forming and maintaining friendships. Drinking behaviors are frequently perceived as an effective strategy for social integration and a productive activity to enhance social capital (Peters & Stringham, 2006; Cheadle et al., 2013; Lui, 2019). The decision to engage in drinking to pursue social capital benefits is termed the <u>social motive</u> for college students’ drinking. (2) If college students fail to invest in or maintain their friendship networks (e.g. due to social exclusion or low social proximity), it may result in insufficient or decreased individual social capital, thereby limiting their access to social support. The decision to drink in college social activities to avoid or minimize such social capital losses is referred to as the <u>conformity motive</u> for college students’ drinking. In summary, the tension between the strong demand for social support and the inherent instability of social support from college friendship networks serves as a risk factor for the widespread diffusion of college drinking behavior (Crosnoe et al., 2004).

Results from our simulation study elucidate how social motives and conformity motives in college drinking, as observed in empirical research, stem from behavior decision-making processes driven by social capital. This result aligns well with a substantial body of empirical evidence.

- <u>Social Motives</u>

  Extensive empirical research has reported that in environments where alcohol consumption is deeply ingrained in the culture, college drinking often serves to facilitate social interactions and enhance peer acceptance, thereby yielding potential social capital benefits (Linden et al., 2014; Kong & Bergman, 2010; Smith et al., 1995; Young et al., 2006; Wood et al., 2001; Simons et al., 2000; Cronin, 1997; Stewart et al., 1996; Schulenberg and Maggs, 2002; Buettner and Debies-Carl, 2012; Gilles, 2006; Thombs, 1993). For instance, some college students report deliberately engaging in risky drinking behavior, carefully rationalizing the benefits and risks of heavy drinking in various college drinking contexts and strategizing their level of drinking and social companions to achieve desired social outcomes (Tan ,2012; Howard et al., 2007; DeJong et al., 2010). In a study by LaBrie et al. (2007) investigating the college drinking behaviors, interviewed students cited numerous reasons for drinking, particularly social reasons. Their report highlights how some drawbacks of alcohol consumption are perceived by students as opportunities for social bonding, such as taking care of intoxicated friends, being cared for when drunk, and enduring the pain of a hangover.

- <u>Conformity Motives</u>

  The prioritization of maintaining friendship significantly influences behavior decision-making, leading individuals to modify their actions in response to perceived threats to their social support system (Ham and Hope, 2003; Norberg et al., 2011; Windle and Windle, 2012). For instance, Bainter and Ackerman (2022) suggest that behaviors exhibited by college students during emerging adulthood, seemingly aimed at bolstering self-esteem, are in fact aimed at enhancing social compatibility and preventing potential relational value losses due to social exclusion (Tyler and Branch 2015; Cacioppo and Cacioppo 2014; Machin and Jeffries 2016). Consequently, in their pursuit of social integration and social capital, college students may engage in self-destructive behaviors, such as excessive drinking, as a means to gain social approval and cultivate favorable self-perceptions (Machin and Jeffries, 2016). Hiltunen et al. (2022) research on Swedish students' drinking behavior reveals that alcohol consumption is an obligation for those who wish to be part of the collective community. Thus, college drinking behavior serves as a sorting principle for inclusion and exclusion based on collective identity. The surveyed students indicated that those who oppose the drinking culture risk having their social identity questioned and face a significant risk of being entirely excluded from social events (Supski et al., 2017), which further escalates alcohol consumption driven by conformity motives to avoid negative social consequences.

Additionally, when explaining the widespread phenomenon of college drinking, the indispensability of social capital in the decision-making process of college students also aligns with and elucidates three key empirical observations:

- Reports on the widespread drinking behavior in college settings highlight the particular significance of alcohol consumption for first-year students, especially during “freshman week” or the beginning of the academic term (Martinez et al., 2014; Pascarella, 2005; Jacobs et al., 2018; Borsari et al., 2007). These empirical observations align with the finding of our simulation research, as first-year college students may encounter various life adjustment challenges, such as being away from loved ones, depression, isolation, seeking independence, and academic stress (Rayle and Chung, 2007). Consequently, investing in the development of friendship networks to accrue sufficient social capital becomes one of the primary objectives for first-year students (Christie and Dinham, 1991; Borsari et al., 2007).

  Notably, research indicates that the likelihood of new friendships among freshman students diminishes over the course of the first year (Van De Bunt et al., 1999). If students are unable to form friendships within their initial term, they may have limited opportunities for the remainder of their time at university (Jacobs et al., 2018). Consequently, the first year of college, particularly at the beginning of the academic term, is seen as a valuable time slot for establishing social connections and making new friends. Wolburg's (2016) research highlights how some first-year students perceive the process of cultivating friendships upon entering campus, depicting it as a "friend scramble...where everyone is so alone that they're just trying to latch on to whoever is next to them" (Wolburg, 2016: 84; Schaefer et al., 2021). There are often numerous parties at the beginning of the first year, with many new friends eager to participate in welcoming each other, and participating freshmen often cite social facilitation, a sense of belonging, and the desire to "fit in" as significant reasons for drinking (Johnson et al., 2005; Hiltunen et al., 2022; Murphy et al., 2006; McEwan, 2013; Thomas, 2000; Grant-Vallone et al., 2004).

Conversely, refusing to participate in drinking activities may result in exclusion from social opportunities and a lack of social support, especially during the start of their university experience. Jacobs et al. (2018) conducted semi-structured interviews with eight non-drinking first-year UK undergraduates, revealing that being a non-drinker often resulted in exclusion from social opportunities during Fresher's Week, leading to a loss of social capital. Moreover, non-drinkers had very limited alternatives, as opportunities for socializing without alcohol were scarce during this time.

- Drinking alone is rare and not encouraged (Creswell, 2021; Christiansen and Jarchow, 2002). For instance, Terry-McElrath et al. (2023) found that only 13.6% of surveyed American college students reported consuming alcohol alone. While motivational models of drinking indicate internal-dimension motives for college student drinking, such as enhancement motives (drinking to enhance internal emotional state) and coping motives (drinking to alleviate negative mood states), empirical observations show that alcohol consumption on college campuses primarily occurs in social settings. Our simulation study explains this: college students' drinking behavior is driven by social capital. Drinking alone may offer internal emotional benefits, but it does not contribute to social capital benefits. Particularly in college social scenarios, drinking alone may be perceived as having problems or being negatively portrayed as unsupportive companions, potentially leading to social exclusion (Kloep et al., 2001; Kropp et al., 2004; Knecht et al., 2011).

- Drinking games are widely prevalent in college drinking activities, and most drinking students have engaged in them (Beccaria and Sande, 2003; Borsari et al., 2007). This empirical observation aligns with the predictions of our simulation study, as most drinking games are meticulously designed to enhance ritualistic experiences, promote social interactions, and create shared moments of "hedonism" or "adventure" among participants.

2. Our simulation research indicates that while the preference for friendships based on identity homophily associated with similar drinking behaviors poses a risk factor for the diffusion of college drinking behavior, it is the social exclusion faced by drinkers towards non-drinkers (stemming from identity heterogeneity) that constitutes an indispensable condition for the widespread prevalence of drinking behavior. Excluding the mechanism of identity-based exclusion of non-drinkers by drinkers would preclude the emergence of target social patterns, even if drinkers retained an advantage in terms of identity homophily towards non-drinkers.

Eisenstadt and Giesen (1995) emphasize that social identities are not naturally generated; rather, they are the products of social construction. Within the collegiate social culture, the cultural significance of drinking behavior requires students to navigate an apparent binary in terms of contrasting associations: between participating in drinking (associated with collective fun, belonging, maturity) and rejecting drinking (perceived as being uptight and unsocial) (Supski et al., 2017). In this context, acceptance of drinking behavior is thus seen as an intentional drawing of collective identity boundaries to demarcate the collective entity and determine who and what belongs inside and who and what belongs outside. Such demarcation inherently involves processes of social inclusion and exclusion (Tempelman, 1999). As Jenkins (2000) succinctly summarized, "To construct an 'us,' we also need a 'them.'"

Social inclusion based on shared collective identity significantly enhances cohesion within drinking groups, facilitating faster, stronger, and denser formations of friendships among "us." Conversely, social exclusion based on identity heterogeneity effectively reduces the flow of social capital from the drinking group to the outside ("them"), allowing its members to access a higher level of social capital internally. In contrast, students who refuse to drink or participate less in drinking activities are more likely to report initial difficulties in establishing friendships and typically require a longer time to form peer groups (Brown and Murphy, 2020).

Our simulation study highlights the indispensability of social exclusion of non-drinkers by drinkers based on identity heterogeneity in the diffusion process of college drinking behavior. This aligns with and explains the following two significant empirical observations:

- Most empirical studies report that male college students have significantly higher drinking rates than their female counterparts (American College Health Association, 2016). This may be related to drinkers being more inclusive towards female non-drinkers. Research has suggested that it might be more socially acceptable for women to abstain from drinking compared to men, with female non-drinkers often receiving praise or remaining inclusive within social groups (Monaco et al., 2020). The absence of social exclusion of non-drinking females by drinkers may prevent the diffusion of drinking behavior among female college students, as indicated by the simulation results.
- Reports of college students refusing to engage in social drinking due to strong identity recognition are predominantly concentrated in the initial stages of the first year when college friendship networks are in their formative stages (Brown and Murphy, 2020; Fenton et al., 2023). This aligns with the expectations of our simulation study, as changing drinking behavior within mature friendship networks faces substantial social capital loss due to the mechanism of social exclusion. Therefore, students who engage in drinking early in their college experience are more likely to maintain this behavior throughout the remainder of their college years, allowing drinking behavior to sustain its dominant position within the college social network.

Real-World Policy Implications

While our model is a POM ABM rather than a highly realistic "case-based" model, which limits our ability to make specific policy recommendations for specific real-world cases, the analysis of the mechanisms producing real-world social patterns yields several potential policy suggestions: If the goal of potential policy recommendations is to reduce the risk of widespread alcohol consumption within college friendship networks, the HPE derived from our simulation study indicates the following strategies that might help achieve policy intervention goals under the given conditions:

1. **Facilitating Alternatives to Alcohol-Centric Social Integration**: Providing alternative social activities that promote student integration without alcohol, thereby removing the centrality of alcohol from college social life, could help control the spread of drinking to some extent. Our simulation findings suggest that drinking behavior decisions, driven by social capital dynamics, contribute to the diffusion of drinking behaviors within friendship networks. However, empirical studies have reported a lack of non-alcoholic social event options that can facilitate student integration in the college social environment, where the majority of activities are centered around drinking (Jacobs et al., 2018). Therefore, we suggest that colleges or student organizations host and promote alternatives to alcohol-focused events (including non-alcoholic or low-alcohol options) to provide all students with relatively equal social opportunities and alleviate the social challenges faced by non-drinking students. Specifically, these alternative activities should primarily target first- and second-year students, ensuring a broader range of non-alcoholic event options during freshman week or the beginning of the academic term.
2. **Promoting Inclusivity in Alcohol-Related Events**: For events involving alcohol on college campuses, school alcohol policies should emphasize the importance of inclusivity. By encouraging a more inclusive campus drinking culture and fostering an attitude shift where drinking students respect non-drinkers' decisions to abstain, the social exclusion of non-drinkers in alcohol-related social events can be reduced, potentially controlling the spread of drinking behavior to some extent.

   Similarly, encouraging the reduction in highly scripted drinking games during events can also weaken the ritualistic nature of drinking and lower the risk of excessive drinking and binge drinking among college students. Conversely, an overemphasis on the dangers of drinking as a form of non-conformist behavior may reinforce the perception of college drinking as a socially constructed ritual, which could hinder efforts to control the spread of drinking behaviors.

Chapter 7: Conclusion

Original Contributions to Existing Knowledge

- Methodological Originality: In existing research, analytical sociologists Hedström and Bearman (2009: 16) have outlined a typical "generative methodology" research strategy, claiming that "[it] is generally applicable and it is a crucial part of the analytical toolbox":

  1. Defining the Expanandum: "We start with a clearly delineated social fact that is to be explained."
  2. Formulation of a Causal Hypothesis: "We formulate different hypotheses about relevant micro-level mechanisms."
  3. Translation: "We translate the theoretical hypotheses into computational models."
  4. Running the Simulation Model: "We simulate the models to derive the type of social facts that each micro-level mechanism brings about."
  5. Outcome Validation: "We compare the social facts generated by each model with the actually observed outcomes."

  (Bearman and Hedström, 2009:16; Manzo, 2021: 3; Epstein, 2006; León-Medina,2017b).

  While Hedström and Bearman's framework provides an essential scaffold for generative social science, its five steps remain highly generalized. For its practical application in ABM-based research, particularly under the epistemological guidance of structural individualism, a more granular and operationalized workflow is required. Therefore, this research proposes a refined seven-step "generative methodology" that elaborates on the original strategy:

  1. We begin with a clearly defined macro-level social phenomenon[43] that is to be explained (Explanandum).
  2. We identify potential explanatory factors (Explanans) based on existing research or

[43] In Chapter 3, we have delineated the conceptual relationship and distinctions between "social facts" and "social phenomena" within the context of this study.

research interests.

3. Utilizing the refined "Coleman boat" diagram, we analyze the potential causal linkages between Explanandum and Explanans and formulate "Macro-Micro-Macro" styled Mechanism-Based Explanation (MBE) hypotheses to bridge Explanans and Explanandum. In line with the epistemological foundation of structural individualism, MBE hypotheses should describe the interactions of structured real entities (with causal power) under the causal effect of social structures as conditions likely to trigger a process to regularly bring about a well-defined outcome.

4. We translate and formalize the MBE hypotheses into an appropriate type of ABM with an appropriate level of empirical calibration, employing both qualitative and quantitative empirical data.

5. We adhere to the principles of abductive reasoning in conducting the generative sufficient test (including face validation and uncertainty quantification) on the constructed ABM model to assess the model's capability to viably and stably reproduce the target social phenomenon, thereby establishing it as a candidate MBE. If the ABM model fails to pass generative sufficient test, the micro-specification is not a viable candidate explanation of the phenomenon, and the researcher has demonstrated the falsity of the MBE hypothesis (Salgado and Gilbert, 2013).

6. For candidate MBE that pass the generative sufficient test, we perform a “Retroduction” analysis. Typically utilizing counterfactual methods, we evaluate the indispensable explanatory components within the candidate MBE and their roles in the process of reproducing the Explanandum, thereby assessing the extent to which the candidate MBE can be considered "the best explanation" under abductive reasoning.

7. Based on the outcomes of social simulation, we refine the candidate MBE to better align with the criteria for "the best explanation".

We posit that this refinement describes an appropriate ABM-based "generative methodology" research paradigm for constructing and testing MBEs on the emergent properties of social phenomena. This feasible and replicable research paradigm, congruent with the structural individualism epistemology foundation, includes a clear multi-level (micro-macro) analytical framework that aids in tracking and analyzing the interactive processes among components embedded within social structures. The advancement of this research paradigm signifies a proactive and exploratory attempt to address the existing methodological challenges within the social complexity framework.

- Technical Contributions: The study has made several exploratory practices in addressing the technical issues of ABM modeling:
  1. Adaptive Agent Modeling: We attempted to develop an RL-based ABM model utilizing the DRQN algorithm to address the widespread issue of insufficient adaptivity in current ABM models. The introduction of the prioritized DRQN algorithm endows agents with the capacity for adaptive decision-making in partially observable scenarios and allows agents to remember and learn from experience data to continuously improve their decision-making capabilities iteratively.
  2. Distributed Control of Agents: We applied suggestions from Gupta et al. (2017) regarding model control, employing a shared experience data pool to train controllers for distributed control of agents, providing a solution to the control issues of multi-agent interactions within social network structures. To the best of our knowledge, these Multi-Agent Reinforcement Learning (MARL) techniques have not previously been used in the development of ABM models, and this study makes a beneficial attempt in this direction.
- Substantive Knowledge Contributions: Grounded in the perspective of social complexity theory, our analysis of the targeted social phenomena enables a granular dissection of the nonlinear interaction dynamics at the micro-level, specifically focusing on the co-evolutionary processes between drinking behavior and friendship dynamics. This approach elucidates the micro-to-macro transition, shedding light on how these phenomena emerge from interpersonal dynamics. The application of social simulation methods allows for the generation of extensive empirical data at a low cost and facilitates controlled experiments on factors of interest. Our findings from social simulations bridge existing knowledge gaps concerning the social mechanisms by which social capital and the cultural significance of college drinking behavior, as social structural factors, exert causal influence via situational mechanisms to constrain individual actions and, thereby,

impact the emergent patterns of the social phenomena under study:

1. Mechanisms of Social Capital Influence: We clarified how college students' pursuit of social capital influences the dynamic evolution of drinking behavior and friendship relationships through social mechanisms. Specifically, college students' pursuit of an appropriate level of future social capital can manifest as internal social motives and conformity motives in their drinking behavior decisions, leading to modest rejection of drinking by agents with less social support, who are more likely to eventually accept drinking. Conversely, moderate drinkers with a greater number of friends, higher average strength of friendships, more social support, and a higher proportion of friends who drink, are likely to continue drinking.
2. Mechanisms of college drinking culture influence: We elucidated how the cultural significance of college students' drinking behavior affects the diffusion of drinking behavior within friendship networks through social mechanisms. Simulation results reveal the importance of social exclusion in the diffusion of drinking behavior among college students. While past research has emphasized that college drinking behavior is welcomed and diffused within friendship networks because it is believed to enhance friendship (social inclusion), our simulation results indicate that social exclusion is a necessary condition during the interaction process. Mere social inclusion is insufficient to trigger the diffusion of drinking behavior within social networks; it must act in conjunction with similarity-based social exclusion (particularly the exclusion of non-drinkers by drinkers) to contribute to the emergence of the target social phenomenon.

Limitations

- Constraints in Empirical Grounding and Validation Scope: The empirical calibration of this study was constrained by the limited availability of quantitative empirical data. Consequently, qualitative empirical evidence and established social theories were primarily utilized to define the target patterns for model validation. This reliance on qualitative data shaped the scope and depth of our validation process in two significant ways. First, it necessitated the use of qualitative pattern-matching for face validation, rather than employing more stringent quantitative goodness-of-fit statistics to measure the gap between simulated and real-world data. Second, it limited the extent of our uncertainty quantification. These pragmatic choices mean that while the model is appropriate for testing the plausibility of a theoretical mechanism, the robustness of its findings across different parameter settings remains an open question. These limitations may also restrict the model's direct real-world applicability.

- Reinforcement Learning and MARL Development: The rapid development in the field of machine learning, especially in Multi-Agent Reinforcement Learning (MARL) methods, has seen the emergence or ongoing development of higher-performance algorithms. The DRQN algorithm used in this study, while mature, is relatively outdated and thus has room for improvement. Additionally, the control theory for multi-agent agents is rapidly evolving. In this study, all agents share the same DRQN controller, which to some extent limits the heterogeneity of agents' learning and decision-making. The rapid development in the field of reinforcement learning indicates the limitations of this study while also pointing to greater potential for development in the field.
- Computational Costs of RL-based ABM: While ABM based on RL endows agents with higher decision-making adaptability, it significantly increases computational costs. Limited by the time and computational resources of this study, the developed RL model was characterized by a reduced parameter scale, a smaller agent population, a more restricted action space for agents, and limitations in both the capacity and optimization iterations of the experience replay mechanism. Moreover, each adjustment of the artificial social environment parameters requires retraining the DRQN network and conducting extensive simulation experiments to collect output data. This iterative process is highly intensive in terms of both time and computational power. Consequently, the resource constraints rendered the systematic application of optimization algorithms for parameter calibration, or the comprehensive execution of sensitivity testing and uncertainty analysis on the calibrated parameter settings, exceedingly challenging. This resulted in an omission of these critical analyses in the present study, which means that the robustness of our findings across the entire parameter space remains an open question, which may temper the overall credibility and generalizability of the simulation

findings.

- Interpretability Issues in Agents' Decision-Making Processes: While the incorporation of RL-based algorithms can partially address the issue of insufficient adaptability in agents' behavioral decisions within ABM modeling, the over-parameterized black-box nature of deep learning models also introduces significant interpretability limitations. Consequently, researchers are unable to observe and understand the decision-making processes of agents as intuitively as they can in rule-based ABM.
- Model Realism and Complexity: As introduced in Chapter 3, identifying an appropriate level of realism and complexity for an ABM is considered as a major challenge. Decisions regarding individual drinking behavior or friendship behavior in the real world are influenced by multiple factors and combine rational and emotional elements. This study only demonstrates drinking behavior under the pursuit of social capital and friendship behavior influenced by similarity homophily, which we are interested in. The personal preference is completely ignored in this study. Factors such as family background, religion, and other influences on college students' drinking behavior are also ignored. There may be differences in decision-making preferences among different genders, which are also overlooked.

Avenues for Future Research

- Integration of Generative Models and Data-Driven Causal Inference: Although this study employs an ABM-based generative approach to pursue vertical MBEs of complex social phenomena, it does not reject the validity of horizontal MBEs. Existing research emphasizes that social simulation methods and variable sociology methods (e.g., causal inference based on the potential outcome framework) can provide necessary and complementary evidence of causality, thereby establishing a "division of labor" (Manzo, 2022: 103; Casini and Manzo, 2016; Morgan and Winship, 2015). From the perspective of realist ontology, the ABM method contributes by developing "how-possible" and "how-plausible" oriented computational models that illustrate “why” and “how” the counterfactual dependency between cause and outcome holds. It connects the relata of the counterfactual causal dependence relations, as derived from variable sociology research, to the knowledge about structured entities and social relations underlying them.

Conversely, data-driven causal inference methods add plausibility to ABMs by providing real-world empirical information that constrains the modeler's theoretical creativity on both the input and output sides. Therefore, our simulation research contributes to the substantive field by offering a vertical MBE reference for further empirical data-based researchers to formulate horizontal MBE research hypotheses, potentially serving as a starting point for their case studies (Halas, 2011).

- Advanced ML Algorithms: Building upon the exploration of constructing RL-based ABM for explaining complex social phenomena in this study, future studies can experiment with more advanced or suitable reinforcement learning algorithms to train models, aiming to enhance the decision-making capabilities of agents. Moreover, other ML methods that imbue the decision-making process of agents with adaptability are rapidly advancing. For instance, research on training agents' decision-making processes using large language models (LLM) is progressing swiftly (Chopra et al., 2024; Gürcan, 2024).
- Diversifying Multi-Agent Control Strategies: Given that all agents in this study's ABM model can be considered as the same category in reinforcement learning, with the same objective to optimize social support from friend agents, and no explicit cooperation or competition, all agents follow the same behavioral logic or rules. Consequently, a single DRQN network is used for all agents' decision-making. In future research, if agents in the ABM model have explicit cooperation or competition relationships, or if agents are different types of decision-makers with diverse objectives, researchers may need to explore other multi-agent control methods, such as deploying different neural networks for different types of decision-makers. The rapid development in the field of Multi-Agent Reinforcement Learning (MARL) offers a rich arsenal of methodologies to address these complex agent interactions.
- Incorporating Inverse Reinforcement Learning for Enhanced Realism: In the pursuit of heightened realism in an ABM, researchers could leverage inverse reinforcement learning techniques. By learning from actual human behavior and decision-making patterns,

modelers can imbue agents with decision-making processes that mirror real-world complexity, thereby enhancing the model's verisimilitude.

- Empirical Data Calibration for Model Realism: Refinement of the current ABM model through extensive calibration with empirical datasets can significantly improve its realism. This approach transforms the model into a "Case-based Model," tailored for in-depth analysis of specific real-world cases.
- Enhancement of "Coleman's Boat" Diagram: The "Coleman's Boat" diagram served as a crucial heuristic in this study. A significant avenue for future methodological contribution lies in formalizing its role as a rigorous pipeline for translating social theory into a computational model. Developing the "Coleman's Boat" from a conceptual diagram into a formal methodological tool (e.g., developing a more standardized protocol) would greatly enhance the transparency, comparability, and replicability of ABM-based research in sociology.

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Appendix A: Tables

Table 7: Drinker proportion data with repeated observations

Subject	Steps of the game													
	Step 0	Step 1	…	Step 10	…	Step 20	…	Step 30	…	Step 40	…	Step 50	…	Step 60
1	0	0.433	…	0.733	…	0.717	…	0.65	…	0.783	…	0.75	…	0.75
2	0	0.517	…	0.567	…	0.533	…	0.75	…	0.7	…	0.7	…	0.417
3	0	0.567	…	0.1	…	0.867	…	0.617	…	0.817	…	0.517	…	0.45
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
499	0	0.467	…	0.917	…	0.683	…	0.767	…	0.633	…	0.567	…	0.517
500	0	0.5	…	0.783	…	0.767	…	0.733	…	0.717	…	0.667	…	0.75
Mean	0	0.484	…	0.527	…	0.637	…	0.644	…	0.641	…	0.641	…	0.642

Table 9: Tests of Within-Subjects Effects (Proportion of Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	280.575	8.32	33.723	185.124	<0.001
Error(step)	756.287	4151.648	0.182		

Table 10: Tests of Within-Subjects Effects (Proportion of Committed Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	239.068	9.656	24.758	221.635	<0.001
Error(step)	538.25	4818.439	0.112		

Table 11: Tests of Within-Subjects Effects (proportion of Modest Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	133.084	15.37	8.659	168.465	<0.001
Error(step)	394.201	7669.579	0.051		

Table 12: Tests of Within-Subjects Effects (proportion of Committed Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	40.885	6.487	6.302	53.794	<0.001
Error(step)	379.253	3237.047	0.117		

Table 13: Tests of Within-Subjects Effects (proportion of Modest Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	361.768	14.189	25.496	454.229	<0.001
Error(step)	397.426	7080.472	0.056		

Table 14: Pairwise comparison (proportion of Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	-.484*	1	0	.484*	10	0	.527*
	10	-.527*		10	-.043*		1	.043*
	20	-.637*		20	-.153*		20	-.110*
	30	-.644*		30	-.161*		30	-.117*
	40	-.641*		40	-.157*		40	-.114*
	50	-.641*		50	-.157*		50	-.114*
	60	-.642*		60	-.158*		60	-.114*
30	0	.644*	40	0	.641*	50	0	.641*
	1	.161*		1	.157*		1	.157*
	10	.117*		10	.114*		10	.114*
	20	0.007		20	0.004		20	0.004
	40	0.003		30	-0.003		30	-0.003
	50	0.003		50	0		40	0
	60	0.003		60	-0.001		60	0

***. The mean difference is significant at the 0.05 level.**

Table 15: Pairwise comparison (proportion of non-drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	.484*	1	0	-.484*	10	0	-.527*
	10	.527*		10	.043*		1	-.043*
	20	.637*		20	.153*		20	.110*
	30	.644*		30	.161*		30	.117*
	40	.641*		40	.157*		40	.114*
	50	.641*		50	.157*		50	.114*
	60	.642*		60	.158*		60	.114*
30	0	-.644*	40	0	-.641*	50	0	-.641*
	1	-.161*		1	-.157*		1	-.157*
	10	-.117*		10	-.114*		10	-.114*
	20	-0.007		20	-0.004		20	-0.004
	40	-0.003		30	0.003		30	0.003
	50	-0.003		50	0		40	0
	60	-0.003		60	0.001		60	0

***. The mean difference is significant at the 0.05 level.**

Table 16: Pairwise comparison (proportion of Committed Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	0	**1**	**0**	0	**10**	**0**	.245*	**20**	**0**	.373*
	10	-.245*		**10**	-.245*		**1**	.245*		**1**	.373*
	20	-.373*		**20**	-.373*		**20**	-.128*		**10**	.128*
	30	-.401*		**30**	-.401*		**30**	-.156*		**30**	-.027*
	40	-.406*		**40**	-.406*		**40**	-.161*		**40**	-.033*
	50	-.407*		**50**	-.407*		**50**	-.162*		**50**	-.034*
	60	-.407*		**60**	-.407*		**60**	-.162*		**60**	-.034*
30	**0**	.401*	**40**	**0**	.406*	**50**	**0**	.407*	**60**	**0**	.407*
	1	.401*		**1**	.406*		**1**	.407*		**1**	.407*
	10	.156*		**10**	.161*		**10**	.162*		**10**	.162*
	20	.027*		**20**	.033*		**20**	.034*		**20**	.034*
	40	-0.005		**30**	0.005		**30**	0.006		**30**	0.007
	50	-0.006		**50**	-0.001		**40**	0.001		**40**	0.001
	60	-0.007		**60**	-0.001		**60**	0		**50**	0

***. The mean difference is significant at the 0.05 level.**

Table 17: Pairwise comparison (proportion of Modest Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	-.484*	**1**	**0**	.484*	**10**	**0**	.282*	**20**	**0**	.264*
	10	-.282*		**10**	.202*		**1**	-.202*		**1**	-.220*
	20	-.264*		**20**	.220*		**20**	0.018		**10**	-0.018
	30	-.244*		**30**	.240*		**30**	.038*		**30**	.020*
	40	-.235*		**40**	.249*		**40**	.047*		**40**	.029*
	50	-.234*		**50**	.250*		**50**	.048*		**50**	.030*
	60	-.235*		**60**	.249*		**60**	.048*		**60**	.029*
30	**0**	.244*	**40**	**0**	.235*	**50**	**0**	.234*	**60**	**0**	.235*
	1	-.240*		**1**	-.249*		**1**	-.250*		**1**	-.249*
	10	-.038*		**10**	-.047*		**10**	-.048*		**10**	-.048*
	20	-.020*		**20**	-.029*		**20**	-.030*		**20**	-.029*
	40	0.009		**30**	-0.009		**30**	-0.01		**30**	-0.009
	50	0.01		**50**	0.001		**40**	-0.001		**40**	-0.001
	60	0.009		**60**	0.001		**60**	0		**50**	0

***. The mean difference is significant at the 0.05 level.**

Table 18: Pairwise comparison (proportion of Committed Non-Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	-.045*	**1**	**0**	.045*	**10**	**0**	.187*	**20**	**0**	.144*
	10	-.187*		**10**	-.141*		**1**	.141*		**1**	.098*
	20	-.144*		**20**	-.098*		**20**	.043*		**10**	-.043*
	30	-.149*		**30**	-.103*		**30**	.038*		**30**	-0.005
	40	-.154*		**40**	-.109*		**40**	.033*		**40**	-0.01
	50	-.155*		**50**	-.110*		**50**	.032*		**50**	-0.011
	60	-.159*		**60**	-.114*		**60**	.028*		**60**	-0.015
30	**0**	.149*	**40**	**0**	.154*	**50**	**0**	.155*	**60**	**0**	.159*
	1	.103*		**1**	.109*		**1**	.110*		**1**	.114*
	10	-.038*		**10**	-.033*		**10**	-.032*		**10**	-.028*
	20	0.005		**20**	0.01		**20**	0.011		**20**	0.015
	40	-0.005		**30**	0.005		**30**	0.006		**30**	0.01
	50	-0.006		**50**	-0.001		**40**	0.001		**40**	0.005
	60	-0.01		**60**	-0.005		**60**	-0.004		**50**	0.004

***. The mean difference is significant at the 0.05 level.**

Table 19: Pairwise comparison (proportion of Modest Non-Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	.529*	**1**	**0**	-.529*	**10**	**0**	-.714*	**20**	**0**	-.781*
	10	.714*		**10**	.185*		**1**	-.185*		**1**	-.252*
	20	.781*		**20**	.252*		**20**	.067*		**10**	-.067*
	30	.793*		**30**	.264*		**30**	.079*		**30**	0.012
	40	.795*		**40**	.266*		**40**	.081*		**40**	.014*
	50	.796*		**50**	.267*		**50**	.082*		**50**	.015*
	60	.801*		**60**	.271*		**60**	.087*		**60**	.020*
30	**0**	-.793*	**40**	**0**	-.795*	**50**	**0**	-.796*	**60**	**0**	-.801*
	1	-.264*		**1**	-.266*		**1**	-.267*		**1**	-.271*
	10	-.079*		**10**	-.081*		**10**	-.082*		**10**	-.087*
	20	-0.012		**20**	-.014*		**20**	-.015*		**20**	-.020*
	40	0.002		**30**	-0.002		**30**	-0.003		**30**	-0.007
	50	0.003		**50**	0.001		**40**	-0.001		**40**	-0.005
	60	0.007		**60**	0.005		**60**	0.004		**50**	-0.004

***. The mean difference is significant at the 0.05 level.**

Table 21: Tests of Within-Subjects Effects (Social Support of Drinkers)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	512.814	4.741	108.169	1368.621	<0.001
Error(step)	186.972	2365.687	0.079		

Table 22: Tests of Within-Subjects Effects (Social Capital of Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	39.346	10.229	3.846	37.708	<0.001
Error(step)	520.683	5104.408	0.102		

Table 23: Tests of Within-Subjects Effects (Social Capital of Committed Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	886.591	8.879	99.85	848.303	<0.001
Error(step)	521.522	4430.729	0.118		

Table 24: Tests of Within-Subjects Effects (Social Capital of Modest Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	623.054	13.366	46.613	251.677	<0.001
Error(step)	1235.326	6669.847	0.185		

Table 25: Tests of Within-Subjects Effects (Social Capital of Committed Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	406.422	12.952	31.38	113.755	<0.001
Error(step)	1782.811	6462.86	0.276		

Table 26: Tests of Within-Subjects Effects (Social capital of Modest Non-Drinker)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
step	35.517	15.735	2.257	13.489	<0.001
Error(step)	1313.882	7851.829	0.167		

Table 27: Pairwise comparison (Social Capital of Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	-1.051*	1	0	1.051*	10	0	.967*	20	0	1.009*
	10	-.967*		10	.084*		1	-.084*		1	-.042*
	20	-1.009*		20	.042*		20	-.042*		10	.042*
	30	-1.020*		30	.031*		30	-.053*		30	-.011*
	40	-1.018*		40	.033*		40	-.051*		40	-0.009
	50	-1.015*		50	.036*		50	-.048*		50	-0.006
	60	-1.010*		60	.041*		60	-.043*		60	-0.001
30	0	1.020*	40	0	1.018*	50	0	1.015*	60	0	1.010*
	1	-.031*		1	-.033*		1	-.036*		1	-.041*
	10	.053*		10	.051*		10	.048*		10	.043*
	20	.011*		20	0.009		20	0.006		20	0.001
	40	0.002		30	-0.002		30	-0.005		30	-.010*
	50	0.005		50	0.003		40	-0.003		40	-.008*
	60	.010*		60	.008*		60	0.005		50	-0.005

***. The mean difference is significant at the 0.05 level.**

Table 28: Pairwise comparison (Social Capital of Non-Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	.055*	1	0	-.055*	10	0	-.069*	20	0	-.110*
	10	.069*		10	.014*		1	-.014*		1	-.054*
	20	.110*		20	.054*		20	.040*		10	-.040*
	30	.121*		30	.066*		30	.052*		30	0.012
	40	.113*		40	.058*		40	.044*		40	0.003
	50	.113*		50	.058*		50	.044*		50	0.004
	60	.121*		60	.066*		60	.051*		60	0.011
30	0	-.121*	40	0	-.113*	50	0	-.113*	60	0	-.121*
	1	-.066*		1	-.058*		1	-.058*		1	-.066*
	10	-.052*		10	-.044*		10	-.044*		10	-.051*
	20	-0.012		20	-0.003		20	-0.004		20	-0.011
	40	-0.008		30	0.008		30	0.008		30	0.001
	50	-0.008		50	0		40	0		40	-0.008
	60	-0.001		60	0.008		60	0.007		50	-0.007

***. The mean difference is significant at the 0.05 level.**

Table 29: Pairwise comparison (Social Capital of Committed Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	0	**1**	**0**	0	**10**	**0**	.862*	**20**	**0**	.926*
	10	-.862*		**10**	-.862*		**1**	.862*		**1**	.926*
	20	-.926*		**20**	-.926*		**20**	-.064*		**10**	.064*
	30	-.940*		**30**	-.940*		**30**	-.078*		**30**	-.014*
	40	-.940*		**40**	-.940*		**40**	-.079*		**40**	-0.014
	50	-.937*		**50**	-.937*		**50**	-.075*		**50**	-0.011
	60	-.936*		**60**	-.936*		**60**	-.074*		**60**	-0.01
30	**0**	.940*	**40**	**0**	.940*	**50**	**0**	.937*	**60**	**0**	.936*
	1	.940*		**1**	.940*		**1**	.937*		**1**	.936*
	10	.078*		**10**	.079*		**10**	.075*		**10**	.074*
	20	.014*		**20**	0.014		**20**	0.011		**20**	0.01
	40	0		**30**	0		**30**	-0.003		**30**	-0.004
	50	0.003		**50**	0.003		**40**	-0.003		**40**	-0.004
	60	0.004		**60**	0.004		**60**	0.001		**50**	-0.001

***. The mean difference is significant at the 0.05 level.**

Table 30: Pairwise comparison (Social Capital of Modest Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	**1**	-1.051*	**1**	**0**	1.051*	**10**	**0**	1.017*	**20**	**0**	1.088*
	10	-1.017*		**10**	.035*		**1**	-.035*		**1**	.037*
	20	-1.088*		**20**	-.037*		**20**	-.072*		**10**	.072*
	30	-1.120*		**30**	-.069*		**30**	-.103*		**30**	-.031*
	40	-1.117*		**40**	-.066*		**40**	-.101*		**40**	-.029*
	50	-1.126*		**50**	-.075*		**50**	-.109*		**50**	-.037*
	60	-1.103*		**60**	-.052*		**60**	-.087*		**60**	-0.015
30	**0**	1.120*	**40**	**0**	1.117*	**50**	**0**	1.126*	**60**	**0**	1.103*
	1	.069*		**1**	.066*		**1**	.075*		**1**	.052*
	10	.103*		**10**	.101*		**10**	.109*		**10**	.087*
	20	.031*		**20**	.029*		**20**	.037*		**20**	0.015
	40	0.003		**30**	-0.003		**30**	0.006		**30**	-0.016
	50	-0.006		**50**	-0.009		**40**	0.009		**40**	-0.014
	60	0.016		**60**	0.014		**60**	0.022		**50**	-0.022

***. The mean difference is significant at the 0.05 level.**

Table 31: Pairwise comparison (Social Capital of Committed Non-Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	-.678*	1	0	.678*	10	0	.709*	20	0	.701*
	10	-.709*		10	-0.031		1	0.031		1	0.023
	20	-.701*		20	-0.023		20	0.008		10	-0.008
	30	-.720*		30	-.042*		30	-0.011		30	-0.019
	40	-.732*		40	-.054*		40	-0.023		40	-.031*
	50	-.729*		50	-.051*		50	-0.02		50	-0.028
	60	-.718*		60	-.040*		60	-0.009		60	-0.017
30	0	.720*	40	0	.732*	50	0	.729*	60	0	.718*
	1	.042*		1	.054*		1	.051*		1	.040*
	10	0.011		10	0.023		10	0.02		10	0.009
	20	0.019		20	.031*		20	0.028		20	0.017
	40	-0.012		30	0.012		30	0.009		30	-0.002
	50	-0.009		50	0.003		40	-0.003		40	-0.014
	60	0.002		60	0.014		60	0.011		50	-0.011

***. The mean difference is significant at the 0.05 level.**

Table 32: Pairwise comparison (social capital of Modest Non-Drinker)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	.036*	1	0	-.036*	10	0	-0.012	20	0	-.049*
	10	0.012		10	-.024*		1	.024*		1	-0.013
	20	.049*		20	0.013		20	.037*		10	-.037*
	30	.064*		30	.028*		30	.052*		30	0.015
	40	.043*		40	0.008		40	.032*		40	-0.006
	50	.050*		50	0.014		50	.038*		50	0.001
	60	.071*		60	.035*		60	.059*		60	0.022
30	0	-.064*	40	0	-.043*	50	0	-.050*	60	0	-.071*
	1	-.028*		1	-0.008		1	-0.014		1	-.035*
	10	-.052*		10	-.032*		10	-.038*		10	-.059*
	20	-0.015		20	0.006		20	-0.001		20	-0.022
	40	-0.021		30	0.021		30	0.014		30	-0.007
	50	-0.014		50	0.007		40	-0.007		40	-0.028
	60	0.007		60	0.028		60	0.021		50	-0.021

***. The mean difference is significant at the 0.05 level.**

Table 33: Pairwise Comparisons (Committed Drinker and Modest Non-Drinker)

(I) step	(J) step	Mean Difference (I-J)
baseline (=0)	0	1
	1	.964*
	2	-.204*
	3	-.298*
	4	-.183*
	5	-0.024
	6	.089*
	7	.149*
	8	.153*
	9	.148*
	10	.127*
	11	.105*
	12	.080*
	13	.087*
	14	.065*
	15	.056*
	16	.045*
	17	.040*
	18	0.026
	19	0.025
	20	0.025
	21	0.016
	22	0.01
	23	0.017
	24	0.004
	25	0.006
	26	0.013
	27	0.007
	28	0.011
	29	0.003
	30	-0.004
	31	0.004
	32	-0.004
	33	-0.005
	34	-0.011
	35	0.001
	36	-0.006
	37	0.006
	38	0.001
	39	0.006
	40	0.016
	41	0.007
	42	0.003
	43	-0.003
	44	0.002
	45	-0.004
	46	-0.001
	47	0.005
	48	0.001
	49	0.006
	50	0.013
	51	0.022
	52	0.009
	53	0.009
	54	-0.003
	55	0
	56	0.009
	57	-0.014
	58	-0.004
	59	-0.015
	60	-0.007

*. The mean difference is significant at the 0.05 level.

Table 36: Pairwise comparison (number of agents driven by conformity motives)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1		1	0		10	0		20	0	
	10			10	-24.714*		1	24.714*		1	26.784*
	20			20	-26.784*		20	-2.070*		10	2.070*
	30			30	-27.306*		30	-2.592*		30	-0.522
	40			40	-27.156*		40	-2.442*		40	-0.372
	50			50	-27.090*		50	-2.376*		50	-0.306
	60			60	-26.816*		60	-2.102*		60	-0.032
30	0		40	0		50	0		60	0	
	1	27.306*		1	27.156*		1	27.090*		1	26.816*
	10	2.592*		10	2.442*		10	2.376*		10	2.102*
	20	0.522		20	0.372		20	0.306		20	0.032
	40	0.15		30	-0.15		30	-0.216		30	-0.49
	50	0.216		50	0.066		40	-0.066		40	-0.34
	60	0.49		60	0.34		60	0.274		50	-0.274

*. The mean difference is significant at the 0.05 level.

Table 38: Pairwise comparison (modularity)

step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)	step(I)	step(J)	Mean Difference(I-J)
0	1	-.170*	1	0	.170*	10	0	.123*	20	0	.148*
	10	-.123*		10	.047*		1	-.047*		1	-.022*
	20	-.148*		20	.022*		20	-.025*		10	.025*
	30	-.155*		30	.015*		30	-.032*		30	-0.007
	40	-.160*		40	0.01		40	-.037*		40	-.013*
	50	-.158*		50	.012*		50	-.035*		50	-0.011
	60	-.158*		60	.012*		60	-.035*		60	-0.01
30	0	.155*	40	0	.160*	50	0	.158*	60	0	.158*
	1	-.015*		1	-0.01		1	-.012*		1	-.012*
	10	.032*		10	.037*		10	.035*		10	.035*
	20	0.007		20	.013*		20	0.011		20	0.01
	40	-0.005		30	0.005		30	0.003		30	0.003
	50	-0.003		50	0.002		40	-0.002		40	-0.002
	60	-0.003		60	0.002		60	0.001		50	-0.001

*. The mean difference is significant at the 0.05 level.

Table 41: Drinker proportion data with repeated observations

Subject	Network Type	Steps of the game													
		Step 0	Step 1	…	Step 10	…	Step 20	…	Step 30	…	Step 40	…	Step 50	…	Step 60
1	0	0	0.4	…	0.15	…	0.7	…	0.7	…	0.75	…	0.567	…	0.617
2	0	0	0.55	…	0.417	…	0.867	…	0.85	…	0.8	…	0.867	…	0.433
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
199	0	0	0.317	…	0.65	…	0.55	…	0.467	…	0.633	…	0.717	…	0.783
200	0	0	0.467	…	0.15	…	0.733	…	0.517	…	0.65	…	0.383	…	0.567
201	1	0	0.35	…	0.517	…	0.5	…	0.55	…	0.55	…	0.583	…	0.533
202	1	0	0.3	…	0.417	…	0.55	…	0.6	…	0.583	…	0.467	…	0.433
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
399	1	0	0.417	…	0.583	…	0.517	…	0.5	…	0.483	…	0.567	…	0.6
400	1	0	0.383	…	0.367	…	0.4	…	0.483	…	0.6	…	0.483	…	0.65
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1001	5	0	0.017	…	0	…	0	…	0.017	…	0	…	0	…	0.017
1002	5	0	0	…	0	…	0.017	…	0	…	0	…	0.017	…	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1199	5	0	0	…	0	…	0.017	…	0	…	0	…	0	…	0
1200	5	0	0	…	0	…	0	…	0	…	0.017	…	0	…	1

Table 43: Drinker proportion data with repeated observations

Subject	Gamma level	Steps of the game													
		Step 0	Step 1	…	Step 10	…	Step 20	…	Step 30	…	Step 40	…	Step 50	…	Step 60
1	0	0	0.433	…	0.733	…	0.717	…	0.65	…	0.783	…	0.75	…	0.75
2	0	0	0.517	…	0.567	…	0.533	…	0.75	…	0.7	…	0.7	…	0.417
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
499	0	0	0.467	…	0.917	…	0.683	…	0.767	…	0.633	…	0.567	…	0.517
500	0	0	0.5	…	0.783	…	0.767	…	0.733	…	0.717	…	0.667	…	0.75
501	1	0	0.067	…	0.383	…	0.45	…	0.7	…	0.667	…	0.467	…	0.35
502	1	0	0.117	…	0.067	…	0.667	…	0.8	…	0.85	…	0.7	…	0.433
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
999	1	0	0.1	…	0.967	…	0.967	…	0.583	…	0.383	…	0.533	…	0.7
1000	1	0	0.1	…	0.817	…	0.8	…	0.517	…	0.833	…	0.567	…	0.383
1001	2	0	0	…	0.75	…	0.75	…	0.75	…	0.75	…	0.75	…	0.75
1002	2	0	0.033	…	0.483	…	0.467	…	0.35	…	0.4	…	0.767	…	0.717
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1199	2	0	0.033	…	0.433	…	0.717	…	0.4	…	0.517	…	0.5	…	0.783
1200	2	0	0.033	…	0.317	…	0.267	…	0.2	…	0.2	…	0.2	…	0.183

Table 44: two-factor repeated measures ANOVA result

Gamma Level	T0	T1	T10	T20	T30	T40	T50	T60	F	P
gamma=0.9(n=500)	0±0	0.48±0.07a,c	0.53±0.26a	0.64±0.2a,c	0.64±0.18c	0.64±0.17c	0.64±0.17c	0.64±0.18c	1459.905	<0.001
gamma=0.8(n=500)	0±0	0.12±0.04a,b	0.52±0.33a	0.52±0.28b	0.54±0.27a,b	0.55±0.25b	0.56±0.25b	0.55±0.23b	151.16	<0.001
gamma=0.7(n=500)	0±0	0.05±0.03a,b,c	0.49±0.21a,b	0.49±0.2b,c	0.47±0.2a,b,c	0.47±0.21b,c	0.47±0.2b,c	0.47±0.2b,c	162.894	<0.001
F	.	11453.727	2.371	57.528	85.528	81.192	84.708	82.438		
P	.	<0.001	0.094	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =417.54, p<0.001; F_{gamma}=196.706, p<0.001; $F_{step*gamma}$=91.322, p<0.001;

Table 46: The analysis results for committed drinker

Gamma Level	**T0**	**T1**	**T10**	**T20**	**T30**	**T40**	**T50**	**T60**	**F**	**P**
gamma=0.9(n=500)	0±0	0±0	0.24±0.17a	0.37±0.17a,c	0.4±0.16a,c	0.41±0.15c	0.41±0.16c	0.41±0.15c	591.053	<0.001
gamma=0.8(n=500)	0±0	0±0	0.23±0.21a	0.29±0.2a,b	0.33±0.21a,b	0.35±0.2b	0.35±0.2b	0.35±0.19b	66.098	<0.001
gamma=0.7(n=500)	0±0	0±0	0.21±0.16a,b	0.24±0.15a,b	0.23±0.15b,c	0.24±0.16b,c	0.24±0.15b,c	0.24±0.15b,c	40.894	<0.001
F	.	.	4.238	72.945	120.877	121.709	122.94	124.536		
P	.	.	0.015	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =548.893, p<0.001; F_{gamma}=242.716, p<0.001; $F_{step*gamma}$=50.286, p<0.001;

Table 47: The analysis results for modest drinker

Gamma Level	**T0**	**T1**	**T10**	**T20**	**T30**	**T40**	**T50**	**T60**	**F**	**P**
gamma=0.9(n=500)	0±0	0.48±0.07a,c	0.28±0.18a	0.26±0.14a,c	0.24±0.11a,c	0.24±0.11c	0.23±0.11c	0.23±0.11c	1212.245	<0.001
gamma=0.8(n=500)	0±0	0.12±0.04a,b	0.29±0.23a	0.23±0.17a,b	0.21±0.15a,b	0.21±0.15b	0.2±0.15b	0.2±0.13b	110.482	<0.001
gamma=0.7(n=500)	0±0	0.05±0.03a,b,c	0.28±0.17a	0.25±0.15a,c	0.23±0.14a,c	0.23±0.13c	0.23±0.13c	0.23±0.13c	146.635	<0.001
F	.	11453.727	0.38	7.669	8.466	7.197	7.005	11.818		
P	.	<0.001	0.684	<0.001	<0.001	0.001	0.001	<0.001		

F_{step} =180.429, p<0.001; F_{gamma}=46.214, p<0.001; $F_{step*gamma}$=69.992, p<0.001;

Table 48: The analysis results for committed non-drinker

Gamma Level	**T0**	**T1**	**T10**	**T20**	**T30**	**T40**	**T50**	**T60**	**F**	**P**
gamma=0.9(n=500)	0±0	0.05±0.03a,c	0.19±0.2a,c	0.14±0.14a,c	0.15±0.13c	0.15±0.13c	0.16±0.13c	0.16±0.14c	23.372	<0.001
gamma=0.8(n=500)	0±0	0.75±0.05a,b	0.23±0.26a,b	0.24±0.23,b	0.24±0.21b	0.24±0.2b	0.24±0.2b	0.25±0.19b	2491.004	<0.001
gamma=0.7(n=500)	0±0	0.12±0.04a,b,c	0.27±0.18a,b,c	0.29±0.17a,b,c	0.31±0.16a,b,c	0.32±0.17b,c	0.33±0.17b,c	0.32±0.17b,c	297.235	<0.001
F	.	39849.245	17.275	80.294	113.806	119.419	130.625	112.438		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =130.38, p<0.001; F_{gamma}=2 33.36, p<0.001; $F_{step*gamma}$=132.288, p<0.001;

Table 49: The analysis results for modest non-drinker

Gamma Level	T0	T1	T10	T20	T30	T40	T50	T60	F	P
gamma=0.9(n=500)	1±0	0.47±0.07a,c	0.29±0.18a,c	0.22±0.13a,c	0.21±0.12	0.2±0.11	0.2±0.11	0.2±0.11	2344.352	<0.001
gamma=0.8(n=500)	1±0	0.12±0.04a,b	0.25±0.17a,b	0.24±0.15b	0.22±0.14a	0.21±0.13	0.2±0.13	0.2±0.12	3347.932	<0.001
gamma=0.7(n=500)	1±0	0.83±0.05a,b,c	0.24±0.16a,b	0.22±0.14a,c	0.22±0.13	0.21±0.13	0.21±0.13	0.21±0.13	1490.675	<0.001
F	.	20895.977	8.738	4.044	1.629	0.414	0.146	0.834		
P	.	<0.001	<0.001	0.018	0.196	0.661	0.864	0.434		

F_{step}=1327.28, p<0.001; F_{gamma}=5.646, p=0.004; $F_{step*gamma}$=104.218, p<0.001;

Table 57：proportion of committed drinker

Exclusivity Type	T0	T1	T10	T20	T30	T40	T50	T60	F	P
both	0±0	0±0	0.24±0.17a,c	0.36±0.17a,c	0.39±0.16a,c	0.4±0.16c	0.41±0.16c	0.41±0.16c	565.963	<0.001
state 1	0±0	0±0	0.33±0.18a,b	0.5±0.19a,b	0.58±0.19a,b	0.63±0.17a,b	0.65±0.17a,b	0.67±0.17a,b	392.654	<0.001
none	0±0	0±0	0±0.02b,c	0.01±0.03b,c	0.01±0.03b,c	0±0.01b,c	0±0.01b,c	0±0.02b,c	0.108	1
F	.	.	694.028	1438.018	2048.212	2632.86	2958.699	3048.46		
P	.	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =966.364, p<0.001; F_{type}=5464.263, p<0.001; $F_{step*type}$=382.586, p<0.001;

Table 58：proportion of modest drinker

Exclusivity Type	T0	T1	T10	T20	T30	T40	T50	T60	F	P
both	0±0	0.48±0.07a,c	0.28±0.18a,c	0.26±0.13a,c	0.24±0.11a,c	0.24±0.12	0.24±0.11	0.24±0.11	1068.425	<0.001
state 1	0±0	0.28±0.06a,b	0.46±0.19a,b	0.34±0.17a,b	0.29±0.15a,b	0.25±0.14a	0.23±0.14a	0.22±0.14a	510.619	<0.001
none	0±0	0±0.01a,b,c	0.09±0.12a,b,c	0.08±0.11b,c	0.05±0.1a,b,c	0.04±0.07a,b,c	0.04±0.07b,c	0.03±0.05b,c	5.717	<0.001
F	.	10473.113	613.368	480.301	511.008	577.53	566.623	583.792		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =301.073, p<0.001; F_{type}=1537.198, p<0.001; $F_{step*type}$=105.394, p<0.001.

Table 59：proportion of committed non-drinker

Exclusivity Type	T0	T1	T10	T20	T30	T40	T50	T60	F	P
both	0±0	0.04±0.03a,c	0.21±0.22a,c	0.15±0.16a,c	0.15±0.15c	0.16±0.15c	0.16±0.15c	0.15±0.14c	44.302	<0.001
state 1	0±0	0.11±0.04a,b	0.06±0.09a,b	0.04±0.08b	0.03±0.07b	0.03±0.06b	0.03±0.05b	0.03±0.05b	110.828	<0.001
none	0±0	0.83±0.04a,b,c	0.57±0.23a,b,c	0.63±0.17a,b,c	0.68±0.15a,b,c	0.71±0.13a,b,c	0.73±0.12a,b,c	0.75±0.12a,b,c	4855.252	<0.001
F	.	70164.414	960.954	2418.637	3768.684	4622.687	5293.185	5825.067		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =260.453, p<0.001; F_{type}=7937.977, p<0.001; $F_{step*type}$=225.833, p< 0.001.

Table 60: proportion of modest non-drinker

Exclusivity Type	T0	T1	T10	T20	T30	T40	T50	T60	F	P
both	1±0	0.47±0.07a,c	0.27±0.18a,c	0.22±0.13a,c	0.21±0.12c	0.2±0.11c	0.2±0.11c	0.2±0.11c	2101.989	<0.001
state 1	1±0	0.62±0.06a,b	0.16±0.17a,b	0.11±0.13a,b	0.1±0.11a,b	0.09±0.1b	0.08±0.1b	0.08±0.1b	1674.14	<0.001
none	1±0	0.16±0.04a,b,c	0.33±0.17a,b,c	0.29±0.12a,b,c	0.25±0.11a,b,c	0.24±0.11a,b,c	0.23±0.1a,b,c	0.22±0.1b,c	2791.132	<0.001
F	.	7857.064	129.91	229.659	269.037	288.264	279.845	244.051		
P	.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001		

F_{step} =1848.452, p<0.001; F_{type}=335.648, p<0.001; $F_{step*type}$=215.063, p<0.001;

Appendix B: Code for DRQN Training

```
import math, random
import numpy as np
import networkx as nx
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from collections import deque
from torch.utils.tensorboard import SummaryWriter
from matplotlib.colors import ListedColormap
from matplotlib import pyplot as plt
import itertools
import csv
import numpy as np
import random
from typing import Any, Callable, Generic, Iterable, List, Mapping, Optional, Sequence, Text, Tuple, TypeVar
import collections

#This ABM model includes the neural network training module for training the deep Q-network.
class Model(): #Create a model class for building the interaction environment of agents.
    def __init__(self, N):
        """Note:N describe the number of agents in the network"""
        self.num_agents = N # parameter N describe the number of agents in the environment
```

```
        self.Agent_List = [] #Create a list to store information of all agents in the environment, where each element of the list is an agent object.
        self.G = [] # Create an empty list to serve as a social network graph, for storing friendship information between agents.
        self.obv_list = [] #Create an empty list to record the current observations of agents.
        self.act_list = []# Create an empty list to record the behavior state of agents in this round (the behavior state space is [state 1, state 2, state 3, state 4]).
        self.reward_list = []#Create an empty list to record the social capital recieved by the agents in this round.
        self.each_epi_record = [] #Create an empty list to record the SARS data of the agents in this round.
        self.social_capital_trajectory = deque([], maxlen=2) #Create a queue container to store the social capital values received by agents in the previous round and the current round.
        self.move = []#Create an empty list to record the decision choices made by the agent in this round, where the decision space of agents is [decision 1, decision 2, decision 3].

    def reset(self):    # The reset() function is used to initialize the Model environment before the game starts.
        self.Agent_List = [] #Clear the list storing agent objects.
        self.G = 0 #clear social network graph
        self.G = self.InitialNet(self.num_agents) #Create a social network graph with N nodes.
        """Note:add agents to the initial network"""
        for i in range(self.num_agents):
            a = MyAgent(i, self)    # Instantiate N agent objects.
            # set the initial state of the agent
```

```python
            a.ID = i #The ID of the agent corresponds to the ID of the node in the social network graph.
            act_opt = [0, 1, 2, 3] #Agents have four different behavior states.
            prob = [0, 0, 0, 1]
            action = random.choices(act_opt, prob, k=1)
            a.state = action[0] #Set the initial behavior state of all agents to behavior state 4.
            self.Agent_List.append(a) #Add the instantiated N agent objects to the agents list for storage.
        self.social_capital_trajectory = deque([], maxlen=2) # Clear the queue container storing records of social capital.
        self.record_social_capital() #Re-record the initial social capital of all agents in the social network.

    def InitialNet(self, N): #The InitialNet() function is used to initialize the social network graph. The input parameter N describes the size of the graph, and it outputs a Networkx graph object.
        G = nx.erdos_renyi_graph(N, 0.1) #The initial network is an ER network with N nodes and an initial connection probability of 10%.
        isolates = list(nx.isolates(G))
        while len(isolates) > 0: #Check if there are isolated nodes in the initial network. If there are isolated nodes in the initial network, regenerate the initial network repeatedly until it is a fully connected network without isolated nodes.
            G = nx.erdos_renyi_graph(N, 0.1)
            isolates = list(nx.isolates(G))
        A = nx.to_numpy_array(G, weight='weight') #Set the weight of all edges in the initial network to 1.
        for i in range(N):
            for j in range(N):
                if A[i][j] != 0:
```

```
                    A[i][j] = 1
                    A[j][i] = A[i][j]
                else:
                    A[i][j] = 0
        graph = nx.from_numpy_array(A, create_using=nx.Graph) #The initial network is a weighted undirected graph.
        return graph

    def get_obv(self): #The get_obv() function is used to iterate through all agents, obtain the current observation of each agent.
        self.obv_list = []
        for i in self.Agent_List:
            self.obv_record = i.obv()
            self.obv_list.append(self.obv_record)
        return self.obv_list

    def act_decision(self): #Iterate through each agent in the network, input the current observation of the agent into the Q-network to obtain the decision action output by the Q-network for this round. Based on this decision action, determine the new behavior state of the agent according to the rules specified in the state transition table, and record it.
        self.act_list = []
        self.move = []
        for i in self.Agent_List:
            move = i.select_action(self.obv_list[i.ID])
            act_record = 0
            if i.state == 0 and move == 0:
                act_record = 0
            elif i.state == 0 and move == 1:
```

```
                act_record = 0
            elif i.state == 0 and move == 2:
                act_record = 1
            elif i.state == 1 and move == 0:
                act_record = 0
            elif i.state == 1 and move == 1:
                act_record = 1
            elif i.state == 1 and move == 2:
                act_record = 3
            elif i.state == 3 and move == 0:
                act_record = 1
            elif i.state == 3 and move == 1:
                act_record = 3
            elif i.state == 3 and move == 2:
                act_record = 2
            elif i.state == 2 and move == 0:
                act_record = 3
            elif i.state == 2 and move == 1:
                act_record = 2
            elif i.state == 2 and move == 2:
                act_record = 2
            self.act_list.append(act_record)
            self.move.append(move)
        return self.act_list, self.move #this function returns the decision actions of all agents for this round and their updated behavior states.

    def update_agent_act(self): #Update the behavior states of all agent objects.
        for i in self.Agent_List:
            i.state = self.act_list[i.ID]
```

```python

    def getneighbor_List(self, ID): #The getneighbor_List() function is used to obtain the IDs of first-order and second-order neighbor nodes of an agent. The function takes the ID of the agent as input  and outputs a list that records the IDs of all first-order and second-order neighbors of that agent.
        first_order_neighbors = []
        first_order_neighbors = list(self.G.neighbors(ID))
        second_order_neighbors = []
        for n in first_order_neighbors:
            second_order_neighbors += list(self.G.neighbors(n))
        second_order_neighbors = list(set(second_order_neighbors) - set(first_order_neighbors))
        output = first_order_neighbors + second_order_neighbors
        return output

    def node_group_matrix(self):    #The node_group_matrix function iterates through each agent. The function outputs a two-dimensional list, where each row of the list records the IDs of the first-order and second-order neighbors of an agent.
        Agent_group = []
        for i in range(self.num_agents):
            node_Nei = self.getneighbor_List(i)
            Agent_group.append(node_Nei)
        return Agent_group

    def Update_Network(self):    #The Update_Network() function is used for pairwise interactions between agents. The interaction process is based on the current behavior states of the two agents, and according to the interaction rules spec
```

```
ified in the Interaction Rules Table, it updates the friendship relationship between the two agents.
Aj = nx.to_numpy_array(self.G, weight='weight')
sn = 1.8 # parameter c in the Interaction Rules Table. NOTE: for the retroductive analysis of the role of drinking culture, when we need to conduct simulation experiments under different levels of identity homophily, we only need to adjust the size of parameter c, such as c=1.6, c=1.7, c=2, c=3, etc.
hm = 1 #parameter b in the Interaction Rules Table
nm = 0.5 #parameter a in Interaction Rules Table
Node_groups = self.node_group_matrix()
for i in range(self.num_agents):
    for j in range(i + 1, self.num_agents):
        if j in Node_groups[i]:
            a = self.Agent_List[i]
            b = self.Agent_List[j]
            if a.state == 0 or b.state == 0:
                if a.state == 0 and b.state == 0:
                    Aj[i][j] += sn + sn
                elif a.state == 1 or b.state == 1:
                    Aj[i][j] += sn + hm
                elif a.state == 2 or b.state == 2:
                    Aj[i][j] = 0
                elif a.state == 3 or b.state == 3:
                    Aj[i][j] = 0
            elif a.state == 1 or b.state == 1:
                if a.state == 1 and b.state == 1:
                    Aj[i][j] += hm + hm
                elif a.state == 2 or b.state == 2:
                    Aj[i][j] = 0
                elif a.state == 3 or b.state == 3:
```

```
                        Aj[i][j] += nm +nm
                    elif a.state == 2 or b.state == 2:
                        if a.state == 2 and b.state == 2:
                            Aj[i][j] += hm + hm
                        elif a.state == 3 or b.state == 3:
                            Aj[i][j] += hm + hm
                    elif a.state == 3 and b.state == 3:
                        Aj[i][j] += hm + hm
                    Aj[j][i] = Aj[i][j]
                else:
                    pass
    self.G = nx.from_numpy_array(Aj, create_using=nx.Graph) # Update the social network graph after pairwise interactions.

#NOTE: for the retroductive analysis of the role of drinking culture, when we need to conduct simulation experiments under different types of identity exclusivity, we need to change the pairwise interactions rules above:
#For the "None" group, i.e., excluding the identity exclusivity mechanism. The pairwise interactions rules will be changed as follows:
"""for i in range(self.num_agents):
        for j in range(i + 1, self.num_agents):
            if j in Node_groups[i]:
                a = self.Agent_List[i]
                b = self.Agent_List[j]
                if a.state == 0 or b.state == 0:
                    if a.state == 0 and b.state == 0:
                        Aj[i][j] += sn + sn
                    elif a.state == 1 or b.state == 1:
                        Aj[i][j] += sn + hm
                    elif a.state == 2 or b.state == 2:
```

```
                                Aj[i][j] = nm + nm
                            elif a.state == 3 or b.state == 3:
                                Aj[i][j] = nm + nm

                        elif a.state == 1 or b.state == 1:
                            if a.state == 1 and b.state == 1:
                                Aj[i][j] += hm + hm
                            elif a.state == 2 or b.state == 2:
                                Aj[i][j] = nm +nm
                            elif a.state == 3 or b.state == 3:
                                Aj[i][j] += nm +nm
                        elif a.state == 2 or b.state == 2:
                            if a.state == 2 and b.state == 2:
                                Aj[i][j] += hm + hm
                            elif a.state == 3 or b.state == 3:
                                Aj[i][j] += hm + hm
                        elif a.state == 3 and b.state == 3:
                            Aj[i][j] += hm + hm
                        Aj[j][i] = Aj[i][j]
                    else:
                        pass"""
    #For the "state 1" group, i.e., only state 1 agents have identity exclusivity. The pairwise interactions rules will be changed as follows:
        """for i in range(self.num_agents):
                for j in range(i + 1, self.num_agents):
                    if j in Node_groups[i]:
                        a = self.Agent_List[i]
                        b = self.Agent_List[j]
                        if a.state == 0 or b.state == 0:
                            if a.state == 0 and b.state == 0:
```

```
                        Aj[i][j] += sn + sn
                    elif a.state == 1 or b.state == 1:
                        Aj[i][j] += sn + hm
                    elif a.state == 2 or b.state == 2:
                        Aj[i][j] = 0
                    elif a.state == 3 or b.state == 3:
                        Aj[i][j] = 0

                elif a.state == 1 or b.state == 1:
                    if a.state == 1 and b.state == 1:
                        Aj[i][j] += hm + hm
                    elif a.state == 2 or b.state == 2:
                        Aj[i][j] = nm +nm
                    elif a.state == 3 or b.state == 3:
                        Aj[i][j] += nm +nm
                elif a.state == 2 or b.state == 2:
                    if a.state == 2 and b.state == 2:
                        Aj[i][j] += hm + hm
                    elif a.state == 3 or b.state == 3:
                        Aj[i][j] += hm + hm
                elif a.state == 3 and b.state == 3:
                    Aj[i][j] += hm + hm
                Aj[j][i] = Aj[i][j]
            else:
                pass    """


    def cal_bonding_capital(self): #The cal_bonding_capital() function is used to calculate the social capital values that each agent currently receives from their first-order neighbors.
```

```python
        A = nx.to_numpy_array(self.G, weight='weight')#1. Obtain the adjacency matrix of the current social network graph.
        row_sums = np.sum(A, axis=1) #2. Calculate the sum of elements in each row of the adjacency matrix.
        with np.errstate(divide='ignore', invalid='ignore'):# 3. Update all elements in the adjacency matrix to be the element divided by the sum of elements in the row where the element belongs (to avoid division by 0). Use broadcasting to perform the division.
            new_array = np.where(row_sums[:, np.newaxis] == 0, 0, A / row_sums[:, np.newaxis])
        col_sums = np.sum(new_array, axis=0) #4. Calculate the sum of each column in the new matrix, which represents the social capital values that the corresponding agent currently receives from its first-order neighbors.
        return col_sums

    def cal_mixed_social_capital(self):    #Call the cal_bonding_capital() function to calculate the social capital values of agents, and convert the returned value (np.array) into a list.
        mixed_social_capital_list = []
        bondc_array = self.cal_bonding_capital()
        mixed = bondc_array
        mixed_social_capital_list = mixed.tolist()
        return mixed_social_capital_list

    def record_social_capital(self): #Record the current social capital list in a queue container. social_capital_trajectory is a queue container with a length of 2, containing the social capital data of the agents for the current round and the social capital data from the previous round.
        self.social_capital_trajectory.append(self.cal_mixed_social_capital())

```

```
    def get_reward(self):    #The get_reward() function calls the record_social_capital function to record the current social capital, and the social capital obtained by agents in this round is recorded as the reward for the agent in this round.
        self.record_social_capital()
        self.reward_list = []
        for i in range(self.num_agents):
            if len(self.social_capital_trajectory) > 1:
                reward = self.social_capital_trajectory[1][i]
                self.reward_list.append(reward)
            else:
                self.reward_list = [0] * self.num_agents
        return self.reward_list

    def get_sars(self): #The get_sars() function will record the observations, decesion choice, rewards, and new observations of all agents in the current round of the game.
        obv = self.get_obv()    # Call self.get_obv() function to allow all agents to obtain their respective local observations of the network environment.
        act_move = self.act_decision()    #Call self.act_decision() function to return the decision choices and new states of all agents for this round.
        move= act_move[1]    # get the current decesion choice of the agents.
        self.update_agent_act()    # Update the behavior states of all agent objects.
        self.Update_Network()    # After the agent updates its state, call self.Update_Network() to allow agents to interact with first-order and second-order neighbors in pairs, and update the friendship network based on the interaction rules.
        reward = self.get_reward()    # After updating the friendship network, recalculate the social capital obtained by all agents in the updated friendship netwo
```

```
rk, which represents the rewards obtained by agents from the environment in this round.
        new_obv = self.get_obv()    # Call the self.get_obv() function again to allow agents to obtain new observations of the updated friendship network environment.
        self.each_epi_record = []
        for i in range(self.num_agents): #Iterate through each agent, separately record their observations, states, rewards, and new observation data for this round of the game, and store them in an empty list.
            agent_obv = obv[i]
            agent_act = move[i]
            agent_reward = reward[i]
            agent_new_obv = new_obv[i]
            agent_sars = (agent_obv, agent_act, agent_reward, agent_new_obv)
            self.each_epi_record.append(agent_sars)
        return self.each_epi_record    # The function returns a two-dimensional list storing the SARS data of all agents for this round.


    def add_memory_buffer(self, sars):    # Store the SARS data recorded by the get_sars() function for this round in the experience replay buffer to be used as training data for the Q-network.
        for i in self.each_epi_record:
            memory.push((i[0], [i[1]], [i[2]], i[3]))

    def step(self):    # The step() function defines the procedures to be executed in each round of the game.
        sars = self.get_sars()
        self.add_memory_buffer(sars)
        for i in range(Agent_number):
```

```
            if memory_tree.tree.write == 0: #As the neural network training uses prioritized replay buffer, we set the newly stored SARS data in the experience replay buffer to have the highest priority when randomly drawn.
                error = 1
                memory_tree.add(error, memory_tree.tree.write)
            else:
                error = memory_tree.tree.get_max_p()
                memory_tree.add(error, memory_tree.tree.write)

    def draw(self): #The draw() function is used for visualization and plotting, and will not be executed during the actual neural network training process.
        for i in range(self.num_agents):
            a = self.Agent_List[i]
            self.G.nodes[i]["ID"] = i
            self.G.nodes[i]["action"] = a.state
            self.G.nodes[i]["SC"] = round(self.social_capital_trajectory[-1][i], 3)
        pos = nx.kamada_kawai_layout(self.G)
        cmap = ListedColormap(["g", "b", "r", "y"])
        states = []
        for i in range(self.num_agents):
            states.append(self.G.nodes[i]["action"])
        colors = [cmap(j) for j in states]
        nx.draw(self.G, pos, node_color=colors)
        node_lables = {}
        for i in range(self.num_agents):
            node_attri = {}
            node_attri["ID"] = self.G.nodes[i]["ID"]
            node_attri["SC"] = self.G.nodes[i]["SC"]
            node_lables[i] = node_attri
        nx.draw_networkx_labels(self.G, pos, labels=node_lables, alpha=0.5)
```

```python
        plt.show()


class MyAgent(): #MyAgent class defines agent objects, which include two attributes: the agent's unique ID and the agent's current behavior state.
    def __init__(self, unique_id, Model):
        self.ID = unique_id
        self.state = 1
        self.model = Model

    def obv(self): #The obv() function defines the information that an agent can observe about the social network environment, including the agent's own ID, the agent's current behavior state, the agent's current social capital, the friendship strength between the agent and all its first-order neighbors, and the current behavior state of all its first-order neighbors.
        G = np.array(nx.adjacency_matrix(self.model.G).todense())    # Obtain the adjacency matrix of the current social network graph.
        obv_nei = G[self.ID]    # The row of the adjacency matrix where the agent is located describes the agent's friendship relationships with its first-order neighbors.
        obv_nei = obv_nei.tolist()
        obv_id = [0] * Agent_number
        obv_id[self.ID] = 1  # Get the agent's own ID in the form of a one-hot vector.
        ovb_self_act = [0] * 4
        ovb_self_act[self.state] = 1  # Get the agent's current state in the form of a one-hot vector.
        obv_act = []
```

```
        for i in range(self.model.num_agents): #Obtain the observations of the current states of all first-order neighbors of the agent, and convert them into one-hot vectors.
            if i == self.ID:
                obv_act.append(self.state)
            elif obv_nei[i] != 0:
                Agent = self.model.Agent_List[i]
                obv_act.append(Agent.state)
            elif obv_nei[i] == 0:
                obv_act.append(4)
        count = 0
        dic = {0: [1, 0, 0, 0, 0], 1: [0, 1, 0, 0, 0], 2: [0, 0, 1, 0, 0], 3: [0, 0, 0, 1, 0],
               4: [0, 0, 0, 0, 1]}
        for j in obv_act:
            obv_act[count] = dic[j]
            count += 1
        obv_act = list(itertools.chain(*obv_act))
        self_sc = 0
        self_sc = self.model.social_capital_trajectory[-1][self.ID]
        observation = np.hstack((obv_id, ovb_self_act, self_sc, obv_nei, obv_act))
        observation = observation.tolist()
        return observation

    def select_action(self, obs):    # The agent inputs the current observation into the Q-network, and the Q-network outputs the decision choice of the agent for this round.
        obs = [obs]
        obs = torch.tensor(np.array(obs), dtype=torch.float)
        obs = obs.to(device)
```

```
        global steps_done
        sample = random.random()   # As this program is used for neural network training and follows common training methods of DQN, during the initial stages of training, agents will have a certain probability of making random decisions to explore the decision policy space and improve training effectiveness. For the ABM model used in simulation experiments, agents will strictly follow the decision choices output by a well-trained Q-network.
        eps_threshold = eps_end + (eps_start - eps_end) * math.exp(-1 * steps_done / eps_decay) #As the neural network training progresses, the probability of agents making random decisions will gradually decrease, and agents will rely more on the results output by the Q-network for decision-making.
        if sample > eps_threshold:
            with torch.no_grad():
                P = policy_network(obs).view([3])
                return P.max(0)[1].view(1, 1).item()
        else:
            return random.randrange(3)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
tb_writer = SummaryWriter(log_dir="D:/text")


class ReplayMemory(object):   # The ReplayMemory class serves as the experience replay buffer, where the (s, a, r, s) data generated by each agent in every step of the game is stored in the experience replay buffer as the training dataset.
    def __init__(self, capacity):
        self.memory = deque([], maxlen=capacity)   # The experience replay buffer is a queue container with a capacity of "capacity".
        self.pos = 0  # self.pos is used as a pointer to record which number of (s, a, r, s) data is currently being stored.
```

```

    def push(self, x):    #The push() function is used to store SARS data in the queue.
        self.memory.append(x)
        self.pos += 1

    def sample(self, batch_size, seq_size):    #    Randomly select a batch of data with a size of "batch_size" from the replay memory as training data. The probability of selecting a SARS data is related to its current TD error value; the larger the TD error value, the more likely it is to be selected.
        random_batch_sample_seq = []
        random_batch_sample_seq_idx = []
        random_batch_sample_seq_ISWeights = []
        all_epi = (steps_done - 1) // steps_each_episode
        step_now_epi = (steps_done - 1) % steps_each_episode
        start_list = []
        while len(start_list) < seq_size:
            random_idx = memory_tree.sample()
            random_step = random_idx // Agent_number
            random_round = random_step // steps_each_episode
            random_now_step = random_step % steps_each_episode
            if random_round < all_epi:
                end_idx = (random_round + 1) * steps_each_episode - 1
                if end_idx - random_step >= (batch_size - 1):
                    start_index = random_idx
                    start_list.append(start_index)
                else:
                    gap_step = batch_size - end_idx + random_step - 1
                    start_index = random_idx - (gap_step * Agent_number)
                    start_list.append(start_index)
```

```python
            elif random_round == all_epi:
                end_idx = step_now_epi
                if end_idx >= (batch_size - 1):
                    if end_idx - random_now_step >= (batch_size - 1):
                        start_index = random_idx
                        start_list.append(start_index)
                    else:
                        gap_step = batch_size - end_idx + random_now_step - 1
                        start_index = random_idx - (gap_step * Agent_number)
                        start_list.append(start_index)
        min_p = memory_tree.tree.get_min_p()
        min_prob = min_p / memory_tree.tree.total()
        for i in start_list:
            random_batch_sample = []
            random_batch_sample_idx = []
            random_batch_sample_ISWeight = []
            for j in range(batch_size):
                idx = i + j * Agent_number
                random_batch_sample.append(self.memory[idx])
                random_batch_sample_idx.append(idx)
                p = memory_tree.tree.p_data[idx]
                prob = p / memory_tree.tree.total()
                ISWeights = np.power(prob / min_prob, -memory_tree.beta)
                random_batch_sample_ISWeight.append(ISWeights)
            random_batch_sample_seq.append(random_batch_sample)
            random_batch_sample_seq_idx.append(random_batch_sample_idx)
            random_batch_sample_seq_ISWeights.append(random_batch_sample_ISWeight)
        return random_batch_sample_seq, random_batch_sample_seq_idx, random_batch_sample_ISWeight
```

```
    def __len__(self):
        return len(self.memory)

class DQN(nn.Module): #Create a neural network class.
    def __init__(self, obs_dim, act_dim):    #The input dimension of the neural network is the dimension of the observation, and the output dimension is the dimension of the decision choices.
        super(DQN, self).__init__()
        #Constructing a 6-layer DRQN network .
        self.rnn = nn.GRU(obs_dim, 128, 1, batch_first=True)    # The first layer is a GRU layer.
        self.fc1 = nn.Linear(128, 512)    # The second layer is a fully connected layer.
        self.fc2 = nn.Linear(512, 256)# The third layer is a fully connected layer.
        self.fc3 = nn.Linear(256, 128)# The fourth layer is a fully connected layer.
        self.fc4 = nn.Linear(128, 64)# The fifth layer is a fully connected layer.
        self.fc5 = nn.Linear(64, act_dim)# The sixth layer is a fully connected layer.

        for m in self.modules(): #Initialize the neural network parameters.
            if isinstance(m, nn.Linear):
                nn.init.kaiming_uniform_(m.weight)
                nn.init.zeros_(m.bias)
            elif isinstance(m, nn.RNN):
                nn.init.kaiming_uniform_(m.weight_ih_l0)
                nn.init.orthogonal_(m.weight_hh_l0)
                nn.init.zeros_(m.bias_ih_l0)
                nn.init.zeros_(m.bias_hh_l0)
```

```
    def forward(self, x, hidden=None):
        x = x.to(device)
        seq = seq_size
        if len(x.shape) == 2:
            x = x.view([1, 1, obs_dim])
            seq = 1
        else:
            pass
        if not hidden:
            hidden = torch.zeros([1, seq, 128]).to(device)
        out, h = self.rnn(x, hidden)
        x = F.relu(self.fc1(out))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = F.relu(self.fc4(x))
        x = self.fc5(x)
        if seq == 1:
            x = x.view(-1, act_dim)
        else:
            pass
        return x

class SumTree: #The SumTree class is a tree structure container used as a sampler for priority sampling during neural network training.
    def __init__(self, capacity):
        self.capacity = capacity
        self.tree = np.zeros(2 * capacity - 1)
        self.p_data = np.zeros(capacity, dtype=object)
        self.write = 0

```

```
    def _propagate(self, idx, change):
        parent = (idx - 1) // 2
        self.tree[parent] += change
        if parent != 0:
            self._propagate(parent, change)

    def update(self, idx, p):
        idx_tree = idx + self.capacity - 1
        change = p - self.tree[idx_tree]
        self.tree[idx_tree] = p
        self.p_data[idx] = p
        self._propagate(idx_tree, change)

    def add(self, p, data):
        self.update(data, p)
        self.write += 1
        if self.write >= self.capacity:
            self.write = 0

    def _retrieve(self, idx, s):
        left = 2 * idx + 1
        right = left + 1
        if left >= len(self.tree):
            return idx
        if s <= self.tree[left]:
            return self._retrieve(left, s)
        else:
            return self._retrieve(right, s - self.tree[left])

    def get(self, s):
```

```
        idx = self._retrieve(0, s)
        dataIdx = idx - self.capacity + 1
        return dataIdx

    def get_max_p(self):
        return np.max(self.p_data)

    def get_min_p(self):
        n = self.write
        data_p = self.p_data[:n]
        return np.amin(data_p)

    def total(self):
        return self.tree[0]


class Memory:   # The Memory class instantiates a SumTree class and stores the priority values of each SARs data. It is used as a sampler for priority sampling during neural network training.
    def __init__(self, capacity):
        self.tree = SumTree(capacity)
        self.beta = 0.4
        self.capacity = capacity
        self.e = 0.01
        self.a = 0.6

    def _getPriority(self, error):
        return (error + self.e) ** self.a

    def add(self, error, sample):
```

```
        p = self._getPriority(error)
        self.tree.add(p, sample)
    def sample(self):
        segment = self.tree.total()
        s = random.uniform(0, segment)
        dataidx = self.tree.get(s)
        return dataidx
    def update(self, idx, error):
        p = self._getPriority(error)
        self.tree.update(idx, p)

#Below is the main program of the ABM.
Agent_number = 60  # The parameter "Agent_number" describes the number of agents in the environment.
env = Model(Agent_number)    # Instantiate an environment object containing 60 agents.
seq_size = 30  # During each neural network training session, randomly sample the SARS data of "seq_size" agents based on priorities.
batch_size = 8  # For each randomly selected agent, there are "batch-size" consecutive SARS data for that agent.
gamma = 0.9

eps_start = 1
eps_end = 0.05
eps_decay = 3000

target_update = 15  # Update the parameters of the Q-network with one training update every target_update rounds of the game.
LR = 8e-7  # learning rate
TAU = 0.01  # Update rate of the target network
```

```


    obs_dim = 7 * Agent_number + 5
    act_dim = 3
    policy_network = DQN(obs_dim, act_dim).to(device)    # Create a policy network and a target network, which is a classic method in DQN training.
    target_network = DQN(obs_dim, act_dim).to(device)
    target_network.load_state_dict(policy_network.state_dict())
    target_network.eval()
    optimizer = optim.AdamW(policy_network.parameters(), lr=LR, amsgrad=True)
    capacity = 421000
    memory = ReplayMemory(capacity)    # Instantiate a ReplayMemory object with a capacity of "capacity".
    memory_tree = Memory(capacity)    # Instantiate a Memory object with a capacity of "capacity".

    steps_done = 0
    count_tensorboard = 0
    count_path = 0

    def train(epoch): #The train() function updates the parameters of the Q-network using the TD algorithm.
        running_loss = 0
        n = 15
        for m in range(n):
            sample_null = memory.sample(batch_size, seq_size)
            samples = sample_null[0]
            samples_id = sample_null[1]
            samples_weight = sample_null[2]
```

```
    samples_weight = torch.from_numpy(np.array(samples_weight, dtype=np.float32)).to(device)
    samples_id_array = np.array(samples_id)
    samples_id_flat = samples_id_array.flatten()
    obv = []
    act = []
    rew = []
    new_obv = []
    for i in samples:
        obv_a = []
        act_a = []
        rew_a = []
        new_obv_a = []
        for j in i:
            obv_a.append(j[0])
            act_a.append(j[1])
            rew_a.append(j[2])
            new_obv_a.append(j[3])
        obv.append(obv_a)
        act.append(act_a)
        rew.append(rew_a)
        new_obv.append(new_obv_a)
    obv = torch.from_numpy(np.array(obv, dtype=np.float32))
    act = torch.from_numpy(np.array(act, dtype=np.int64))
    rew = torch.from_numpy(np.array(rew, dtype=np.float32))
    new_obv = torch.from_numpy(np.array(new_obv, dtype=np.float32))

    obv = obv.to(device)
    act = act.to(device)
    rew = rew.to(device)
```

```
        new_obv = new_obv.to(device)
        pred_q_value = policy_network(obv).gather(2, act)
        with torch.no_grad():
            next_q_value = target_network(new_obv).max(2)[0].view(seq_size, batch_size,1)
        expected_state_action_values = (next_q_value * gamma) + rew    # Calculate the TD error.

        with torch.no_grad():
            errors_cpu = torch.abs(pred_q_value - expected_state_action_values).data.cpu()
            errors = errors_cpu.numpy()
            errors_flatten = errors.flatten()
            writ = 0
            for i in errors_flatten:
                idx = samples_id_flat[writ]
                memory_tree.update(idx, i)
                writ += 1
        optimizer.zero_grad()
        criterion = nn.MSELoss()
        loss_1 = criterion(pred_q_value, expected_state_action_values)
        loss = (samples_weight * loss_1).mean()
        running_loss += loss.item()
        loss.backward()    #backward
        optimizer.step()
        if memory_tree.beta < 1:
            memory_tree.beta += 0.0002

    #Every 10 training iterations, save the current neural network parameters to a file.
```

```
    if epoch != 0 and epoch % 10 == 0:
        global count_path
        torch.save(target_network.state_dict(), "D:/text/a.pth")
        if count_path==699:
            torch.save(target_network.state_dict(),'D:/text/a1.pth')
        count_path += 1

    if epoch != 0 and epoch % 10 == 0:
        global count_tensorboard
        tb_writer.add_scalar("training loss", running_loss / n, epoch)
        running_loss = 0
        count_tensorboard += 1

# The training main program.
if torch.cuda.is_available():
    num_episodes = 30000000
else:
    num_episodes = 200
steps_each_episode = 60  # Each complete game consists of 60 rounds(steps).

for i_episode in range(num_episodes):
    # Initialize the environment and get it's state
    env.reset()
    for i_step in range(steps_each_episode):
        #env.draw() #Used for visualization and plotting.
        env.step()
        steps_done += 1
        if steps_done != 0 and steps_done % 10 == 0:
            train(steps_done)
        if steps_done != 0 and steps_done % target_update == 0:
```

```
        target_net_state_dict = target_network.state_dict()
        policy_net_state_dict = policy_network.state_dict()
        for key in policy_net_state_dict:
            target_net_state_dict[key] = policy_net_state_dict[key] * TAU + target_net_state_dict[key] * (1 - TAU)
        target_network.load_state_dict(target_net_state_dict)
tb_writer.close()
```

Appendix C: Code for Social Simulation Test

```
import math, random
import numpy as np
import networkx as nx
from sklearn import preprocessing
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from collections import deque
from torch.utils.tensorboard import SummaryWriter
from matplotlib.colors import ListedColormap
from matplotlib import pyplot as plt
import itertools
import csv
import pandas as pd
import copy
from networkx.algorithms.community import greedy_modularity_communities
from networkx.algorithms.community.quality import modularity
from networkx.algorithms.community import girvan_newman
import statistics
from networkx.algorithms.community import greedy_modularity_communities
from networkx.algorithms.community.quality import modularity
import statistics
import community
```

```python
#This ABM model utilizes a well-trained deep Q-network to control agents' decision-making for conducting social simulation experiments. The model includes data collection modules to    record the results data of the simulation.
#This ABM model is used for generative sufficient test and retroductive analysis of the role of social capital.
class Model(): #Create a model class for building the interaction environment of agents.
    def __init__(self, N):
        """Note:N describe the number of agents in the network"""
        self.num_agents = N
        self.Agent_List=[]
        self.obv_list=[]
        self.act_list =[]
        self.reward_list = []
        self.each_epi_record=[]
        self.social_capital_trajectory= deque([], maxlen =2)
        self.G=[]
        self.move = []
        self.record_reward=[]
        self.record_change = []
        self.modularity = [] #Record the modularity of the social network graph at each step of the game.
        self.initial_sc = []
        self.last_aj_matrix = []
        self.recent_action =[]
        self.step_count =0

    def reset(self): # The reset() function is used to initialize the Model environment before the game starts.
```

```
        self.Agent_List=[]
        self.G = 0
        self.G= self.InitialNet(self.num_agents)
        self.modularity = []
        self.record_reward=[]
        self.step_count =0
        self.initial_sc = []
        self.record_change = []
        self.last_aj_matrix = []
        self.recent_action =[]
        """Note:add agents to the initial network"""
        for i in range(self.num_agents):
            a = MyAgent(i, self)        #instantiation MyAgent class
            # set the initial state of the agent
            a.ID = i
            act_opt=[0,1,2,3]
            prob=[0,0,0,1]
            action = random.choices(act_opt, prob,k=1)
            a.state=action[0] #Set the initial behavior state of all agents to behavior state 4.
            a.action_list.append(a.state) #Each agent records its own trajectory of behavior states.
            self.Agent_List.append(a) #Add the instantiated N agent objects to the agents list for storage.
        self.social_capital_trajectory= deque([], maxlen =2)
        self.record_social_capital() #Record the initial social capital of each agent.
        self.initial_sc = self.social_capital_trajectory[0]
        self.record_accumulat_social_capital()

```

```
    def InitialNet(self, N): #The InitialNet() function is used to initialize the social network graph. The input parameter N describes the size of the graph, and it outputs a Networkx graph object.
        G = nx.erdos_renyi_graph(N, 0.1)
        isolates = list(nx.isolates(G))
        while len(isolates) > 0:
            G = nx.erdos_renyi_graph(N, 0.1)
            isolates = list(nx.isolates(G))
        A= nx.to_numpy_array(G, weight='weight')
        for i in range(N):
            for j in range(N):
                if A[i][j]!=0:
                    A[i][j]= 1
                    A[j][i]=A[i][j]
                else:
                    A[i][j]=0
        graph = nx.from_numpy_array(A, create_using=nx.Graph)
        return graph

    def get_obv(self): #The get_obv() function is used to iterate through all agents, obtain the current observation of each agent.
        self.obv_list = []
        for i in self.Agent_List:
            self.obv_record= i.obv()
            self. obv_list.append(self.obv_record)
        return self. obv_list

    def act_decision_test(self):#Iterate through each agent in the network, input the current observation of the agent into the Q-network to obtain the decision action output by the Q-
```

```
network for this round. Based on this decision action, determine the new behavior state of the agent according to the rules specified in the state transition table, and record it.
        self.act_list = []
        self.move = []
        self.recent_action =[]
        for i in self.Agent_List:
            self.recent_action.append(i.state) #Before agents make decisions and transition states, record their current behavior state.
            move=0
            move= i.select_action_test(self.obv_list[i.ID])
            act_record = 0
            if i.state == 0 and move == 0:
                act_record = 0
            elif i.state == 0 and move == 1:
                act_record = 0
            elif i.state == 0 and move == 2:
                act_record = 1
            elif i.state == 1 and move == 0:
                act_record = 0
            elif i.state == 1 and move == 1:
                act_record = 1
            elif i.state == 1 and move == 2:
                act_record = 3
            elif i.state == 3 and move == 0:
                act_record = 1
            elif i.state == 3 and move == 1:
                act_record = 3
            elif i.state == 3 and move == 2:
                act_record = 2
```

```
            elif i.state == 2 and move == 0:
                act_record = 3
            elif i.state == 2 and move == 1:
                act_record = 2
            elif i.state == 2 and move == 2:
                act_record = 2
            self.act_list.append(act_record)
            self.move.append(move)
        return self. act_list, self.move

    def update_agent_act(self): #Update the behavior states of all agent objects.
        for i in self.Agent_List:
            i.state = self. act_list[i.ID]

    def getneighbor_List(self,ID): #The getneighbor_List() function is used to obtain the IDs of first-order and second-order neighbor nodes of an agent. The function takes the ID of the agent as input and outputs a list that records the IDs of all first-order and second-order neighbors of that agent.
        first_order_neighbors = list(self.G.neighbors(ID))
        second_order_neighbors = []
        for n in first_order_neighbors:
            second_order_neighbors += list(self.G.neighbors(n))
        second_order_neighbors = list(set(second_order_neighbors) - set(first_order_neighbors))
        output=first_order_neighbors + second_order_neighbors
        return output

```

```
    def node_group_matrix(self): #The node_group_matrix function iterates through each agent. The function outputs a two-dimensional list, where each row of the list records the IDs of the first-order and second-order neighbors of an agent.
        Agent_group=[]
        for i in range (self.num_agents):
            node_Nei=self.getneighbor_List(i)
            Agent_group.append(node_Nei)
        return Agent_group

    def Update_Network(self): #The Update_Network() function is used for pairwise interactions between agents. The interaction process is based on the current behavior states of the two agents, and according to the interaction rules specified in the Interaction Rules Table, it updates the friendship relationship between the two agents.
        Aj=nx.to_numpy_array(self.G, weight='weight')
        self.last_aj_matrix = copy.deepcopy(Aj) # Record the adjacency matrix of the current social network graph before the interaction process.
        sn = 1.8 # parameter c in Interaction Rules Table.
        hm = 1 # parameter b in Interaction Rules Table
        nm = 0.5 # parameter a in Interaction Rules Table
        Node_groups = self.node_group_matrix()
        for i in range(self.num_agents):
            for j in range(i + 1, self.num_agents):
                if j in Node_groups[i]:
                    a = self.Agent_List[i]
                    b = self.Agent_List[j]
                    if a.state == 0 or b.state == 0:
                        if a.state == 0 and b.state == 0:
                            Aj[i][j] += sn + sn
```

```
                        elif a.state == 1 or b.state == 1:
                            Aj[i][j] += sn + hm
                        elif a.state == 2 or b.state == 2:
                            Aj[i][j] = 0
                        elif a.state == 3 or b.state == 3:
                            Aj[i][j] = 0
                    elif a.state == 1 or b.state == 1:
                        if a.state == 1 and b.state == 1:
                            Aj[i][j] += hm + hm
                        elif a.state == 2 or b.state == 2:
                            Aj[i][j] = 0
                        elif a.state == 3 or b.state == 3:
                            Aj[i][j] += nm +nm
                    elif a.state == 2 or b.state == 2:
                        if a.state == 2 and b.state == 2:
                            Aj[i][j] += hm + hm
                        elif a.state == 3 or b.state == 3:
                            Aj[i][j] += hm + hm
                    elif a.state == 3 and b.state == 3:
                        Aj[i][j] += hm + hm
                    Aj[j][i] = Aj[i][j]
                else:
                    pass
        self.G = nx.from_numpy_array(Aj, create_using=nx.Graph) # Update the social network graph after pairwise interactions.

    def cal_bonding_capital(self): #The cal_bonding_capital() function is used to calculate the social capital values that each agent currently receives from their first-order neighbors.
        A = nx.to_numpy_array(self.G, weight='weight')
```

```
        row_sums = np.sum(A, axis=1)
        with np.errstate(divide='ignore', invalid='ignore'):
            new_array = np.where(row_sums[:, np.newaxis] == 0, 0, A / row_sums[:, np.newaxis])
        col_sums = np.sum(new_array, axis=0)
        return col_sums

    def cal_mixed_social_capital(self):    #Call the cal_bonding_capital() function to calculate the social capital values of agents, and convert the returned value (np.array) into a list.
        mixed_social_capital_list=[]
        bondc_array = self.cal_bonding_capital()
        mixed =    bondc_array
        mixed_social_capital_list = mixed.tolist()
        return mixed_social_capital_list

    def record_social_capital(self):#Record the current social capital list in a queue container. social_capital_trajectory is a queue container with a length of 2, containing the social capital data of the agents for the current round and the social capital data from the previous round.
        i_sc = self.cal_mixed_social_capital()
        self.social_capital_trajectory.append(i_sc)

    def record_initial_social_capital(self): #The record_initial_social_capital() function is used to record the initial social capital values of all agents objects for subsequent data analysis.
        sc_list = self.cal_mixed_social_capital()
        count = 0
        for i in self.Agent_List:
            i.initial_social_capital = sc_list[count]
```

```
            count += 1

    def record_accumulat_social_capital(self): #The record_accumulated_social_capital() function is used to record the accumulated social capital values of all agent objects for subsequent data analysis.
        sc_list = self.social_capital_trajectory[-1]
        count = 0
        for i in self.Agent_List:
            i.accumulate_social_capital += sc_list[count]
            count += 1

    def get_reward(self): ##The get_reward() function calls the record_social_capital function to record the current social capital
        self.record_social_capital()
        self.record_accumulat_social_capital()
        self.reward_list = []
        for i in range(self.num_agents):
            if len(self.social_capital_trajectory)>1:
                reward= self.social_capital_trajectory[1][i]
                self.reward_list.append(reward)
            else:
                self.reward_list=[0]*self.num_agents

        record_step_reward =[] #Iterate through all agents, record the behavior state of each agent in this round and the corresponding social capital gains for subsequent data analysis
        for j in range(Agent_number):
            ag_re =[]
            ag = self.Agent_List[j]
            ag_re.append(ag.state)
```

```
            ag_re.append(self.reward_list[j])
            record_step_reward.append(ag_re)
        self.record_reward.append(record_step_reward)

        record_move = [] #Iterate through all agents, record the following data for each agent in this round for subsequent data analysis:
        for k in self.Agent_List:
            ag_move_re =[]
            ag_move_re.append(k.ID)# 1.agent's ID
            ag_move_re.append(self.step_count) # 2.The current round number of the current game.
            last_act= self.recent_action[k.ID]
            ag_move_re.append(last_act) #3.The behavior state of the previous round.
            ag_move_re.append(k.state) #4.The behavior state of the current round.
            move_type =0
            if last_act == 0 and k.state == 0:
                move_type =0
            elif last_act == 0 and k.state == 1:
                move_type =1
            elif last_act == 1 and k.state == 0:
                move_type =2
            elif last_act == 1 and k.state == 1:
                move_type =3
            elif last_act == 1 and k.state == 3:
                move_type =4
            elif last_act == 3 and k.state == 1:
                move_type =5
            elif last_act == 3 and k.state == 3:
```

```
                move_type =6
            elif last_act == 3 and k.state == 2:
                move_type =7
            elif last_act == 2 and k.state == 3:
                move_type =8
            elif last_act == 2 and k.state == 2:
                move_type =9
            ag_move_re.append(move_type)#5.The behavior state transition type of the agent in this round.
            ag_move_re.append(self.social_capital_trajectory[0][k.ID]) #6. Record the social capital of the agent in the previous round.
            sum_sc = sum(self.social_capital_trajectory[0])
            len_sc = len(self.social_capital_trajectory[0])
            ave_sc = sum_sc/len_sc
            ag_move_re.append(self.social_capital_trajectory[0][k.ID] - ave_sc) #7. Record the deviation of the social capital of the agent from the overall average social capital in the previous round.
            ag_move_re.append(self.social_capital_trajectory[1][k.ID]) #8. Record the social capital of the agent in the current round.
            ag_move_re.append(self.social_capital_trajectory[1][k.ID] - self.social_capital_trajectory[0][k.ID]) #9. Record the change in social capital caused by the behavior state transition of the agent in this round.
            Gra= nx.from_numpy_array(self.last_aj_matrix, create_using=nx.Graph)
            ag_move_re.append(Gra.degree[k.ID]) #10 Record the number of first-order neighbors of the agent in this round.
            sc_source = [0]*4
            row_sums = np.sum(self.last_aj_matrix, axis=1)
            with np.errstate(divide='ignore', invalid='ignore'):
```

```
            new_array = np.where(row_sums[:, np.newaxis] == 0, 0, self.last_aj_matrix/ row_sums[:, np.newaxis])
        for i in range(self.num_agents):
            if new_array[i][k.ID] != 0:
                state = self.Agent_List[i].state
                sc_source[state] += new_array[i][k.ID]
            else:
                pass
        for j in sc_source:
            ag_move_re.append(j)    # 11 to 14: Record the sources of the agent's social capital, namely the values of social capital from first-order neighbors in state 1, state 2, state 3, and state 4.
        ag_move_re.append(row_sums[k.ID]) #15 Record the total sum of friendship relationship weights of the agent.
        if Gra.degree[k.ID] != 0:
            ave_weight = row_sums[k.ID]/Gra.degree[k.ID]
        else:
            ave_weight = 0
        ag_move_re.append(ave_weight) #16 Record the average friendship relationship weight of the agent.
        action_comformity = k.get_pre_comform()
        if action_comformity == k.state:
            action_comformity = 1
        else:
            action_comformity =0
        action_best_fri = k.get_pre_imi_best()
        if action_best_fri == k.state:
            action_best_fri = 1
        else:
            action_best_fri =0
```

```
            action_high_fre = k.get_pre_imi_highest()
            if action_high_fre == k.state:
                action_high_fre = 1
            else:
                action_high_fre =0
            ag_move_re.append(action_comformity)    #17 Record whether the agent's decision in this round conforms to the conformity strategy.
            ag_move_re.append(action_best_fri)    #18 Record whether the agent's decision in this round conforms to the imitation of best friend strategy.
            ag_move_re.append(action_high_fre) #19 Record whether the agent's decision in this round conforms to the imitation of highest social capital friend strategy.
            record_move.append(ag_move_re)
        self.record_change.append(record_move)
        return self.reward_list

    def cal_modularity(self): #The cal_modularity() function is used to calculate the modularity value of the current social network.
        node_types={}
        for i in self.Agent_List:
            if i.state ==2 or i.state ==3:
                node_types[i.ID] = 0
            elif i.state ==0:
                node_types[i.ID] = 1
            else:
                node_types[i.ID] = 2
        nx.set_node_attributes(self.G, node_types,"type")
        communities = {}
        for node in self.G.nodes():
            node_type = self.G.nodes[node]['type']
```

```
            if node_type not in communities:
                communities[node_type] = [node]
            else:
                communities[node_type].append(node)
        modularity = nx.algorithms.community.quality.modularity(self.G, list(communities.values()),weight ="weight")
        self.modularity.append(modularity)

    def get_sars_test(self):# Calling the get_sars_test() function will prompt agents to execute observation of the environment, make behavioral decisions, engage in pair interactions, and update the friendship network.
        self.cal_modularity()
        obv=self.get_obv()
        act_move=self.act_decision_test()
        act=act_move[0]
        move = act_move[1]
        self.update_agent_act()
        self.Update_Network()
        reward = self.get_reward()
        self.step_count += 1

    def draw(self): #The draw() function is used for visualization. If the ABM model is run for collecting simulation result data, the draw() function will not be called.
        for i in range(self.num_agents):
            a = self.Agent_List[i]
            self.G.nodes[i]["ID"]= i
            self.G.nodes[i]["action"]= a.state
            self.G.nodes[i]["SC"]= round(self.social_capital_trajectory[-1][i],1 )
        pos = nx.kamada_kawai_layout(self.G)
```

```
        cmap = ListedColormap(["g", "b","r", "y"])
        states=[]
        for i in range(self.num_agents):
            states.append(self.G.nodes[i]["action"])
        colors = [cmap(j) for j in states]
        nx.draw(self.G, pos, with_labels=True, node_color=colors)
        node_lables = {}
        for i in range(self.num_agents):
            node_attri={}
            node_attri["ID"] = self.G.nodes[i]["ID"]
            node_attri["SC"] = self.G.nodes[i]["SC"]
            node_lables[i]=node_attri
        nx.draw_networkx_labels(self.G, pos, labels=node_lables, alpha=0.5)
        plt.show()

    def report_state_num(self): #The report_state_num() function is used to calculate and record the number of agents in each behavior state in the social network.
        num_A=0
        num_B=0
        num_C=0
        num_D=0
        for i in self.Agent_List:
            if i.state == 0:
                num_A +=1
            elif i.state == 1:
                num_B += 1
            elif i.state ==2:
                num_C += 1
            elif i.state ==3:
```

```
                num_D += 1
        return num_A,num_B,num_C,num_D


class MyAgent():#MyAgent class defines agent objects, which include two attributes: the agent's unique ID and the agent's current behavior state.
    def __init__(self, unique_id, Model):
        self.ID = unique_id
        self.state= 1
        self.model = Model
        #The following attributes record the simulated data of the agent for data analysis.
        self.act_list = []
        self.move = 0
        self.strategy = [0]*num_stategy
        self.initial_social_capital = 0
        self.accumulate_social_capital = 0
        self.action_list = []
        self.num_drink = 0
        self.num_zero = 0
        self.num_one = 0
        self.num_two = 0
        self.num_three = 0

    def obv(self): ##The obv() function defines the information that an agent can observe about the social network environment, including the agent's own ID, the agent's current behavior state, the agent's current social capital, the friendship strength between the agent and all its first-order neighbors, and the current behavior state of all its first-order neighbors.
        G=np.array(nx.adjacency_matrix(self.model.G).todense())
```

```
obv_nei = G[self.ID]
obv_nei=obv_nei.tolist()
obv_id =[0]*Agent_number
obv_id[self.ID] = 1
ovb_self_act = [0] * 4
ovb_self_act[self.state] = 1
obv_act = []
for i in range(self.model.num_agents):
    if i == self.ID:
        obv_act.append(self.state)
    elif obv_nei[i] != 0:
        Agent = self.model.Agent_List[i]
        obv_act.append(Agent.state)
    elif obv_nei[i] == 0:
        obv_act.append(4)
count=0
dic={0:[1,0,0,0,0],1:[0,1,0,0,0],2:[0,0,1,0,0],3:[0,0,0,1,0],4:[0,0,0,0,1]}
for j in obv_act:
    obv_act[count]=dic[j]
    count +=1
obv_act = list(itertools.chain(*obv_act))
self_sc = 0
self_sc =    self.model.social_capital_trajectory[-1][self.ID]
observation= np.hstack(( obv_id,ovb_self_act, self_sc, obv_nei, obv_act))

observation=observation.tolist()
return observation

```

```
    def select_action_test(self, obs):# The agent inputs the current observation into the Q-network, and the Q-network outputs the decision choice of the agent for this round.
        act_drink = 0
        obs=[obs]
        obs= torch.from_numpy(np.array(obs, dtype=np.float32))
        obs=obs.to(device)
        with torch.no_grad():
            Q=policy_network_test(obs).view([3]) #Input the current observation of agents into the deep Q-network. As this program is used for simulation experiments, agents will strictly follow decisions made based on the output of the deep Q-network.
        move = Q.max(0)[1].view(1,1).item()

        act_record = 0 #Based on the rules defined in the state transition table, determine and record the new behavior state of the agent.
        if self.state == 0 and move == 0:
            act_record = 0
        elif self.state == 0 and move == 1:
            act_record = 0
        elif self.state == 0 and move == 2:
            act_record = 1
        elif self.state == 1 and move == 0:
            act_record = 0
        elif self.state == 1 and move == 1:
            act_record = 1
        elif self.state == 1 and move == 2:
            act_record = 3
        elif self.state == 3 and move == 0:
            act_record = 1
```

```
        elif self.state == 3 and move == 1:
            act_record = 3
        elif self.state == 3 and move == 2:
            act_record = 2
        elif self.state == 2 and move == 0:
            act_record = 3
        elif self.state == 2 and move == 1:
            act_record = 2
        elif self.state == 2 and move == 2:
            act_record = 2
        action = act_record

        a=self.get_pred_act() #Obtain the new behavior state after making decisions using the conformity strategy, imitation of best friend strategy, and imitation of highest social capital friend strategy under the current observation.
        one_str = 0
        for i in range(num_stategy -1):
            if self.act_list[i] == action: # Compare the new state of the agent after making decisions following three classic strategies with the new state after making decisions under the control of the Q-network, and record their consistency.
                self.strategy [i] += 1
                one_str =1
            else:
                pass
        if one_str ==0: #If none of the three classic strategies predict correctly, it is recorded as the fourth strategy.
            self.strategy [num_stategy -1] += 1
        else:
            pass
        self.action_list.append(action)
```

```
        return move

    def get_pre_comform(self): #Calling get_pre_comform() function will obtain the new state of the agent after making decisions using the conformity strategy under the current observation.
        act_record = self.state
        num_cout =[0] * 4
        Neibor=list(self.model.G.neighbors(self.ID))
        for i in Neibor:
            Nei=self.model.Agent_List[i]
            if Nei.state== 0:
                num_cout[0] += 1
            elif Nei.state== 1:
                num_cout[1] += 1
            elif Nei.state== 2:
                num_cout[2] += 1
            elif Nei.state== 3:
                num_cout[3] += 1
        max_index = num_cout.index(max(num_cout))
        if self.state == 0:
            if max_index == 0:
                act_record = 0
            else:
                act_record =1
        elif self.state ==1:
            if max_index ==0:
                act_record = 0
            elif max_index ==1:
                act_record =1
            else:
```

```
                act_record =3
        elif self.state ==2:
            if max_index ==2:
                act_record ==2
            else:
                act_record =3
        elif self.state ==3:
            if max_index ==2:
                act_record =2
            elif max_index ==3:
                act_record =3
            else:
                act_record =1
        return act_record

    def get_pre_imi_best(self): #Calling get_pre_imi_best() function will obtain the new state of the agent after making decisions using the imitation of best friend strategy under the current observation.
        act_record =    self.state
        Mat = nx.to_numpy_array(self.model.G, weight='weight')
        Fri= Mat[self.ID]
        max_index = np.where(Fri == np.max(Fri))[0]
        random_max_index = np.random.choice(max_index)
        Nei=self.model.Agent_List[random_max_index]
        max_index = Nei.state
        if self.state == 0:
            if max_index == 0:
                act_record = 0
            else:
                act_record =1
```

```
        elif self.state ==1:
            if max_index ==0:
                act_record = 0
            elif max_index ==1:
                act_record =1
            else:
                act_record =3
        elif self.state ==2:
            if max_index ==2:
                act_record ==2
            else:
                act_record =3
        elif self.state ==3:
            if max_index ==2:
                act_record =2
            elif max_index ==3:
                act_record =3
            else:
                act_record =1
        return act_record

    def get_pre_imi_highest(self): #Calling get_pre_imi_highest() will obtain the new state of the agent after making decisions using the imitation of highest social capital friend strategy under the current observation.
        act_record = self.state
        max_index = 0
        social_capital_dic = {}
        Neibor =   list(self.model.G.neighbors(self.ID))
        sc_list = self.model.social_capital_trajectory [-1]
        if not Neibor:
```

```
            pass
        else:
            for j in Neibor:
                social_capital_dic[j]= sc_list[j]
            max_fri_id = max(social_capital_dic, key=social_capital_dic.get)
            Nei=self.model.Agent_List[max_fri_id]
            max_index = Nei.state
        if self.state == 0:
            if max_index == 0:
                act_record = 0
            else:
                act_record =1
        elif self.state ==1:
            if max_index ==0:
                act_record = 0
            elif max_index ==1:
                act_record =1
            else:
                act_record =3
        elif self.state ==2:
            if max_index ==2:
                act_record ==2
            else:
                act_record =3
        elif self.state ==3:
            if max_index ==2:
                act_record =2
            elif max_index ==3:
                act_record =3
            else:
```

```
            act_record =1
        return act_record

    def get_pred_act(self):
        self.act_list = []
        self.act_list.append( self.get_pre_comform())
        self.act_list.append( self.get_pre_imi_best())
        self.act_list.append( self.get_pre_imi_highest())

    def count_num_zero(self): #Record the number of rounds in which the agent is in behavior state 1 in this game.
        num_a = 0
        for i in self.action_list:
            if i == 0 :
                num_a +=1
        self.num_zero = num_a

    def count_num_one(self): #Record the number of rounds in which the agent is in behavior state 2 in this game.
        num_a = 0
        for i in self.action_list:
            if i == 1 :
                num_a +=1
        self.num_one = num_a

    def count_num_two(self): #Record the number of rounds in which the agent is in behavior state 3 in this game.
        num_a = 0
        for i in self.action_list:
            if i == 2 :
```

```
                num_a +=1
        self.num_two = num_a

    def count_num_three(self): #Record the number of rounds in which the agent is in behavior state 4 in this game.
        num_a = 0
        for i in self.action_list:
            if i == 3 :
                num_a +=1
        self.num_three = num_a

    def count_num_drink(self): #Record the number of rounds in which the agent drinks alcohol (is in state 1 or state 2) in this game.
        num_a = 0
        for i in self.action_list:
            if i == 0 or i == 1:
                num_a +=1
        self.num_drink = num_a


device = torch.device("cuda" if torch.cuda.is_available() else "cpu") #Use CUDA for tensor computation.
class DQN(nn.Module): #Create a neural network class.
    def __init__(self, obs_dim, act_dim):
        super(DQN, self).__init__()

        self.rnn = nn.GRU(obs_dim, 128,1,batch_first = True)
        self.fc1 = nn.Linear(128, 512)
        self.fc2 = nn.Linear(512, 256)
        self.fc3 = nn.Linear(256, 128)
```

```
        self.fc4 = nn.Linear(128, 64)
        self.fc5 = nn.Linear(64,act_dim)

        for m in self.modules():
            if isinstance(m, nn.Linear):
                nn.init.kaiming_uniform_(m.weight)
                nn.init.zeros_(m.bias)
            elif isinstance(m, nn.RNN):
                nn.init.kaiming_uniform_(m.weight_ih_l0)
                nn.init.orthogonal_(m.weight_hh_l0)
                nn.init.zeros_(m.bias_ih_l0)
                nn.init.zeros_(m.bias_hh_l0)

    def forward(self, x , hidden =None):
        x=x.to(device)
        seq=seq_size
        if len(x.shape) == 2:
            x=x.view([1,1,obs_dim])
            seq = 1
        else:
            pass
        if not hidden:
            hidden=torch.zeros([1,seq,128]).to(device)
        out,h =self.rnn(x,hidden)
        x = F.relu(self.fc1(out))
        x = F.relu(self.fc2(x))
        x= F.relu(self.fc3(x))
        x= F.relu(self.fc4(x))
        x= self.fc5(x)

```

```
        if seq ==1:
            x=x.view(-1,act_dim)
        else:
            pass
        return x

#Below is the main program of the ABM.
Agent_number=60  # The parameter "Agent_number" describes the number of agents in the environment.
env=Model(Agent_number) # Instantiate an environment object containing 60 agents.
seq_size=1
num_stategy = 4 #There are 4 behavior states for agents.
obs_dim= 7 * Agent_number +5
act_dim = 3
policy_network_test=DQN(obs_dim,act_dim).to(device)
policy_network_test.load_state_dict(torch.load("D:/python_doc/DQN_training_data.pth" )) #Import well-trained parameters of the deep Q-network.
step_each_game = 60 ## Each complete game consists of 60 rounds(steps).
count_network = 0 #Counter to record which game iteration (simulation experiment) it is currently.

for i in range(500): #A total of 500 simulation experiments will be conducted.
    env.reset()
    Rec=[]
    record_initial_social_capital= env.record_initial_social_capital()
    for j in range(step_each_game):
        env.get_sars_test()

```

```
    #Calculate the proportion of agents who identify with the drinking culture at the end of each game, and record it.
    num_sn_end = 0
    for i in  env.Agent_List:
        if i.state == 0 :
            num_sn_end += 1
        else:
            pass
    sn_prop_end = num_sn_end /Agent_number
    Rec.append(sn_prop_end)

    #Calculate the proportion of agents in the network who accept drinking behavior at the end of the game, and record it.
    num_dk_end = 0
    for i in  env.Agent_List:
        if i.state == 0 or i.state == 1:
            num_dk_end += 1
        else:
            pass
    dk_prop_end = num_dk_end /Agent_number
    Rec.append(dk_prop_end)

    # Calculate the network modularity at the end of this game and record it.
    communities_1 = list(greedy_modularity_communities(env.G))
    mod_1 = modularity(env.G, communities_1, weight = "weight")
    Rec.append(mod_1)

    #The ABM simulation experiment code ends here. The following code is used to record and store the results of the simulation experiment.

```

```
    #Create a CSV file to store individual-level data.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/AgentData.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        for i in env.Agent_List:
            agent_data_list = i.strategy #The first 4 rows represent the frequencies of correct predictions by each classic strategy.
            agent_data_list.append(i.initial_social_capital) #The 5th row represents the initial social capital of the agent.
            ave_social_capital = i.accumulate_social_capital/(step_each_game+1)
            agent_data_list.append(ave_social_capital) #The 6th row represents the average social capital of the agent.
            final_social_capital = env.social_capital_trajectory[-1][i.ID]#The 7th row represents the final social capital of the agent.
            agent_data_list.append(final_social_capital)

            i.count_num_zero()
            agent_data_list.append(i.num_zero) #The 8th row represents the number of rounds in which the agent is in behavior state 1 in this game.

            i.count_num_one()
            agent_data_list.append(i.num_one) #The 9th row represents the number of rounds in which the agent is in behavior state 2 in this game.

            i.count_num_two()
            agent_data_list.append(i.num_two) #The 10th row represents the number of rounds in which the agent is in behavior state 3 in this game.

            i.count_num_three()
```

```
            agent_data_list.append(i.num_three) #The 11th row represents the number of rounds in which the agent is in behavior state 4 in this game.

            i.count_num_drink()
            agent_data_list.append(i.num_drink)#The 12th row represents the number of rounds in which the agent is in drinking state (state 1 or state 2) in this game.
            agent_data_list.insert(0, count_network)
            write.writerow(agent_data_list)

    #Create a CSV file to store the proportion of agents accepting drinking behavior in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/drinking_rate.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            for j in i:
                if j[0] == 0 or j[0]== 1:
                    count += 1
                else:
                    pass
            ave_drinking_rate = count/Agent_number
            ave_accept.append(ave_drinking_rate)
        ave_accept.insert(0,0)
        write.writerow(ave_accept)

    #create a CSV file to store the average social capital data of agents    accepting drinking behavior in each round of the game.
```

```python
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/drink_reward.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_drink = []
        for i in env.record_reward:
            count = 0
            sum_drink = 0
            for j in i:
                if j[0] == 0 or j[0]== 1:
                    sum_drink += j[1]
                    count += 1
                else:
                    pass
            if count == 0:
                ave =0
            else:
                ave=sum_drink/count
            ave_drink.append(ave)
        ave_drink.insert(0,0)
        write.writerow(ave_drink)

    #Create a CSV file to store the proportion of agents not accepting drinking behavior in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/not_drinking_rate.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            for j in i:
```

```
            if j[0] == 2 or j[0]== 3:
                count += 1
            else:
                pass
        ave_drinking_rate = count/Agent_number
        ave_accept.append(ave_drinking_rate)
    ave_accept.insert(0,1)
    write.writerow(ave_accept)

#create a CSV file to store the average social capital data of agents who refuse to drink alcohol in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/not_drink_reward.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    ave_not_drink = []
    for i in env.record_reward:
        count = 0
        sum_not_drink = 0
        for j in i:
            if j[0] == 2 or j[0]== 3:
                sum_not_drink += j[1]
                count += 1
            else:
                pass
        if count == 0:
            ave =0
        else:
            ave=sum_not_drink/count
        ave_not_drink.append(ave)
    total = sum(env.initial_sc)
```

```
    mean = total / len(env.initial_sc)
    ave_not_drink.insert(0,mean)
    write.writerow(ave_not_drink)

#Create a CSV file to store the proportion of agents in state 1 in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/accept_drinking_rate.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    ave_accept = []
    for i in env.record_reward:
        count = 0
        for j in i:
            if j[0] == 0:
                count += 1
            else:
                pass
        ave_drinking_rate = count/Agent_number
        ave_accept.append(ave_drinking_rate)
    ave_accept.insert(0,0)
    write.writerow(ave_accept)

#Create a CSV file to store the average social capital value of agents in state 1 in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_zero_reward.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    ave_drink = []
    for i in env.record_reward:
        count = 0
```

```
            sum_drink = 0
            for j in i:
                if j[0] == 0:
                    sum_drink += j[1]
                    count += 1
                else:
                    pass
            if count == 0:
                ave =0
            else:
                ave=sum_drink/count
            ave_drink.append(ave)
        ave_drink.insert(0,0)
        write.writerow(ave_drink)

    #Create a CSV file to store the proportion of agents in state 2 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_one_rate.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            for j in i:
                if j[0] == 1:
                    count += 1
                else:
                    pass
            ave_drinking_rate = count/Agent_number
            ave_accept.append(ave_drinking_rate)
```

```
        ave_accept.insert(0,0)
        write.writerow(ave_accept)

    #Create a CSV file to store the average social capital value of agents in state 2 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_one_reward.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_drink = []
        for i in env.record_reward:
            count = 0
            sum_drink = 0
            for j in i:
                if j[0] == 1:
                    sum_drink += j[1]
                    count += 1
                else:
                    pass
            if count == 0:
                ave =0
            else:
                ave=sum_drink/count
            ave_drink.append(ave)
        ave_drink.insert(0,0)
        write.writerow(ave_drink)

    #Create a CSV file to store the proportion of agents in state 3 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_two_rate.csv", "a",encoding="utf-8", newline="") as f:
```

```
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            for j in i:
                if j[0] == 2:
                    count += 1
                else:
                    pass
            ave_drinking_rate = count/Agent_number
            ave_accept.append(ave_drinking_rate)
        ave_accept.insert(0,0)
        write.writerow(ave_accept)

    #Create a CSV file to store the average social capital value of agents in state 3 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_two_reward.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            sum_accept = 0
            for j in i:
                if j[0] == 2:
                    sum_accept += j[1]
                    count += 1
                else:
                    pass
            if count == 0:
```

```
                ave =0
            else:
                ave=sum_accept/count
            ave_accept.append(ave)

        ave_accept.insert(0,0)
        write.writerow(ave_accept)

    #Create a CSV file to store the proportion of agents in state 4 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_three_rate.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        ave_accept = []
        for i in env.record_reward:
            count = 0
            for j in i:
                if j[0] == 3:
                    count += 1
                else:
                    pass
            ave_drinking_rate = count/Agent_number
            ave_accept.append(ave_drinking_rate)
        ave_accept.insert(0,1)
        write.writerow(ave_accept)

    #Create a CSV file to store the average social capital value of agents in state 4 in each round of the game.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/action_three_reward.csv", "a",encoding="utf-8", newline="") as f:
```

```
    write=csv.writer(f)
    ave_accept = []
    for i in env.record_reward:
        count = 0
        sum_accept = 0
        for j in i:
            if j[0]== 3:
                sum_accept += j[1]
                count += 1
            else:
                pass
        if count == 0:
            ave =0
        else:
            ave=sum_accept/count
        ave_accept.append(ave)
    total = sum(env.initial_sc)
    mean = total / len(env.initial_sc)
    ave_accept.insert(0,mean)
    write.writerow(ave_accept)

#Create a CSV file to store the modularity values of the social network in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/modularity.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    env.cal_modularity()
    write.writerow(env.modularity)

```

```
    #Create a CSV file to store the type of state transition for each round of the game, and the resulting changes in social capital for the agent after 5 rounds and 10 steps.
    with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/change_record.csv", "a",encoding="utf-8", newline="") as f:
        write=csv.writer(f)
        for i in env.record_change:
            for j in i:
                j.insert(0,count_network)
                agent_id = j[1]
                cur_step = j[2]
                cur_sc = j[6]
                cur_step_five = 0
                cur_step_ten = 0
                if cur_step < 50:
                    cur_step_five = cur_step + 5
                    cur_step_ten = cur_step +10
                elif cur_step < 55:
                    cur_step_five = cur_step + 5
                    cur_step_ten = 59
                else:
                    cur_step_five =59
                    cur_step_ten = 59
                social_capital_five = env.record_reward[cur_step_five][agent_id][-1]
                social_capital_ten = env.record_reward[cur_step_ten][agent_id][-1]
                social_capital_gap_five = social_capital_five - cur_sc
                social_capital_gap_ten = social_capital_ten - cur_sc
                j.append(social_capital_five)
                j.append(social_capital_ten)
```

```
            j.append(social_capital_gap_five)
            j.append(social_capital_gap_ten)
            write.writerow(j)

#Create a CSV file to store the social capital values obtained by each agent in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/social_capital.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    sc_rec = []
    for i in env.record_reward:
        acc_sc = 0
        for j in i:
            acc_sc += j[-1]
        sc_rec.append(acc_sc)
    total = sum(env.initial_sc)
    sc_rec.insert(0,total)
    sc_rec_mean = [x / Agent_number for x in sc_rec]
    write.writerow(sc_rec_mean)

#Create a CSV file to store the coefficient of variation of social capital distribution among agents in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/social_capital_dvindex.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    sc_dv_rec = []
    for i in env.record_reward:
        each_sc = []
        for j in i:
            each_sc.append(j[-1])
```

```
        mean_bc = sum(each_sc) / len(each_sc)
        std_dev_bc = statistics.stdev(each_sc)
        coefficient_of_variation_bc = (std_dev_bc / mean_bc) * 100
        sc_dv_rec.append(coefficient_of_variation_bc)
    step_zero = sum(env.initial_sc) / len(env.initial_sc)
    std_dev_step_zero = statistics.stdev(env.initial_sc)
    coefficient_of_variation_bc = (std_dev_step_zero / step_zero) * 100
    sc_dv_rec.insert(0,coefficient_of_variation_bc)
    write.writerow(sc_dv_rec)

#Create a CSV file to store the standard deviation of social capital distribution among agents in each round of the game.
with open("D:/python_doc/DQN_test/DQN_training_data/reward_record/social_capital_stdev.csv", "a",encoding="utf-8", newline="") as f:
    write=csv.writer(f)
    sc_dv_rec = []
    for i in env.record_reward:
        each_sc = []
        for j in i:
            each_sc.append(j[-1])
        std_dev_bc = statistics.stdev(each_sc)
        sc_dv_rec.append(std_dev_bc)
    std_dev_step_zero = statistics.stdev(env.initial_sc)
    sc_dv_rec.insert(0,std_dev_step_zero)
    write.writerow(sc_dv_rec)
```