Goal Strength in Consumer Service Settings: Role of Hyper-personalisation and Privacy Framing

SAMAR HICHAM AOUN

Goal Strength in Consumer Service Settings: Role of Hyper-personalisation and Privacy Framing

A Longitudinal Experimental Study in a Telecommunications and Entertainment Service Setting

Durham University
Business School

Presented by: *Samar Aoun*

Supervised by: *Professor Mike Nicholson*

Department of Marketing and Management

Thesis in fulfilment of the requirements for the degree of Doctor of Philosophy in Management

August 5th, 2025

Abstract

Purpose – This study adopts a **Consumer-Dominant Logic (CDL)** perspective to investigate how higher levels of goal-aligned hyper-personalisation influence consumer goal strength over time. Unlike the provider-driven Service-Dominant Logic (SDL), CDL emphasises *consumer agency*, *life contexts*, and *value formation alignment*. This study reframes personalisation from what service providers deliver to how consumers interpret and assign value based on their active life goals and lived experiences. The core aim is to examine whether dynamically generated hyper-personalised content - aligned with consumer goals - enhances motivational engagement across time and under varying privacy framing conditions.

Design/methodology/approach – A **three-wave longitudinal discrete choice experiment (DCE)** was conducted with **1,434** consumers in a Telecommunications and Entertainment AI-enabled service context. Participants selected dynamically constructed content across four progressive hyper-personalisation levels, with **Cluster 4** reflecting highest goal alignment. Respondents were randomly assigned to either **neutral** or **negative privacy framing** groups. Three **Linear Mixed Models (LMMs)** tested the two main hypotheses: (1) the overall impact of hyper-personalisation on consumer goal strength (across between-person and within-person levels), and (2) the moderating role of privacy framing. A post-hoc model explored perceived importance of hyper-personalisation as a psychological factor.

Findings – Both hypotheses were **supported**. Higher levels, goal-aligned hyper-personalisation significantly strengthened consumer goal pursuit, especially when aligned with consumer's active life goals. Neutral privacy framing showed short-term boosts requiring reinforcement over time; negative framing revealed delayed recovery, with motivational resilience once privacy concerns dissipate. Findings confirm hyper-personalisation's multi-dimensional nature and privacy framing's moderating role. Post-hoc analysis showed perceived importance's influence on goal alignment.

Originality/value – This study contributes a novel **CDL-based** behavioural lens, **empirically** linking goal congruence with sustained motivational engagement over time and context. It advances hyper-personalisation literature by validating person-centered, context-aware strategies for consumer engagement. Findings inform privacy-conscious, adaptive implementation of hyper-personalised services.

Keywords – Hyper-personalisation, Goal-aligned personalisation, Consumer-Dominant Logic (CDL), Goal strength, Privacy framing, Motivation, Longitudinal modelling, Consumer engagement

Statement of Copyright

Acknowledgement

I would like to express my deepest appreciation to my supervisor Professor Mike Nicholson for sharing his valuable knowledge, advice, and guidance throughout my PhD journey, for without whom, this project would have never transpired.

I am also grateful to all the staff members at Durham Postgraduate Office for their patience in always responding to and providing answers to all my needs and concerns during my PhD studies. Thank you for your dedication and commitment to the success of every Durham student.

I would also like to thank my husband and my two daughters for their generous love and support throughout my period of study. You were always there for me, every step of the way, at the expense of time spent with you and, for that, I will ever be so grateful. Finally, I would like to thank my parents for encouraging me when things at work and home got out of hand. Your presence was vital to further believe in my abilities.

Samar Hicham Aoun

Table of Contents

List of Figures

List of Tables

Appendices Figures

Appendices Tables

Abbreviations

Abbreviation	Term	Page Number
AI	Artificial Intelligence	Page 11
ANOVA	Analysis of Variance	Page 190
ANCOVA	Analysis of Covariance	Page 190
C2C	Consumer-to-Consumer	Page 54
CCPA	California Consumer Privacy Act	Page 47
CDL	Consumer-Dominant Logic	Page 13
DCE	Discrete Choice Experiment	Page 19
DCM	Discrete Choice Modelling	Page 126
GDPR	General Data Protection Regulation	Page 47
GLMM	Generalised Linear Mixed Model	Page 21
HCI	Human–Computer Interaction	Page 40
IGCM	Individual Growth Curve Modelling	Page 20
LMM	Linear Mixed Model	Page 21
MANOVA	Multivariate Analysis of Variance	Page 190
ML	Machine Learning	Page 27
NLP	Natural Language Processing	Page 27
PDL	Product-Dominant Logic	Page 50
REML	Restricted Maximum Likelihood	Page 180
rmANOVA	Repeated Measures Analysis of Variance	Page 195
SDL	Service-Dominant Logic	Page 51
SDT	Self-Determination Theory	Page 39
TAM	Technology Acceptance Theory	Page 37
XAI	Explainable Artificial Intelligence	Page 89

Chapter 1 – Introduction

1. Chapter 1 - Introduction

1.1 Introduction

Personalised consumer experiences stand today as a key success factor for competitive advantage in digital service ecosystems, attracting sustained academic and managerial interest (Hardcastle et al., 2025; Sipos, 2025; Rafieian and Yoganarasimhan, 2023). The exponential growth in consumer data availability has enabled service providers to personalise their offerings with unprecedented precision, driving significant investments in Artificial Intelligence (AI) technologies designed to enhance value creation, consumer satisfaction, and engagement (Ajiga et al., 2024; Balasubramanian, 2024; Nwanna et al., 2025; Xia et al., 2024).

AI-enabled recommendation systems, integral to major digital platforms such as Netflix and Amazon, tailor offerings based on diverse behavioural and preference data, demonstrating strong behavioural outcomes. Netflix's recommendation engine accounts for 80% of viewer engagement, reflecting sustained consumer interaction (Huang and Rust, 2021; Harshavardhan et al., 2024). Amazon's AI-enabled system predicts purchases with up to 85% accuracy (Ramachandran et al., 2025). Similar strategies are applied across streaming, e-commerce, and social media platforms – such as YouTube and Hulu, enabling large-scale delivery of customised content and improving consumer engagement (Rafieian and Yoganarasimhan, 2023; Mu and Wu, 2023; Niu et al., 2025).

One major advancement in this space is **hyper-personalisation** – leveraging Artificial Intelligence (AI) to integrate real-time, behavioural, contextual, and psychographic data into highly tailored service experiences. This has led to enhanced digital engagement and consumer satisfaction (Desai, 2022; Payne et al., 2021; Rosenbaum et al., 2017, 2021; Weber and Schütte, 2019). Unlike traditional personalisation models that categorise users by static traits such as age or location, hyper-personalisation dynamically adapts to user behaviours, enabling firms to deliver highly relevant content that enhances perceived relevance (Patnaik, 2022; Fang et al., 2025; Ramachandran et al., 2025). AI-enabled recommendation systems predict consumer behaviour by analysing both historical and real-time data, facilitating proactive and context-aware engagement (Ford et al., 2023). Studies show that hyper-personalisation improves engagement and long-term consumer value, with AI-driven campaigns yielding up to 30% more engagement compared to generic targeting (Babatunde et al., 2024; Krishna and Prathapkumar, 2024; Ramachandran et al., 2025).

Beyond engagement, hyper-personalisation fosters interactive value creation by enabling co-creation and adaptive content delivery (Payne et al., 2021; Thomaz et al., 2020). However, these benefits may come at the expense of consumer autonomy, particularly when irrelevant or excessive recommendations conflict with evolving consumer preferences (Gil de Zúñiga et al., 2024; Obiegbu and Larsen, 2024). Concerns around data privacy, misuse, and the intrusiveness of AI-enabled systems emphasise the need to balance personalisation-driven engagement with perceived consumer control (Kumar et al., 2024; Paschen et al., 2020).

In their efforts to influence consumer choices through AI-enabled "*relevant or irrelevant*" data capture, service providers are increasingly pushing the boundaries of consumer data disclosure. While hyper-personalisation aims to enhance engagement, it can simultaneously undermine consumers' autonomy and perceived control, particularly through opaque AI-driven algorithmic targeting (Acquisti et al., 2020; Puntoni et al., 2021; Vimalkumar et al., 2021). At the same time, advances in digital technologies have empowered consumers to reshape value creation, *consciously or unconsciously assigning* subjective meaning to service encounters that may remain invisible to service providers (Nöjd et al., 2020; Rosenbaum et al., 2017; 2021). This duality positions consumers as active co-creators of value, whose experiences and goal-directed behaviours shape how they interpret and respond to AI-enabled personalisation (Lipkin and Heinonen, 2022; Heinonen and Strandvik, 2018, 2022; Čaić et al., 2025).

This shift from *provider-defined* engagement to *consumer-shaped* meaning-making is central to the **Consumer-Dominant Logic (CDL)** perspective, which frames the theoretical foundation of this study. The CDL paradigm argues that provider-defined utility fails to capture consumers' subjective interpretations, evolving experiences, and empowered agency in co-creating value. In this view, value is no longer transactional but continuously constructed through consumers' ongoing life goals, psychological framing, and contextual salience (Heinonen and Strandvik, 2022; Heinonen and Lipkin, 2022). Theories of goal systems and reasoned goal pursuit suggest that individual behaviour is driven by salient, context-specific goals that evolve over time, shaping how consumers evaluate and engage with personalised content (Ajzen and Schmidt, 2020; Kruglanski et al., 2018; Fan et al., 2020). Within this temporal and empowering lens, AI-enabled hyper-personalisation provides a mechanism for observing how dynamic, goal-aligned experiences unfold across time – with *time* being a central conceptual element in CDL. Yet, a persistent misalignment remains between the influence exerted by service providers and what empowered consumers perceive as meaningful or beneficial. Addressing this gap, the current study applies CDL to examine how AI-enabled hyper-personalisation aligns with *consumers' life goals* and *goal strength trajectories* over time – an area that remains underexplored in both theory and practice.

While AI-enabled hyper-personalisation has received increasing scholarly attention, several conceptual and empirical gaps remain. Most hyper-personalisation research continues to adopt a *system-centric* view — prioritising algorithmic optimisation, behavioural prediction, and short-term engagement outcomes (Wang et al., 2025a; Zhu et al., 2023). Even goal-oriented approaches often overlook how consumers internalise and assign meaning to personalisation within the broader context of their ongoing life goals and psychological framings (Jayasinghe and Kasthurirathna, 2022; Zhu et al., 2023; Wang et al., 2025a; 2025b). Integrating longitudinal and context-sensitive perspectives within real-world consumer ecosystems remains underexplored.

A recent study by Teepapal (2025) applied the Stimulus–Organism–Response (S-O-R) framework to examine AI-personalised content in social media. Despite expectations, the study found no significant effects, revealing the limitations of treating personalisation as a one-time external stimulus. In contrast, this study views hyper-personalisation as a co-evolving experience embedded within consumers' ongoing life narratives — attuned to their motivations, psychological responses, and evolving goals. By capturing how personalisation unfolds over time, this approach produced significant engagement effects and insights than the ones observed in static, stimulus-response models.

This study addresses these gaps by examining hyper-personalisation as a *dynamic*, *goal-aligned*, and *time-embedded* process that captures both inter-individual and intra-individual variations in consumer goal strength over time. This approach reflects the Consumer-Dominant Logic (CDL) perspective, where value is not merely delivered by providers but co-created with consumers based on subjective interpretations and personal goal trajectories (Heinonen and Strandvik, 2022; Lipkin and Heinonen, 2022).

Another limitation lies in the broad generalisation of inverted U-shaped models of personalisation, which suggests that moderate personalisation maximises engagement while excessive personalisation becomes intrusively counterproductive (Sun et al., 2025). Such models, however, overlook the individual and contextual variations in how consumers respond to personalisation over time. This study challenges this generalised assumption by demonstrating that consumer goal strength trajectories diverge based on temporal and psychological framing. Notably, consumers exposed to risk-framed stimuli showed delayed but stronger motivational recovery in later waves. This finding underscores the need for dynamic, individually tailored strategies that move beyond demographic and behavioural data to integrate psychological triggers and goal pursuit.

To address these challenges, service providers must shift their focus from static predictions to motivational insight — understanding both ***how*** and ***when*** hyper-personalised content supports evolving consumer goal pursuits. Aligning hyper-personalisation with dynamic life goals enables deeper consumer engagement and enhances the personal relevance of AI-enabled personalisation strategies. Yet, major gaps persist as existing literature rarely accounts for how hyper-personalisation interacts with psychological constructs such as goal salience, personal relevance, and privacy perception across time and contexts. Most studies rely on static models and cross-sectional data, limiting their capacity to capture temporal fluidity and multi-dimensional consumer responses (Mahadevan and Shainesh, 2024; Zhu et al., 2023). Consequently, there is an urgent call for empirical approaches that consider both *inter-* and *intra-individual* variability within dynamic, real-world service ecosystems.

Furthermore, recent research has raised concerns about the limitations of universal, top-down approaches that rely on population-level averages, particularly in domains requiring highly contextualised insights. In contrast, emerging studies advocate a *bottom-up*, *person-centered* paradigm that prioritises lived experiences, subjective interpretations, and contextual nuances of human behaviour (Hackney, 2024; Kaine and Stronge, 2024; Kuper et al., 2024; Talić et al., 2023; van Zyl and Dik, 2025). This shift aligns with calls for granular, dynamic modelling techniques – such as N-of-1 designs – that can capture how psychological cues and preferences fluctuate within individuals over time (Vieira et al., 2017; van Zyl and Dik, 2025).

Accordingly, this study adopts the Consumer-Dominant Logic (CDL) paradigm to examine how increasing levels of AI-enabled hyper-personalisation interact with goal strength, privacy salience, and contextual interpretation. To capture these dynamics, the study investigates both *inter-individual* and *intra-individual* variations in hyper-personalisation over time within multi-actor consumer ecosystems. It responds to identified calls in literature by employing a three-wave experimental design, testing how progressive clusters of hyper-personalised content – particularly those most goal-aligned – influence consumer goal strength. Findings reveal that higher levels of hyper-personalisation, when aligned with active life goals, foster deeper and more sustained motivational engagement.

The study further examines the moderating role of privacy framing, recognising that consumers' perceived control over their personal data can enhance or undermine the motivational effects of personalisation. Beyond testing the core hypotheses, the study also explores the perceived importance of hyper-personalisation as a psychological belief — one that, when endorsed by consumers, amplifies the motivational impact of goal-aligned personalised content over time. This post-hoc analysis offers deeper insight into how consumers' internal validation of hyper-personalisation reinforces long-term goal strength.

Together, these insights make a novel contribution by advancing a psychologically grounded, consumer-centric model of hyper-personalised service delivery. The study proposes a new trajectory for AI-enabled personalisation — one that is responsive, adaptive, and deeply embedded within consumers' lived experiences and evolving life goals. By integrating hyper-personalisation, goal theory, and privacy framing within the Consumer-Dominant Logic (CDL) paradigm, the study offers a comprehensive behavioural framework for researchers and service providers. This framework not only enhances predictive relevance but also fosters deeper and more sustained consumer engagement. Overall, these insights form the foundation of the study's theoretical, methodological, and practical contributions, outlined in *section 1.4*.

In the following sections, the terms *personalisation*, *AI-enabled personalisation,* and *hyper-personalisation* may be used interchangeably for narrative clarity. Unless otherwise specified, *personalisation* refers explicitly to AI-enabled hyper-personalisation. The next section outlines the specific research objectives that guide this investigation.

1.2 Research Objectives

The primary aim of this research is to investigate how higher levels of goal-aligned hyper-personalisation influences consumer goal strength over time, within an AI-enabled, multi-actor consumer ecosystem. Grounded in the Consumer-Dominant Logic (CDL) paradigm, this study moves beyond static, provider-centric approaches. Instead, it reframes personalisation through the lens of consumers' lived experiences, psychological framing, and evolving life goals.

While previous research on personalisation has often adopted linear, uniform, or immediate-effect models, this study advances a more nuanced understanding by utilising a **three-wave longitudinal experimental** design, within a multi-actor Telecommunications and Entertainment service context. This approach allows for a granular exploration of both stable, trait-level (*inter-individual*) and momentary, state-like (*intra-individual*) influences of hyper-personalisation on goal pursuit, while also incorporating dynamic temporal and psychological factors such as privacy framing and perceived importance. The study is situated within a multi-actor CDL consumer ecosystem, where hyper-personalisation arises from the interplay between *brand-oriented* actors (Telecommunications and Entertainment service providers in the context of the study), *individual-oriented*, and *social-oriented* consumer ecosystems. While the study empirically focuses on brand- and individual-oriented consumer ecosystems, the social-oriented consumer ecosystem is conceptually represented through approval-oriented goals (e.g., social recognition, family enjoyment) embedded in participants' self-selected active life goals. The study measures consumer goal strength across both individual- and social-oriented goals, although these goal types are not explicitly differentiated in the empirical model.

Despite the increasing prominence of AI-enabled personalisation, several important knowledge gaps exist in literature:

- **First**, existing studies largely focus on static or cross-sectional contexts. The *dynamic*, *longitudinal* evolution of hyper-personalisation — particularly in shaping consumer goal strength — remains significantly underexplored (Jayasinghe and Kasthurirathna, 2022; Zhu et al., 2023).
- **Second**, while the Consumer-Dominant Logic (CDL) paradigm has been examined conceptually and qualitatively, there is limited empirical studies applying it *quantitatively*, especially in technology-enabled environments (Lipkin and Heinonen, 2022; Nguyen and Menezes, 2024).
- **Third**, inclusion of *multi-actor* ecosystems in personalisation studies is rare, limiting insight into how brand-oriented, individual-oriented, and social-oriented consumer ecosystem actors jointly co-create value in service ecosystem settings.

By addressing these knowledge gaps, this study presents a comprehensive approach that integrates temporal, contextual, psychological, and actor-driven dimensions of hyper-personalisation over time.

Research Objectives

1. To examine how higher levels of goal-aligned hyper-personalisation influence consumer goal strength over time within dynamic, AI-enabled consumer ecosystems.
2. To explore the temporal and psychological mechanisms – including privacy framing and perceived importance of hyper-personalisation – in mediating or moderating its impact.

3. To assess both inter-individual (trait-like) and intra-individual (state-like) variations in consumer responses to hyper-personalisation.

4. To empirically apply and refine the three-actor constellation model of Consumer-Dominant Logic (CDL) ecosystems – which conceptualises value co-creation across three key actors: the **brand**, the **individual consumer**, and the broader **social context** (e.g., family, peers, society) - adapted from Heinonen and Lipkin (2022), by examining value formation dynamics between brand-, individual-, and social-oriented actors.

5. To contribute methodologically by employing a three-wave longitudinal experimental design, capturing sustained engagement and momentary fluctuations in consumer goal strength over time.

Research Questions

The central research question (RQ) guiding this study is:

***RQ: How does goal-aligned hyper-personalisation influence consumer goal strength* in AI-enabled, multi-actor consumer ecosystems *over time*?**

This core question is unpacked into the following sub-questions (RQ1 – RQ5):

- **RQ1**: To what extent does goal-aligned hyper-personalisation predict consumer goal strength across different points in time?

- **RQ2**: What is the role of privacy framing and the perceived importance of hyper-personalisation in moderating or mediating this relationship?

- **RQ3:** How do individual differences (trait-level) and momentary fluctuations (state-level) shape consumer responsiveness to hyper-personalisation?

- **RQ4:** How do brand-oriented, individual-oriented, and social-oriented actors in a Consumer-Dominant Logic (CDL) consumer ecosystem jointly contribute to consumer engagement and value formation?

- **RQ5:** What methodological insights can be drawn from applying a longitudinal experimental design with varying temporal proximities to study hyper-personalisation?

Toward achieving these objectives and answering the research questions, the study aims to explore how increasing the level of hyper-personalisation - particularly when aligned with consumers' active life goals – can influence consumer goal strength (*measured as a product of goal commitment and goal motivation*). This framing aligns with psychological theories suggesting that the pursuit and maintenance of a goal is highly dependent on sustained commitment and behavioural investment toward that goal (Bolos et al., 2022; Bonezzi et al., 2011; Etkin, 2019). Higher levels of goal strength reflect stronger alignment with consumer life goals, while diminished strength may signal reduced engagement or goal dissonance (Kivetz et al, 2006).

Based on the research objectives and underlying conceptual framework (refer to **Chapter 3**), the following hypotheses were formulated for empirical testing:

Hypothesis 1 (H1): *Higher levels of hyper-personalisation significantly increase consumer goal strength over time*

Hypothesis 2 (H2): *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

This research investigates how service providers can successfully utilise hyper-personalisation when designing and delivering services to their consumers in consumer service settings aimed at maximising value delivered to consumers (*goal strength*). Service providers can, hence, positively impact attainment of consumer life goals, influencing in turn consumer behaviour with goals acting as choice drivers.

1.3. Research Methodology

To address the central research question, this study adopts a **positivist quantitative experimental methodology**, underpinned by a **three-wave longitudinal Discrete Choice Experiment (DCE)** design. This approach investigates how increasing levels of goal-aligned hyper-personalisation influence consumer goal strength over time within an **AI-enabled**, **multi-actor consumer ecosystem**. Grounded in the Consumer-Dominant Logic (CDL) paradigm, the study emphasises consumers' lived experiences, psychological framing, life goals, and contextual interpretations as key mechanisms shaping value formation.

By employing repeated measures across time, the study captures both *between-individual (trait-like)* and *within-individual (state-like)* variations in responses to hyper-personalised content. This methodology enables a *temporally* and *contextually* sensitive examination of how hyper-personalisation evolves across time and context.

Methodologically, the design combines a **longitudinal discrete choice experiment (DCE)** with **repeated-measures** mixed modelling to analyse individual decision patterns over time. A **Generalised Linear Mixed Model (GLMM)** with a *multinomial logit link* was employed to estimate part-worth utilities across progressively deeper personalisation levels, establishing the internal validity of the experimental design and confirming systematic variations in choice probabilities across waves and privacy framing conditions. The experimental choice data generated through the DCE provided the empirical foundation for the three subsequent Linear Mixed Models (LMMs), which examined longitudinal changes in consumer goal strength across the three waves, capturing both *between-person* (trait-like) and *within-person* (state-like) variations over time.

This integrated approach provides a unified interpretation of consumer behaviour, linking the validation of preference structures with the longitudinal modelling of motivational dynamics in response to hyper-personalised digital environments.

Methodologically, this integration comprises:

- A **simulation-enhanced** longitudinal Discrete Choice Experiment (DCE) approximating real-time AI-enabled recommendation systems and establishing the internal validity of the hyper-personalisation structure.

- **A three-wave repeated measures** structure tracking sustained and momentary effects of hyper-personalisation over time.

- **Linear Mixed Models (LMMs)** within the broader Individual Growth Curve Modelling (IGCM) framework, applied to analyse unbalanced longitudinal data and examine temporal changes in consumer goal strength.

The empirical context involves a realistic, multi-actor Telecommunications and Entertainment multi-actor ecosystem, simulating a hyper-personalised content delivery experience. The simulation-enhanced longitudinal Discrete Choice Experiment (DCE), embedded within an unbalanced three-wave longitudinal repeated-measures design, captures the *dynamic*, *context-sensitive*, and *goal-congruent* nature of consumer engagement. This hybrid approach provides a more realistic representation of how hyper-personalisation unfolds in adaptive, AI-enabled service environments.

Specifically, the inclusion of an **adaptive learning automaton** within the DCE simulates how AI-enabled systems dynamically refine personalised recommendations through real-time feedback loops. Unlike traditional approaches, this design reflects how goal-aligned hyper-personalisation evolves over time in real-world service settings. Full methodological details – including experimental flow, simulation logic, and data analytical models – are elaborated in **Chapter 4**.

1.4. Research Contribution

This study makes **novel** and **timely** contributions to *theoretical*, *methodological*, and *managerial* domains within the field of AI-enabled hyper-personalisation. While the growing body of literature explores goal-driven personalisation in contexts such learner recommendation systems, researchers tend to narrowly focus on system-centric capabilities or short-term goal support (Jayasinghe and Kasthurirathna, 2022; Wang et al, 2025a; Zhu et al, 2023). In contrast, this study adopts a consumer-centric, longitudinal, and multi-actor ecosystemic approach, reflecting the **multi-dimensional** nature of hyper-personalisation and its **dynamic** interaction with consumers' goal strength *trajectories* across time, actors, and under varying privacy contexts.

Theoretical Contributions

The study contributes to theory in three key ways. **First**, it advances the understanding of goal-aligned hyper-personalisation by shifting the focus from static consumer preferences to dynamic consumer goal strength, grounded in commitment and motivation as a psychological construct. This shift is especially relevant in AI-enabled environments where adaptive engagement depends on evolving motivational states rather than static user profiles (Joseph et al., 2025; Sutton and Barto, 2018). It addresses a notable gap in how evolving consumer life goals shape the impact of personalisation, especially within complex, multi-actor service settings.

Second, the study builds on and refines the Consumer-Dominant Logic (CDL) paradigm (Heinonen and Strandvik, 2022; Nguyen and Menezes, 2024) by empirically applying its conceptual three-actor constellation model (Lipkin and Heinonen, 2019), examining how value unfolds between brand-oriented, individual-oriented, and social-oriented consumer ecosystem actors. This provides a theoretically enriched perspective that captures consumer agency, goal alignment, and psychological investment within AI-enabled personalised ecosystems.

Third, the study is among the **first** to empirically assess how the temporal, contextual, and psychological evolution of hyper-personalisation influences consumer goal strength over time. It illustrates how consumer goal strength can increases, decay, or recover depending on goal congruence, timing, and privacy framing – mechanisms often overlooked in existing AI studies (Joseph et al., 2025; Wang et al., 2025a; 2025b).

Methodological Contributions

Methodologically, the study integrates several innovations that enhance ecological realism and temporal sensitivity without overlooking analytical robustness. Specifically, it embeds a **simulation-driven longitudinal Discrete Choice Experiment (DCE)** within a three-wave longitudinal structure, using a learning automaton to dynamically construct and deliver personalised content – mirroring real-world AI-enabled recommendation systems. The DCE framework validates the internal structure of hyper-personalisation through part-worth utilities and preferences hierarchies. A **Linear Mixed Models (LMM)** framework, situated within **Individual Growth Curve Modelling (IGCM)** then analyses both inter-individual and intra-individual variation in consumer goal strength across the study waves. This integrated methodological configuration enables the study to capture subtle motivational shifts over time while maintaining methodological coherence with real-world AI-enabled environments. Full analytical procedures and simulation logic are detailed in **Chapter 4**.

Practical Implications

From a managerial perspective, this study offers several insights of strategic relevance for service providers operating within AI-enabled hyper-personalised ecosystems. It proposes guiding principles for designing *goal-congruent* personalisation strategies, managing evolving privacy expectations especially for digitally empowered consumers, and implementing psychologically grounded personalisation rather than merely relying on behavioural cues. These implications are further developed in subsequent chapters.

Overall, these insights offer a foundation for developing more goal-congruent, psychologically grounded personalisation strategies in AI-enabled ecosystems. By accounting for evolving privacy expectations and shifting consumer motivations, the study contributes toward building adaptive service models that align with consumers' dynamic life goals. Full theoretical, methodological, and practical implications are elaborated in **Chapter 6**.

1.5 Thesis Structure

Chapter 1 introduces the study by outlining the research background, central question, and objectives. It presents the theoretical motivation, identifies key gaps in existing literature, and summarises the intended theoretical, methodological, and practical contributions. The chapter also positions the study within the Consumer-Dominant Logic (CDL) framework, explaining its relevance to AI-enabled hyper-personalisation in multi-actor consumer ecosystems.

Chapter 2 provides a detailed literature review across hyper-personalisation, CDL, consumer goal strength, and privacy framing. It identifies theoretical foundations, conceptual shortcomings, and empirical shortcomings in understanding value co-creation and digital empowerment, concluding with the specific research gaps this study addresses.

Chapter 3 develops the conceptual framework by linking prior theories to the research questions. It outlines the mechanisms underpinning value formation through the CDL lens and distinguishes *brand-, individual-*, and *social-oriented* consumer ecosystems. This groundwork leads to the formal articulation of the study's two hypotheses.

Chapter 4 details the methodological approach, explaining the rationale for combining a three-wave longitudinal Discrete Choice Experiment (DCE) with Linear Mixed Models (LMM) within an Individual Growth Curve Modelling (IGCM) framework. It outlines sampling, experimental design, ethical considerations, and model specification to capture longitudinal dynamics in consumer goal strength.

Chapter 5 presents the interpretations of the empirical findings in relation to the hypotheses and theoretical framework. The discussion integrates insights from existing literature to address the research questions and reveal broader ethical, societal, and theoretical implications for goal-aligned hyper-personalisation.

Chapter 6 concludes the thesis by summarising the main findings, highlighting theoretical and practical contributions, discussing limitations, and offering directions for future research.

1.6 Chapter Summary

This introductory chapter outlined the study's background, motivation, and overarching research problem. It presented the research aim, objectives, and main hypotheses, while positioning the study within the Consumer-Dominant Logic (CDL) paradigm. The chapter also described how the study addresses key gaps in personalisation literature through a longitudinal, psychologically grounded, and multi-actor consumer ecosystem context. The structure of the research paper was outlined, setting the foundation for subsequent chapters. The literature review is presented next in **Chapter 2**, further examining the constructs and empirical foundations relevant to hyper-personalisation, consumer goal strength, and privacy framing.

Chapter 2 – Literature Review

2. Chapter 2 - Literature Review

This chapter critically reviews existing literature underpinning the study's investigation into AI-enabled hyper-personalisation within multi-actor consumer ecosystems. It examines prior research across four key constructs:

1. Personalisation and hyper-personalisation
2. Consumer-Dominant Logic (CDL) and value formation
3. Consumer goal strength and motivational dynamics
4. Privacy framing in relation to consumer empowerment.

The objective of this review is to establish theoretical linkages among these domains and identify empirical limitations in current approaches to hyper-personalisation, consumer engagement, and value formation.

The review follows a **semi-systematic narrative** approach (Wong et al., 2013; Snyder, 2019) to synthesise relevant concepts rather than provide exhaustive coverage. Thematic analysis, within the semi-systematic narrative approach, helps identify theoretical perspectives, common issues within a specific research discipline or methodology, and establish components of a theoretical concept (Ward et al., 2009). This method allows for flexibility and conceptual integration across literature in marketing, consumer behaviour, and information systems. Key themes were organised using Lipkin and Heinonen's (2022) qualitative framework, which was adapted to develop the conceptual model for this study.

The review is structured as follows:

1. Evolution of personalisation and the emergence of AI-enabled hyper-personalisation.
2. Consumer-Dominant Logic (CDL) paradigm and multi-actor value formation in digital ecosystems.
3. The role of goal theory in understanding consumer motivation, commitment, and adaptive responses to hyper-personalisation.
4. The privacy framing paradox and its implications for consumer empowerment in AI-enabled service contexts.

Each section concludes with a synthesis that highlights how prior research informs the conceptual framework presented in **Chapter 3**.

2.1 Hyper-personalisation

2.1.1 From Personalisation to Hyper-Personalisation

Personalisation involves tailoring content, services, or experiences to meet individual consumer needs using identifiable characteristics such as demographics, preferences, and behaviours (Rosenbaum et al., 2017; Patnaik, 2022). Early models of personalisation were largely **rule-based**, relying on static demographic segmentation and heuristic decision-making, limiting adaptability and effectiveness at scale (Abrahams et al., 2023; Rafieian and Yoganarasimhan, 2023). These traditional approaches to personalisation often fail to capture the complexity of modern consumer behaviour, risking inefficient targeting and suboptimal consumer experience (Joseph et al., 2025).

Recent advancements in **Artificial Intelligence (AI)** have transformed this process into **hyper-personalisation** — an *adaptive*, *data-driven* approach that leverages real-time behavioural, contextual, and psychographic information to dynamically align content with consumer intent (Adaga et al., 2024; Ramachandran et al., 2025; Mehmood et al., 2024). This evolution reflects a shift from predictive to responsive personalisation, where AI and machine learning (ML) continuously refine outputs based on ongoing consumer interactions (Adaga et al., 2024; Adefemi et al., 2024; Huang and Rust, 2021). The foundational mechanisms of AI-enabled hyper-personalisation lie in continuous learning and adaptive tailoring (Divya and Vajravelu, 2025; Mehmood et al., 2023; Nöjd et al., 2020), enabling a more engaging and immersive experience that deeply resonates with consumers at the individual level (Rai and Pandey, 2024; Sun et al., 2025). This enablement facilitates automating decision making, hence, allowing for real-time customisation of service offerings and encounters based on dynamically changing consumer behaviour.

Hyper-personalisation extends beyond traditional segmentation approaches that grouped consumers by demographics or location, focusing instead on dynamic, real-time tailoring enabled by Artificial Intelligence (AI) and predictive analytics (Ford et al., 2023; Ramachandran et al., 2025). AI-driven systems analyse behavioural and contextual data to anticipate consumer needs, enabling proactive and context-aware communication that enhances relevance, emotional resonance, and engagement (Rosenbaum et al., 2017; 2021). Hyper-personalisation marks a shift from *one-size-fits-all* segmentation to dynamic *one-to-one tailoring*, reflecting each individual's evolving digital identity and preferences (Jain et al., 2021; Micu et al., 2022). It leverages behavioural, contextual, and emotional data to improve personalised experiences and deepen consumer connections (Cao, 2021; Teepapal, 2025).

As service providers strive to craft distinctive and memorable consumer experiences, the integration of advanced digital technologies—such as Artificial Intelligence (AI), machine learning, and predictive analytics—has become indispensable (Jain et al., 2021; Micu et al., 2022). These technologies enable a highly contextualised and adaptive form of personalisation, allowing service providers to understand and respond to evolving consumer needs in real time. Hyper-personalisation leverages multi-layered digital architectures that combine real-time analytics, behavioural tracking, and dynamic content generation to deliver uniquely tailored offerings. For example, streaming platforms like Netflix utilise AI to refine recommendations based on individual viewing preferences and emotional engagement cues (Rai and Pandey, 2024; Eklund, 2022; Lobato, 2019).

"*Hyper*" as a prefix denotes a heightened or extreme state implying an exceptionally advanced or intensified level (Rai and Pandey, 2024). Defined as the process of creating adaptive, data-informed experiences that evolve continuously with individual preferences, hyper-personalisation represents the most advanced form of personalised marketing (Campbell et al., 2020; Patnaik, 2022). By leveraging machine learning and real-time insights, AI technologies — characterised by its capacity to learn from data to achieve defined goals — deliver granular, consumer-specific recommendations that replace rule-based segmentation with ongoing behavioural learning and refinement (Davenport, 2023; Huang and Rust, 2021; Haenlein and Kaplan, 2019).

Haenlein and Kaplan (2019) describe Artificial Intelligence as a system capable of processing and learning from external data to achieve defined goals. With hyper-personalisation, AI algorithms uncover hidden behavioural patterns and consumer segments to deliver messages aligned with individual goals and motivations. For example, AI-enabled systems can tailor marketing communications – such as targeted fitness advice or customised discounts – to enhance engagement and relevance (Babatunde et al., 2024). For example, Spotify's AI-enabled recommendation playlists and content are tailored to users' listening patterns, while Peloton uses AI to design bespoke fitness plans based on its users' goals, history, and real-time behavioural cues (Gujar, 2024). Collectively, these technologies expand the strategic capacity of brands to deliver *goal-congruent* hyper-personalised experiences that resonate with evolving consumer needs.

Gaining insights into consumer behaviour – such as preferences, purchasing patterns, and decision-influencing factors - is essential to drive consumer choices (Abdul et. al., 2024, Igwama et. al., 2024). Tufekci (2014) and Yeung (2017) highlight that advanced decision-making technologies can dynamically influence the contexts in which consumers form preferences and make choices. By leveraging behavioural and contextual data – such as search histories, preferences, and locations – AI systems continuously refine interactions through recursive learning cycles, where each consumer action becomes feedback for further personalisation (Zuboff, 2019).

AI-based systems now employ technologies such as Machine Learning (ML), Natural Language Processing (NLP), predictive analytics, and Large Language Models (LLMs) to enable automated, context-aware adaptation. These systems outperform traditional models in precision, conversion, and engagement rates (Bitra, 2025; Iyello et al., 2024; Jain et al., 2021; Micu et al., 2022), offering a new paradigm of consumer–AI co-adaptation—where user behaviour and algorithmic learning mutually shape personalised outputs over time. Machine learning enables future-oriented predictions through trend analysis, while natural language processing (NLP) allows systems to interpret human language, offering valuable insights into sentiment and intent. Deep learning further strengthens forecasting and predictions by modelling complex, high-dimensional data relationships, particularly useful in dynamic market contexts (Iyelolu et al., 2024; Bassey, 2023).

Such systems demonstrate superior responsiveness in domains like e-commerce, entertainment, and FinTech, where algorithmic learning continuously refines personalisation outputs (Ajiga et al., 2024; Joseph et al., 2025; Udeh et al., 2024).

These advances underscore the growing ability of AI-driven systems to predict and respond to individual consumer needs with unprecedented accuracy and timeliness. Furthermore, **Generative AI** — a new class of Artificial Intelligence technologies capable of producing novel outputs such as texts, images, or recommendations based on learned data patterns — enhances the adaptability and creativity of personalised recommendation systems to deliver *context-sensitive* and *real-time* tailored content (Yuan et al., 2024). Unlike earlier rule-based approaches, hyper-personalisation driven by generative AI integrates behavioural, emotional, and contextual cues to dynamically adjust experiences as consumer states evolve.

Across diverse contexts, personalisation strategies now rely on large-scale **behavioural** and **contextual** data to anticipate consumer preferences (Bhattarai, 2023; Hoffmann et al., 2022; Zhai et al., 2022). For example, e-commerce and digital media platforms leverage AI analytics to deliver content aligned with inferred intentions and past interactions (Rafieian and Yoganarasimhan, 2023). This evolution has positioned hyper-personalisation as a critical mechanism in consumer–AI interactions, where systems not only predict but also adapt to behavioural feedback (Babatunde et al., 2024). Desai (2022) posits that hyper-personalisation can provide deeper insights into the desires and needs of consumers, delving into their evolving behaviours, likes, and preferences. By interlinking consumers and service providers, hyper-personalisation can enhance their relationship leading to positive consumer behaviours.

While generative and predictive AI have advanced the precision and scalability of hyper-personalisation, existing studies remain largely system-centric, emphasising algorithmic optimisation and predictive precision over consumer psychology and behavioural change (Wang et al., 2025; Zhu et al., 2023). They prioritise model performance over understanding how personalisation shapes—and is shaped by—consumer *adaptation* over time. Consequently, most studies adopt cross-sectional designs, overlooking how consumer preferences evolve over time through ongoing interactions (Mahadevan and Shainesh, 2024; Teepapal, 2025). This gap provides the empirical and conceptual foundation for the present study's longitudinal investigation of how hyper-personalisation evolves across repeated consumer interactions in dynamic, AI-enabled environments. **Table 1** presents a comparative view of traditional versus AI-enabled hyper-personalisation and addressed gaps.

This study addresses these limitations by examining hyper-personalisation as a **dynamic**, **data-driven** process that unfolds across time. Through a **longitudinal** behavioural perspective, it explores how consumers' personalised experiences develop and adapt across repeated exposures in AI-enabled environments. This approach advances understanding beyond static system efficiency toward capturing the *temporal* and *adaptive* nature of personalisation effectiveness.

Table 1*: Traditional versus AI-enabled Hyper-personalisation and Research Gaps*

Aspect	**Traditional Personalisation**	**AI-driven Hyper-personalisation**	**Gap Addressed by Current Study**
Focus	Static, rule-based targeting	Adaptive, context-aware recommendations	Limited understanding of temporal and contextual evolution of personalisation
Data Type	Demographic and transactional	Behavioural, contextual, and real-time	Over-reliance on static data and cross-sectional models
Objective	Efficiency and segmentation	Responsiveness and engagement	Neglects consumer adaptation and behavioural outcomes
Perspective	System-centric	Consumer-centred interaction	Lacks behavioural insight into evolving engagement processes

Ultimately, the value of hyper-personalisation lies in its capacity to transform deep consumer insight into tangible outcomes—enhancing engagement, satisfaction, and loyalty while driving measurable competitive advantage. The following sub-section examines these benefits in greater detail.

2.1.2 Impacts and Transformative Potential

AI-enabled hyper-personalisation has emerged as a transformative capability in contemporary marketing and service delivery, enabling organisations to tailor interactions that align closely with individual consumers' goals, preferences, and contexts (Li et al., 2025). Through real-time data analytics and predictive modelling, service providers can deliver *adaptive* and *responsive* experiences that anticipate consumer needs and support value co-creation at the individual level (Casaló, 2023; Akdim and Casaló, 2023). This section examines the cognitive, behavioural, and relational impacts of hyper-personalisation, highlighting its broader transformative potential in consumer–brand relationships.

Cognitive and Psychological Impacts

Existing research demonstrates that hyper-personalisation enhances consumer satisfaction and perceived value by delivering information that is both **relevant** and **emotionally** resonant (Choi et al., 2017; Henkens et al., 2021). AI-enabled systems reduce cognitive overload by filtering irrelevant content and increasing the precision of personalised recommendations (Akdim and Casaló, 2023; Amoo et al., 2024). These improvements foster a stronger sense of control and confidence in consumers' decision-making, contributing to self-efficacy, inclusiveness, and perceived empowerment (Decock et al., 2020; Mende et al., 2024). Collectively, these outcomes underscore the cognitive and psychological benefits of hyper-personalisation, which extend beyond efficiency to shape consumers' experiences of agency, ease, and engagement.

Behavioural and Experiential Impacts

Hyper-personalisation also influences consumer behaviour by enabling adaptive, **in-the-moment** engagement. Through continuous feedback and AI-driven learning, service providers can interpret behavioural and contextual cues to modify interactions *dynamically*, leading to greater engagement, adoption, and brand loyalty (Brinson et al., 2019; Kang and Namkung, 2019; Huang and Rust, 2021). These adaptive responses allow service providers to anticipate consumer actions and preferences, facilitating more meaningful exchanges and sustained behavioural involvement (Valdez Mendia and Flores-Cuautle, 2022; Payne et al., 2021). Consequently, consumers experience more seamless and rewarding journeys that evolve alongside their personal and contextual changes. It supports smoother transactions, better decision-making, and behavioural adjustments (Kim et al., 2019; Leischnig et al., 2018). Its relevance lies in leveraging past interactions to accurately anticipate and predict consumer needs and influence decision-making in evolving contexts (Jain et al., 2021; Payne et al., 2021).

Relational and Co-Creation Impacts

Beyond individual or behavioural outcomes, hyper-personalisation contributes to relational and social value through **continuous** *co-creation* between consumers and service providers. This interactional process fosters trust, emotional connection, and mutual learning over time (Guha et al., 2021; Desai, 2022). By enabling real-time responsiveness and reciprocal communication, hyper-personalisation transforms relationships from *transactional* exchanges into **adaptive** partnerships. Through this continuous interplay, firms strengthen consumer–brand relationships, enhance loyalty, and reinforce consumers' perception of shared value creation (Huang and Rust, 2021; Kannan and Kulkarni, 2022).

Behavioural Implications

Building on these relational effects, it is essential to examine the underlying AI-driven mechanisms that enable hyper-personalisation to dynamically adapt and evolve over time. Hyper-personalisation, driven by AI-enabled learning algorithms, relies on advanced techniques such as supervised, unsupervised, and reinforcement learning to interpret and extract consumer data and behavioural patterns (Ma and Sun, 2020). These algorithms enable service providers to influence consumer behaviour *dynamically* through hyper-contextual insights (Tong et al., 2020), allowing for precise, *in-the-moment* targeting of consumer experiences (Kumar et al., 2020; Huang and Rust, 2021). It accounts for individual preferences and contextual cues to create communication messages that resonates *meaningfully* with consumers. By its inherent ability to calculate the likely next step in consumer journey in *real-time*, hyper-personalisation can tailor content delivery even when outcomes appear similar across users (Patnaik, 2022) — making each interaction *distinct* in timing, format, and delivery channel.

Despite these capabilities, most research has primarily focused on the transactional benefits of hyper-personalisation—such as satisfaction, engagement, and loyalty—while overlooking its broader behavioural and motivational implications for consumers. Emerging studies suggest that hyper-personalisation extends beyond short-term engagement to influence ongoing consumer motivation, perceived agency, and adaptive goal pursuit within AI-driven environments (Kabadayi and Tsiotsou, 2022; Lieberman, 2021; Mehmood et al., 2023). This highlights the need to understand how personalised AI interactions shape consumer cognition and motivation over time, driving behavioural change and goal alignment across repeated exposures. However, scholars caution against its dual-edged nature. While it can enhance life experiences, it can potentially limit self-agency or reduce perceived intrusiveness (Mehmood et al., 2024; Henkens et al., 2021; Hutmacher and Appel, 2023).

Practical Implications

From a practical perspective, service providers need to navigate these complexities to deliver more accurate, goal-aligned recommendations. Models of product targeting (Van Osselaer and Janiszewski, 2012) and findings by Böttger et al. (2017) suggest that strategic product presentation can activate consumer goals and increase purchase intentions. More recently, Chen et al. (2025) demonstrated that when algorithmic recommendations align with focal consumer goals, individuals are more likely to engage in both initial and cross-buying behaviours. This aligns with Hu et al. (2021), who highlight that the autonomy facilitated by intelligent personal assistants enhances enjoyment and positive affect by helping consumers achieve self-relevant objectives.

Hence, service providers need to design recommendation strategies that respond to consumer focal goals and motivational states, enhancing personalisation effectiveness. A well-designed personalisation algorithm — capable of capturing individual preferences, goal orientations, and contextual intentions — can strengthen consumer goal commitment and adaptive engagement over time. This **goal-based** approach supports sustained motivation and reduces disengagement or decision fatigue by aligning AI-driven interactions with consumers' evolving aspirations and behavioural contexts.

Overall, these insights reveal the *dual transformative* nature of hyper-personalisation — both empowering and ethically complex — thereby underscoring the need for a longitudinal, behaviourally anchored investigation into how consumer goals and motivations evolve within AI-enabled ecosystems.

Internalisation and Sustained Engagement

While hyper-personalisation demonstrates strong potential in enhancing engagement and perceived value, emerging literature cautions against assuming a linear trajectory of impact. Consumers often adapt to technological advances — a phenomenon known as *hedonic adaptation* — leading to diminishing returns over time and the so-called "*satisfaction gap*", where subjective value plateaus over time despite increasing system capabilities (Ganuthula et al. (2024). Early adopters of AI-enabled technology may experience rapid engagement spikes that gradually stabilises as novelty wears off. Polyportis et al. (2024) highlight that perceived value and engagement with AI-enabled services often follow a logarithmic curve, rather than a linear one. This finding underscores the need for service providers to evaluate not just the technical robustness of hyper-personalisation systems but also how consumer engagement with AI-personalised experiences evolves over time in terms of emotional relevance and temporal sustainability across consumer journeys.

Recent literature on behaviour change technologies and motivational psychology reinforces this perspective, emphasising the importance of aligning technology-driven interventions with users' intrinsic motivations and internalised values to sustain engagement over time (Albert et al.; 2024; Deci and Ryan, 2017). From a **Self Determination Theory (SDT)** standpoint, enduring engagement arises when interventions are perceived as personally meaningful and voluntarily chosen — conditions facilitated through *internalisation,* where individuals integrate the system's goals with their own. This insight is particularly relevant for hyper-personalisation, where sustained engagement depends on how effectively the system resonates with consumers' self-congruent goals rather than externally imposed cues (Deci and Ryan, 2017; Ryan et al., 2022).

Building on this, recent **Human–Computer Interaction (HCI)** research integrates SDT principles — autonomy, competence, and relatedness — into digital design to scaffold intrinsic motivation and long-term engagement (Ballou et al., 2022; Peters et al., 2018). In AI-enabled personalised systems, this underscores the need for models that extend beyond algorithmic optimisation to embrace consumers' **meaning-making** and value co-construction processes. This theoretical shift aligns with Consumer-Dominant Logic (CDL) perspective, which situates personalisation effectiveness with consumers' evolving interpretations of value and relevance over time.

Consequently, understanding how hyper-personalisation aligns with consumers' personal values, goals, and contextual motivations become essential. Such alignment provides a foundation for sustained engagement and deeper consumer-brand relationships. However, empirical research remains limited in exploring how these processes unfold *dynamically*, revealing a clear gap for longitudinal, consumer-centered examination.

While AI-enabled hyper-personalisation demonstrates transformative behavioural potential, limited studies systematically investigate how consumer and service ecosystems dynamically evolve in response to these technologies. Although AI is widely acknowledged for its transformative capabilities (Manser Payne et al., 2021; Ramachandran et al., 2025), there remains a gap in understanding how it reshapes consumer-provider value interactions within dynamic service environments (Barney-McNamara et al., 2021; Haenlein and Kaplan, 2019; Kohtamäkia et al., 2019; Paul et al., 2024). This highlights an ongoing need for frameworks that capture the behavioural, contextual, and longitudinal evolution of hyper-personalisation – emphasising not only technological sophistication but also the importance of contextual relevance and consumer adaptability in AI-enabled systems.

Addressing this gap, the present study integrates the **Consumer-Dominant Logic (CDL)** perspective to explore how AI-enabled hyper-personalisation co-creates value through consumer goal formation and reinforcement. By adopting a **longitudinal**, **behaviourally anchored** approach, this study contributes to a more dynamic understanding of consumer–AI interaction, illustrating how personalisation extends beyond transactional efficiency to shape enduring motivational engagement and cognitive commitment within evolving digital ecosystems.

Building on this, this study empirically examines how varying levels of AI-enabled hyper-personalisation interact with consumers' evolving perspectives and their meaning making process. Recognising that consumer responses may shift over time – particularly as the novelty of hyper-personalised content wears off – this approach also considers the **temporal dimension** of personalisation relevance. This perspective supports a more dynamic understanding of sustained engagement, accounting for how alignment with evolving consumer priorities may influence long-term behavioural outcomes. Further elaboration on Consumer-Dominant Logic (CDL), value formation, and consumer life goals is provided in the following sub-sections, while **Table 2** summarises key insights and gaps derived from hyper-personalisation literature, highlighting the contributions of this study.

***Table 2**: Summary of Insights and Research Gaps in Hyper-Personalisation Literature*

Key Themes	**Key Insights**	**Identified Gaps**	**Study Contribution**
Technological Advancements in AI-driven Personalisation	AI enables real-time, adaptive recommendations based on dynamic consumer data and behavioural cues.	Mainly system-centric, emphasising algorithmic accuracy over behavioural understanding.	Moves beyond technological efficiency by integrating a *behaviourally anchored*, *longitudinal* analysis of hyper-personalisation.
Consumer Engagement and Experience	Hyper-personalisation enhances engagement, satisfaction, and perceived relevance.	Most studies are cross-sectional, short-term, and lacking examination of sustained, goal-driven engagement.	Investigates how hyper-personalisation influences *motivational engagement* and *goal strength* across *time*.
Transformative Potential	AI-enabled personalisation facilitates value co-creation and consumer empowerment.	Psychological and motivational mechanisms underlying sustained engagement remain underexplored.	Integrates *CDL* and motivational perspectives to explain *enduring cognitive* and *behavioural* effects.
Theoretical Integration	Scholars are beginning to link AI-personalisation with consumer-centric frameworks (e.g., SDT, HCI, CDL).	Limited integration between personalisation studies and goal-based, value-formation frameworks.	Positions hyper-personalisation within CDL to conceptualise *dynamic consumer–AI* co-creation processes and *evolving* value systems.

Building on these conceptual insights, the following subsection examines the perceived importance of hyper-personalisation — a key factor in understanding how consumers evaluate the personal relevance and sustained value of AI-enabled interactions.

2.1.3 Perceived Importance of Hyper-personalisation

While AI-enabled hyper-personalisation delivers measurable gains in engagement and satisfaction, its long-term influence depends on how consumers psychologically interpret these experiences. The concept of **perceived importance** — defined as the *subjective significance* individuals attach to a technology or service — offers valuable insight into how consumers assess the meaningfulness and goal relevance of personalised interactions (Guo and An, 2025; Chatterjee et al., 2023). Extending beyond traditional **Technology Acceptance Models (TAM)**, which emphasise usefulness and ease of use, perceived importance captures the emotional and cognitive salience of personalisation: how much it aligns with consumers' personal values, aspirations, and life goals (Dwivedi et al., 2020; Ryan and Deci, 2020). TAM suggests that perceived importance has a profound effect on how consumers emotionally and cognitively engage with personalised technologies.

Although hyper-personalisation can enhance attention and reduce cognitive load (Davenport, 2023), its sustained impact remains underexplored. Short-term, performance-oriented studies rarely consider how valued relevance — rather than mere functional accuracy — drives continued engagement. When consumers perceive personalisation as *important* and *goal-congruent*, they are more likely to experience emotional connection, satisfaction, and deeper engagement (Hu et al., 2021; Mehmood et al., 2023). This means that when users view hyper-personalisation as important to their goals or decision-making, they are more likely to engage with and adopt AI-driven services. Perceived importance can amplify the psychological mechanism of recognition and validation, leading to reduced decision fatigue and enhanced emotional connection with the service provider (Akdim and Casaló, 2023). This psychological interpretation of importance strengthens motivational commitment and helps explain why some AI-personalised interventions succeed in fostering meaningful engagement while others do not.

In this study, perceived importance of hyper-personalisation was explored **post-hoc** to provide complementary insight into the motivational and cognitive dimensions of hyper-personalisation. This exploratory perspective enriches the theoretical understanding of personalisation by recognising that technological precision alone is insufficient; effectiveness also depends on how consumers appraise its personal relevance and alignment with their goals. While not initially hypothesised, the perceived importance emerged as a meaningful factor during the study's preliminary data collection, motivating its inclusion in subsequent post-hoc analysis (refer to **Chapter 4**).

2.1.4 Progressive Levels of Hyper-Personalisation

Hyper-personalisation, enabled by AI technologies, is increasingly recognised as a continuum rather than a fixed state (Maslowska et al., 2022; Rafieian and Yoganarasimhan, 2023). This continuum spans from basic, demographic-based targeting to dynamic, goal-oriented personalisation, where content evolves in real-time with consumer needs and contexts. In contrast to static rule-based models, dynamic AI-enabled hyper-personalisation integrates multiple behavioural cues, contextual data, and predictive intent modelling to deliver adaptive and responsive recommendations (Agarwal and Modanwal, 2025; Ed-Daakouri and Alla, 2025).

Personalisation granularity thus varies according to the **depth** and **diversity** of utilised consumer insights. Earlier forms of personalisation focused on generalised segmentation (e.g., age or gender-based targeting), whereas hyper-personalisation relies on high-dimensional consumer data to deliver individualised, context-aware experiences (Arora et al., 2008; Hoy and Milne, 2010; Hawkins et al., 2008). The more attributes it can capture, the more segmentation comes closer to personalisation (Davenport, 2023). This evolution marks a shift from uniform content delivery to tailored gains, where every consumer receives distinct recommendations informed by their behavioural patterns and preferences (Liberali and Ferecatu, 2022; Maslowska et al; 2022; Rafieian and Yoganarasimhan, 2023).

Although AI technologies have long supported rule-based personalisation, achieving full personalisation has only recently become feasible through advances in machine learning and causal inference (Davenport, 2023; Goli et al., 2020). Early implementations focused on static targeting and short-term optimisation, often leading to sub-optimal engagement or consumer fatigue (Rafieian and Yoganarasimhan, 2023). In contrast, **adaptive** and **forward-looking** models use real-time behavioural data to optimise both immediate and future consumer responses, reflecting a shift toward dynamic, continuously evolving personalisation (Capponi et al., 2021; Liao et al., 2021).

Such models are designed to capture the variability in consumer behaviour over time, predicting future preferences and actions to sustain engagement and long-term value (Liberali and Ferecatu, 2022; Theocharous et al., 2015). This progression from *static* to *adaptive* systems highlights an evolutionary hierarchy of personalisation, where each level integrates a deeper set of behavioural insights to generate more contextually relevant experiences. However, Rafieian and Yoganarasimhan (2023) emphasise that personalisation effectiveness depends on the ability of service providers to influence consumer responses by dynamically optimising tailored rewards at the individual-level.

Rafieian (2022) defines four levels personalisation, reflecting this continuum:

1. *No Personalisation* - generic recommendations without user data.
2. *Demographic Personalisation* – based on demographic features such as location and smartphone brand.
3. *Demographic Historical Personalisation* - adding historical features such as seen ads and previous clicks to the demographic model.
4. *Adaptive Personalisation* - combines demographic, historical, and real-time session-level data to deliver predictive, context-aware recommendations.

Each progressive level enhances the *granularity* and *responsiveness* of AI-driven systems, bringing personalisation closer to hyper-personalisation. While early personalisation models offered incremental improvements, higher-value AI systems — particularly those employing adaptive, real-time learning — have shown significant gains in predictive performance (Rafieian, 2022; Rafieian and Yoganarasimhan, 2023). Rafieian (2022) found 5.76% increase in user clicks, on average, from adaptive forward-looking personalisation compared to static policies. Such models continuously refine outputs through feedback loops, aligning recommendations more closely with evolving consumer preferences and contexts (Nahum-Shani et al., 2018; Yu et al., 2021). These advances have enabled a shift from static delivery to "*just-in-time*" adaptive personalisation, where the right content is presented at the most relevant moment.

However, the value of hyper-personalisation extends beyond algorithmic precision. Recent work introduces the concept of *hyper-relevance*, describing personalisation that becomes seamlessly integrated into consumers' everyday lives (Darrwod and Zwick, 2020; Pukas, 2022). *Hyper-relevance* occurs when marketing dissolves into the lived experience — when brands and technologies co-create ambient, meaningful encounters rooted in consumers' goals, emotions, and contexts. Achieving this state requires not only technical advancement but also a deep understanding of consumer motivations, situational cues, and dynamic decision contexts (Wollan et al., 2017). As such, service providers need to continuously push the boundaries and increase the intensity of their hyper-personalised systems to offer the higher values that consumers are looking for (Chan, 2019).

Despite its promise, achieving and maintaining hyper-relevance poses significant challenges, particularly in capturing accurate, real-time consumer data and sustaining engagement without overstepping privacy or ethical boundaries. These tensions are examined further in the following section — **Challenges of Implementation**.

Based on reviewed literature, this study operationalises hyper-personalisation as a progressive, nested framework that evolves through distinct levels of data integration and behavioural insights (V1 – V4). Each level represented an incremental increase in data depth, contextual alignment, and goal-congruence, reflecting how AI-enabled systems transition from basic profiling toward adaptive, goal-aligned hyper-personalisation:

1. **V1 - Demographic Hyper-personalisation (*lowest value*)**: uses only demographic data (*age, gender, and location*)
2. **V2 - Telecom Hyper-personalisation**: adds consumer's captured Telecommunications transactional and usage history (*frequent used Apps, roaming history*) to demographic data
3. **V3 - Partner Hyper-personalisation**: adds cross-platform data from non-Telecommunications partner consumer preferences *(preferred entertainment genres as streaming preferences)* to demographic and Telecommunications captured data
4. **V4 - Adaptive Goals Hyper-personalisation** (***highest value***): incorporates consumer's self-selected active life goals *(3 top consumer active goals)* to the demographic Telecommunications, and partner captured data,

representing full alignment between system-centric recommendations and both individually and socially oriented motivational goals.

This four-level structure forms the empirical foundation for the longitudinal Discrete Choice Experiment (DCE) presented in **Chapter 4**, enabling a systematic comparison of consumer responses across increasingly goal-aligned levels of personalisation. Since the highest level (V4) is still underdeveloped in real-world Telecommunications and Entertainment contexts, simulated choice conditions were created to examine consumer preferences within these progressive stages.

Despite these advancements, existing frameworks often conceptualise personalisation primarily as a technological hierarchy, emphasising algorithmic sophistication rather than consumer-AI interaction and behavioural adaptation. As a result, there remains limited understanding of how varying levels of hyper-personalisation influence motivation, engagement, and goal persistence over time. Addressing this gap, the present study contributes a longitudinal behavioural perspective, examining how consumers' responses evolve across different degrees of AI-enabled hyper-personalisation. Integrating the Consumer-Dominant Logic (CDL) lens, this study interprets these progressive levels not merely as technical distinctions but as value co-creation processes that dynamically shape consumer engagement and goal reinforcement over time.

The following section discusses the challenges of implementing hyper-personalisation, highlighting the behavioural, practical, and ethical constraints that limit realising these progressive levels and the full transformative potential of hyper-personalisation in dynamic service environments.

2.1.5 Challenges of Implementation

While hyper-personalisation, powered by AI-technologies, holds transformative potential across industries – enabling granular consumer insights, real-time decision making, and contextual experiences – its implementation presents several challenges. These span data fragmentation, technological and infrastructural constraints, and ethical, behavioural, and privacy-related concerns. As service providers advance toward increasingly goal-aligned AI-enabled systems, the gap between strategic vision and practical feasibility often widens. Pukas (2022) argue that service providers need to look beyond traditional consumer journeys to identify and prioritise hyper-relevant offerings that can deliver added value to their consumers.

Data Fragmentation and Integration Issues

A critical challenge in implementing hyper-personalisation lies in managing fragmented data and siloed data infrastructures. Disparate data sources and the absence of real-time synchronisation hinder semantic interoperability (Divya and Vajraveli, 2025), limiting the generation of contextually relevant insights. Although hyper-personalisation aims to provide individualised experiences through behavioural and social listening data, its success is highly dependent on the service provider's capacity to convert raw data into meaningful outputs (Valdez Mendia and Flores-Cuautle, 2022).

This fragmentation also restricts identifying impactful data types (e.g., demographics, behavioural, or contextual), hindering the ability to deliver relevant recommendations (De Keyzer et al., 2022b). Given that consumer data reflects evolving preferences and dynamic contexts (Zhang and Chang, 2021), service providers must determine the optimal data mix that enhances perceived value and avoids bias (Kaspar et al., 2019; Li, 2016). Studies indicate that when consumers perceive personalisation as irrelevant or misaligned, it can lead to lower engagement or message fatigue (Bastani et al., 2022; Maslowska et al., 2016; Windels et al., 2018). Additionally, managing large datasets introduces quality control challenges and computational strain (Ma and Sun, 2020). Traditional demographic or historical data alone are no longer sufficient; instead, service providers must integrate real-time and on-demand data streams to maintain predictive accuracy and responsiveness (Iyelolu et al., 2024).

Evolving Consumer Preferences and Time Drift

Another critical challenge arises from the temporal instability of consumer preferences, referred to *time drift*. AI-enabled personalisation models often assume stable responses over time, yet empirical studies reveal that consumer interests and goals rapidly fluctuate (O'Connell and Kelly, 2021). As preferences evolve, previously relevant recommendations may appear outdated, leading to disengagement (Simester et al., 2020; Sweeny et al., 2020). Hence, service providers need to design adaptive systems capable of recalibrating recommendations continuously based on evolving behavioural cues (Balducci and Marinova, 2018; Blasco-Arcas et al., 2022; Alcañiz et al., 2018). This challenge calls service providers to supervise more effective and robust personalisation strategies when utilising their underlying learning methods.

Cognitive Overload and Decision Fatigue

Beyond technical barriers, consumer cognitive limitations pose another significant challenge in achieving effective hyper-personalisation. Continuous exposure to personalised stimuli can overwhelm consumers, leading to inconsistent or fatigued responses (Hill et al., 1995). This phenomenon, often described as *signal-to-noise* imbalance, reflects natural fluctuations in consumer attention and decision patterns that can distort predictive model accuracy and reliability (Herlocker et al., 2004). Such behavioural variability — sometimes termed the "*magic barrier*" — prevents service providers from designing consistently effective policies, as consumers shifting perceptions and reactions introduce substantial noise into datasets (Rafieian and Yoganarasimhan, 2023). Addressing this requires adaptive learning frameworks that can filter out spurious behavioural heterogeneity and continuously recalibrate recommendations to reflect meaningful engagement signals (Balducci and Marinova, 2018; Krafft et al., 2021).

From a managerial standpoint, the challenge lies in balancing algorithmic sophistication with psychological sensitivity — that is, ensuring systems learn from unstructured, high-volume data without overwhelming consumers or generating redundant options. Achieving this equilibrium is critical to sustaining engagement and ensuring that consumers perceive hyper-personalised interactions as valuable rather than cognitively taxing (Shah and Murthi, 2021; Sheth and Kellstadt, 2021).

Overall, the challenges to ensure optimal perceived value from captured value demand substantial computational resources, particularly as hyper-personalised models evolve with generative AI capabilities. Tiwari (2024) argue that delivering highly tailored content at scale requires high processing speed, adaptive cloud architecture, and continuous data ingestion – all of which raise infrastructure complexities and maintenance costs.

Privacy Concerns and Trust

As hyper-personalisation evolves, balancing service relevance with privacy protection remains one of the most complex challenges. Its data-intensive nature heightens risks of psychological reactance and consumer resistance, particularly when users perceive excessive surveillance or limited control over their data (Pizzi et al., 2021; Korneeva et al., 2024; Wright and Xie, 2019). Deeper integration into consumers' emotional and psychological data intensifies ethical concerns around consent and transparency (Malfacini, 2025; Nira, 2025). The blurring between data-driven convenience and surveillance has triggered increased regulatory scrutiny and consumer anxiety, especially in multi-actor ecosystems (Zeng et al., 2022b).

While many consumers recognise the benefits of personalisation, they remain highly privacy-conscious — over 70% report a desire to control or delete their personal data, while nearly half are reluctant to share information at all (Bleier et al., 2020; Farahani and Pavadech, 2025). This underscores a persistent trust deficit in AI-enabled environments, where opaque algorithms obscure how personal data informs recommendations (Kolotyo-Kulkarni et al., 2021; Mpinganjira and Maduku, 2019; Tucker, 2019). Lack of algorithmic transparency, often termed the "*black box problem*," diminishes consumer trust and autonomy (Ijaiya, 2024; Singh and Kakkar, 2025). Unclear data practices and continuous behavioural tracking may heighten discomfort, fear, or anxiety (Hirschprung et al., 2022; Mani and Chouk, 2018; Puntioni et al., 2021). This creates a "*personalisation-privacy paradox*" (Barth and de Jong, 2017; Kokolakis, 2017), where consumers trade privacy for utility but withdraw once trust or perceived control is lost (Bandara et al., 2020; Kokolakis, 2017; Rowe, 2020; Pukas, 2022).

To address this, service providers must adopt responsible AI frameworks that prioritise fairness, explainability, and consumer agency — ensuring ethical alignment with global regulations such as the General Data Protection Regulation (GDPR), the California Consumer Privacy Act (CCPA), and the forthcoming EU AI Act (Divya and Vajraveli, 2025). A detailed examination of ethical governance mechanisms is presented later in **Section 2.4**.

Behavioural and Motivational Misalignment

Beyond data and ethical issues, sustaining long-term engagement through AI-driven personalisation remains a behavioural challenge. While algorithmic precision enables short-term relevance, many interventions fail to maintain user motivation once external incentives diminish (Mustafa et al., 2022; Tsay et al., 2020). Drawing from Self-Determination Theory (SDT), research highlights that enduring engagement depends on aligning AI-personalised systems with intrinsic motivations — autonomy, competence, and relatedness (Ryan and Deci, 2017; McAlaney et al., 2022). When consumers perceive interventions as externally imposed or manipulative, behavioural persistence declines despite technological sophistication (Schmidt-Kraepelin et al., 2019) — unless the intervention is *internalised* as personally meaningful and goal-aligned (Albert et al., 2024; Chaudhry et al., 2022; Ryan and Deci, 2017; Ryan et al., 2022).

Therefore, effective hyper-personalisation must go beyond algorithmic optimisation to ensure value congruence — connecting system outputs with users' deeper life goals and self-determined values. Aligning algorithmic recommendations with intrinsic motivations transforms personalisation from a transactional mechanism into a meaningful long-lasting engagement experience (Chaudhry et al., 2022; Ryan et al., 2022). It is, therefore, essential that service providers understand what constitutes value for empowered consumers (Ciuchita et al., 2022).

Synthesis and Theoretical Link

To create sustainable value through hyper-personalisation, service providers must integrate *technological*, *ethical*, and *motivational* considerations into design frameworks. As Heinonen and Strandvik (2022) argue, sustaining engagement requires a nuanced understanding of consumer logic and the interpretive roles consumers play in co-shaping digital experiences. Addressing this need, this study therefore adopts a Consumer-Dominant Logic (CDL) perspective to explore how consumers construct value *dynamically* within AI-personalised ecosystems. This behavioural lens provides a theoretical foundation for designing AI-enabled personalisation strategies that are contextually relevant, motivationally aligned, and responsive to evolving consumer behaviours and expectations. **Table 3** summarises the challenges and highlights the corresponding contributions.

Table 3: *Summary of Challenges of Implementing Hyper-Personalisation*

Challenge	**Description**	**Practical Implications and Contribution**
Data Fragmentation and Integration	Fragmented and siloed data limit real-time, context-aware insights.	Emphasises the need for *adaptive*, *interoperable* data systems that enhance consumer relevance.
Evolving Consumer Preferences and Time Drift	Consumer preferences evolve rapidly, reducing model accuracy.	Highlights importance of *longitudinal behavioural* modelling (as used in this study).
Cognitive Overload and Decision Fatigue	Over-personalisation can overwhelm users, causing inconsistent responses.	Calls for *psychologically sensitive* algorithms that balance precision with simplicity.
Privacy and Trust Deficit	Data opacity and surveillance concerns erode consumer confidence.	Reinforces *ethical design* frameworks and *transparency* mechanisms in AI systems.
Behavioural and Motivational Misalignment	AI systems fail to sustain intrinsic motivation or self-determined engagement.	Connects to *CDL-based* approach focusing on *goal congruence* and *meaning-making*.

Building on these insights, addressing the challenges of hyper-personalisation requires a framework that captures how consumers **co-create** and **interpret** value within AI-enabled environments. Existing studies have primarily focused on technological optimisation, often overlooking the consumer's active role in meaning-making, goal alignment, and motivational reinforcement. The following section introduces the Consumer-Dominant Logic (CDL) perspective, which reframes hyper-personalisation as an *evolving value formation* process driven by consumer goals, contextual relevance, and behavioural engagement over time.

2.2 Consumer-Dominant Logic (CDL)

2.2.1 Origins and Conceptual Shift

With increasing market disruption driven by digital technologies, the primary role of consumers remain at the core of service research and practice (Drucker, 1974; Heinonen et al., 2010; Gao and Liu, 2022; Lemon and Verhoef, 2016). However, this focus has often been considered from the perspective of service providers and technological change, rather than from what is deemed important by consumers themselves (Bolton, 2020; Malter et al., 2020). Malter et al. (2020, p. 146) emphasise that the essence of marketing research lies in understanding "*the motivations, thought processes, and experiences of individuals as they consume goods, services, and information*" — underscoring the need to ground value creation in the consumer's reality rather than in the firm's offerings.

Recent shifts in marketing and service research call for a reconceptualisation of value creation, focusing on what consumers deem valuable within their lived experiences (Strandvik and Heinonen, 2022). *Consumer value* is recognised as a multidimensional construct encompassing diverse conceptualisations and measurements (Gallarza et al., 2019; García-Fernández et al., 2018; Holbrook, 1994) and broadly refers to the benefits derived from engaging with products, services, or brands (Heinonen et al., 2019; Kelleher et al., 2020). This process extends beyond functional outcomes to include subjective, emotional, and contextual dimensions of consumer life (Heinonen et al., 2019; Cruz-Cárdenas et al., 2019). Delivering and sustaining value, therefore, depends on how well offerings align with consumer needs and contexts. Increasing consumer participation and empowerment further reinforces the necessity to understand how consumers co-orchestrate value within their everyday experiences (Heinonen, 2023; Macdonald et al., 2016).

Understanding value creation requires recognising both its *individual* and *collective* dimensions, as value emerges through interactions that embed social and experiential meanings (Grönroos, 2006; Heinonen et al., 2019). Rather than being entirely firm-driven, value creation is increasingly seen as co-created by both consumers and providers across multiple touchpoints (Macdonald et al., 2016), challenging traditional firm-led delivery models and highlighting the creative, dynamic nature of consumer engagement. Consequently, understanding how AI-enabled hyper-personalised services influence consumer value creation requires an understanding of what constitutes consumer value in the first place.

From Provider to Consumer Logic

The evolution of service research progressively reframed value creation from being *firm-driven* to *consumer-driven*. Dating back to the 1970s, early marketing perspectives viewed value as something produced by firms and delivered to passive consumers, a view central to the **Product-Dominant Logic (PDL)** – also referred to as *Goods-Dominant Logic* (GDL) (Anker et al., 2015). As markets evolved, the shift from products to services (*service logic* or SL) was followed by the **Service-Dominant Logic (SDL)** (Grönroos and Gummerus, 2014; Vargo and Lusch, 2004, 2008, 2016), proposing that value is co-created through interactions between service providers and consumers. Within SDL, consumers are no longer passive recipients but active participants who co-create value in service exchanges (Akaka and Vargo, 2015).

Despite this paradigm shift, the Service-Dominant Logic (SDL) continues to privilege a *service ecosystem orientation* facilitated by firms and institutional actors. Within SDL, value is co-created through structured touchpoints between providers and consumers — interactions that remain visible and largely facilitated by providers (Grönroos and Voima, 2013; Vargo and Lusch, 2017). While this perspective advances a collaborative view of value creation, it still limits understanding of the **autonomous**, **experiential**, and **invisible** processes through which consumers form and reform value beyond immediate service encounters.

The prominence SDL gives to structured consumer-provider interactions positions the service exchange as the principal mechanism of value co-creation. Value materialises progressively across three interlinked spheres (Grönroos and Voima, 2013), depicted in **Figure 1:**

1. **Provider sphere** (*value facilitation*), where the service provider enables and supports the potential for value creation.
2. **Joint sphere** (*value co-creation*), where consumers and providers collaboratively create value through interaction.
3. **Consumer sphere** (*value-in-use*), where consumers independently realise and experience value, though still *indirectly* facilitated by the service provider.

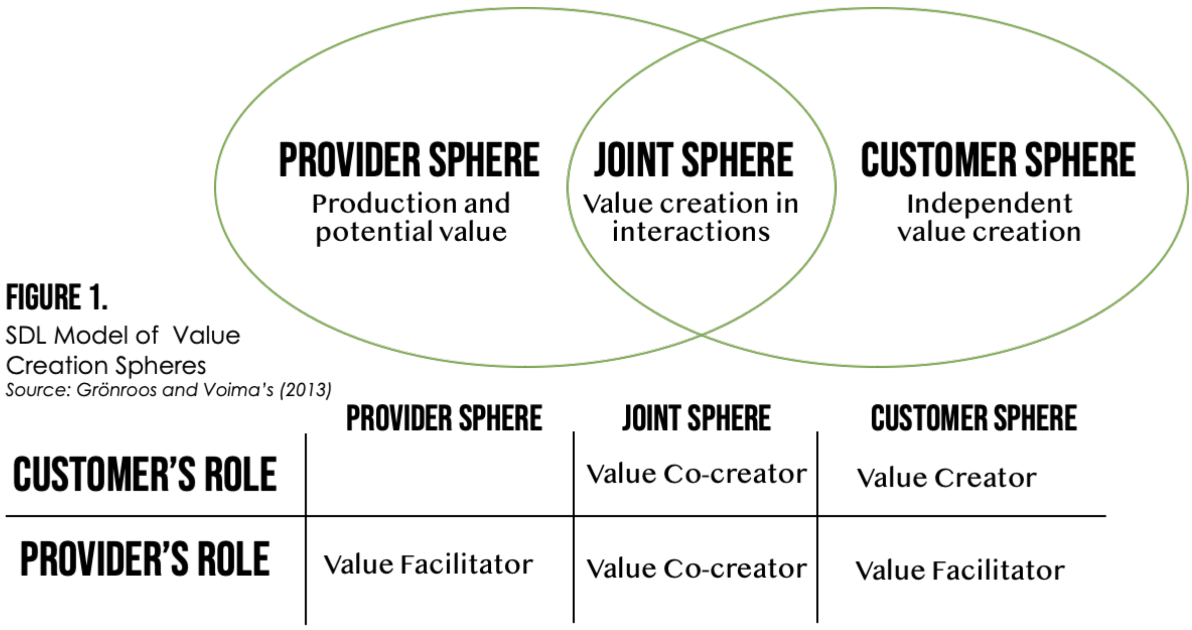


Figure 1: *SDL Model of Value Creation - Source: Grönroos and Voima (2013)*

Throughout the three successive spheres outlined in the SDL framework, value co-creation remains causally linked to provider facilitation and the structured exchange of resources (Medberg and Grönroos, 2020; Anker et al., 2015). Within the consumer sphere (*value-in-use*), value emerges as consumers access and use services, representing an experiential outcome rather than being inherent in the offering (Souiden et al., 2019). However, even this independent consumption remains indirectly shaped by providers and highly dependent on contextual resource embedding (Finsterwalder, 2018; Turetken et al., 2019). Consequently, while SDL recognises the consumer's role as a value creator, it still situates co-creation within institutional and provider-led boundaries (Font et. al, 2021; Loureiro et al., 2020).

The Emergence of Consumer-Dominant Logic (CDL)

Building on the SDL paradigm, **Consumer-Dominant Logic (CDL)** (Heinonen and Strandvik, 2022) reframes value creation as originating primarily from the consumer's world — their lived experiences, goals, and contextual interpretations — rather than from provider-designed interactions. CDL views consumers not merely as co-creators but as **independent agents** who orchestrate value in their own lifeworlds, often outside the provider's visibility.

Here, value is not simply exchanged or co-created within a service system; it is *formed*, *reformed*, and *interpreted* through consumers' personal contexts, intentions, and **meaning-making** processes. Providers play an enabling, but peripheral, role — facilitating rather than defining value outcomes. This reconceptualisation represents a significant departure from SDL by acknowledging that value can exist **without** direct interaction with a service provider. Instead, value is *dynamic*, *experiential*, and *contextually* embedded — shaped through consumers' individual practices and interpretations.

This section established the conceptual foundations of CDL as a theoretical evolution from SDL. While SDL recognises co-creation, CDL advances this perspective by emphasising consumer autonomy, contextual relevance, and invisible meaning-making. This following section elaborates on the core dimensions of CDL, including temporality, context, and consumer-led value formation mechanisms.

2.2.2 Core Dimensions of CDL

Although the concept of value co-creation and value-in-use has been central to service research, particularly within the Service Dominant Logic (SDL) perspective, its focus remains largely within *service ecosystems* coordinated by firms and institutional actors (Lusch and Vargo, 2014). SDL thus privileges the provider's role in facilitating value through structured interactions, positioning consumers primarily as participants within these exchanges. However, as Heinonen et al. (2010; 2020; 2022) argue, this provider-centric orientation falls short of capturing the autonomy, temporality, and evolving behaviour of empowered consumers in digital contexts.

Recent literature demonstrates a paradigm shift from a *provider-based* (firm-centric) to a *consumer-focused* view of value creation (Rihova et al., 2018; Zeithaml et al., 2020a). Consumer-dominant logic (CDL) offers a new perspective by positioning value creation at consumers' center of interest, both within contexts and in their lives. This perspective emphasises understanding consumers' activities and goals as the foundation of value formation rather than as outcomes of provider-designed encounters (Heinonen et al., 2010; 2013; Heinonen and Strandvik, 2015; Lipkin and Heinonen, 2022). Scholars further highlight consumers' increasing **agency** and

intentionality in value formation. Consumers actively seek experiences that align with their goals and contexts, emphasising their central role as *autonomous creators* of value beyond provider-defined service encounters (Ben Gamra Zinelabidine et al., 2018; Fan et al., 2020; Kuuru, 2022). Furthermore, digital enabling technologies have empowered consumers to have a more dynamic and autonomous role in the value formation of their experience (Flavián et al., 2019). Digital self-service channels provide consumers with instantaneous access to the information they need, the ability to use services anytime and anywhere, and an overall newfound sense of control (Tyrväinen and Karjaluoto, 2019; Tueanrat et al., 2021; Vakulenko et al., 2019).

Consumer Centrality and Empowerment

The emergence of digital and AI-enabled environments has amplified consumer autonomy, giving rise to a new perspective that places the consumer — *rather than the service* — as the focal point of value creation. Consumer-Dominant Logic (CDL) represents this paradigmatic shift, positioning consumers as **independent** agents who combine and interpret value in products and services with their own resources (Anker et al., 2015; Heinonen et al., 2020; Voima et al., 2010). From this view, service providers do not create value but rather enable consumers to do so, with service offerings merely acting as contextual enablers within consumers' lifeworlds.

Recent research has increasingly explored consumer experiences as a phenomena that extend beyond *direct* and *dyadic* service interactions, unfolding within consumers' lifeworld and self-chosen ecosystems (Moran, 2002; Helkkula and Kelleher, 2010; Schembri, 2006). Such experiences are mentally grounded, evolving through consumers' ongoing sense-making processes and interpretations of offerings (Heinonen et al., 2010; Lipkin, 2016). From a CDL perspective, this shift also redefines the ***locus*** of value, positioning it within the consumer's experiential and contextual reality rather than provider-facilitated encounters. As such, it introduces a behavioural and phenomenological perspective of value creation where consumers construct value **individually** and **collectively** within their lived realities. This view extends the ***scope*** of value outside provider interactions to encompass relational, consumer-to-consumer (C2C) interactions, and collectives, where customers integrate various resources in their own processes with the goal of creating value (Grönroos and Voima, 2013; Heinonen et al., 2019) - *Chapter 3 details this extended value locus and scope.*

Beyond the Provider's Field of Vision

According to CDL, service is used by consumers *beyond* the control and field of vision of service providers (Gummesson, 2006; Grönroos and Voima, 2013; Heinonen *et al.*, 2010; Mickelsson et al, 2022). Instead of directing the value creation process, service providers are integrated into consumers' private ecosystems (Heinonen and Strandvik, 2020; Mickelsson et al, 2022). Within these ecosystems, consumers orchestrate value processes that align with their personal goals, motives, and life themes. Service providers, often unaware of these internalised processes, participate indirectly in user-defined value constellations — commonly referred as *consumer ecosystem*. Building on these advancements, CDL extends beyond SDL's focus on service ecosystems by situating value creation within *consumer ecosystems* – networks of experiences, actors, and practices embedded in consumers' lifeworlds (Heinonen and Strandvik, 2015; Voima et al., 2011).

This reconceptualisation reframes value co-creation as a contextual, consumer-led process where service providers act as peripheral enablers rather than central facilitators. Hence, CDL moves the analytical focus from provider-managed service encounters to consumer-driven, self-defined ecosystems, revealing how value is formed *invisibly* beyond firm control.

From Provider Orientation to Consumer Primacy

While Service Logic (SL) and Service Dominant Logic (SDL) acknowledge consumer participation, both primarily emphasise consumer orientation rather than consumer primacy (Heinonen et al., 2010; Heinonen and Strandvik, 2022). CDL, in contrast, repositions firms as participants within consumers' lifeworlds rather than coordinators of service ecosystems. This implies that value creation unfolds in consumers' lived contexts — where their goals, experiences, and social practices intersect. Service providers must therefore **engage *into***, rather than simply with, consumers' lives (Lipkin and Heinonen, 2022; McColl-Kennedy et al., 2020). Embracing the CDL perspective reflects that the emphasis changes from how providers engage consumers in their processes to how consumers engage multiple providers in their own ecosystem (Becker and Jaakkola, 2020; Bolton et al., 2018). In this view, CDL replaces transactional aspects of value co-creation with a contextual understanding that emphasises immersion into consumers' lifeworlds for a true unfolding of value formation.

The implications of adopting CDL instead of SDL changes the core business of a firm from "*what services should we offer to our customers*" to "*what are our customers willing to purchase and pay for*?" (Strandvik et al., 2012). The first attempts to involve consumers in the service provider's business whilst the second attempts to involve the service provider in consumer lives - *a significant difference that is*. The first starts from offerings/services and sets to identify the activities a service provider can fit in, based on its resources and capacity. The second sets out to identify the unrealised value of a service through the lens of consumers' own contexts (both physical and mental) and consumer activities, and then identifying what is needed to support these activities within the service provider's offered services and business processes (Heinonen et al., 2010, p. 545).

Temporal Context of Value (Time)

A defining dimension of Consumer Dominant Logic (CDL) is its recognition of ***time*** as a fundamental element in value formation. Consumer experiences and meanings evolve *before*, *during*, and *after* service encounters — accumulating through ongoing use and reinterpretation (Heinonen et al., 2023; Grönroos and Voima, 2013). **Figure 2**, adapted from Heinonen and Strandvik (2020), illustrates this temporal continuum, depicting value formation across the *pre-service*, *in-service*, and *post-service* phases.

While SDL restricts value creation to observable exchanges within firm-defined boundaries, CDL emphasises a **longer timeframe** that includes *before* and *after* service experiences (Heinonen et al., 2019). This view acknowledges that value can emerge from past experiences, anticipated futures, and imagined meanings of the consumer - not just the service process - often before or beyond any direct interaction with service providers (Helkkula et al., 2012; Grönroos and Voima, 2013; Rindell, 2013). By reframing value creation beyond provider-consumer interactions, the **timeframe** of value represents the accumulated reality as *experienced* by the consumer.

Value-in-use thus accumulates *over time* as consumers reinterpret and reform meanings through their ongoing experiences (Medberg and Grönroos, 2020). In this view, consumers dynamically integrate past experiences, present contexts, and future expectations, highlighting the **continuity** and **fluidity** of value across time. This temporal interpretation underscores that value formation is not a single event, but an **evolving** process shaped by contextual and experiential factors that remain largely *invisible* to providers. This temporality contributes an essential lens in understanding value formation within CDL, presenting value as a continuously developing experience-based process beyond the provider's direct influence.

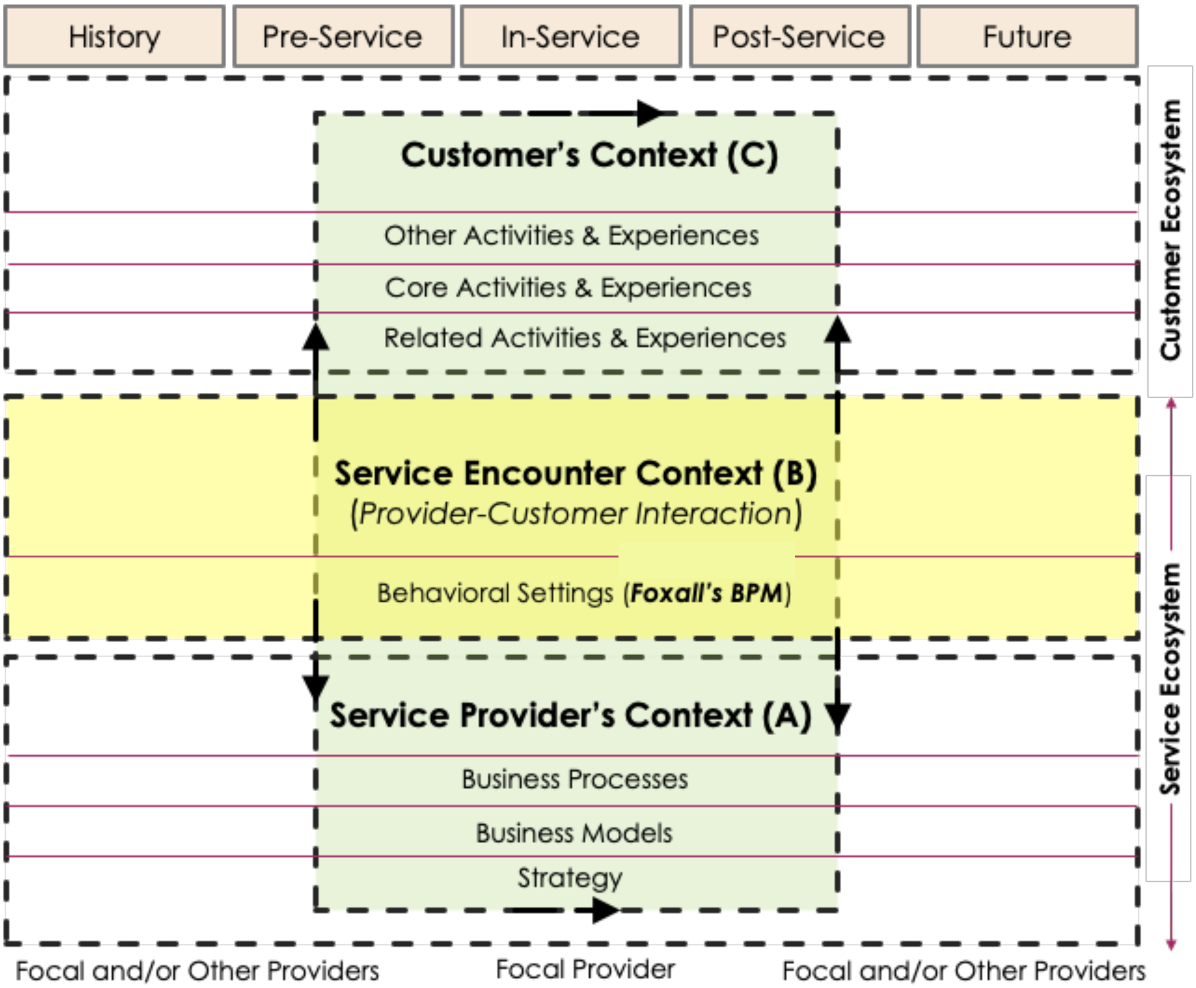


Figure 2: *Customer-dominant Logic of Service - Source: Adapted from Heinonen and Strandvik (2020)*

Figure 2 conceptually illustrates how value formation unfolds across three interlinked contexts:

1. **Provider context (A)** – where strategies, business models, and resources originate.
2. **Service encounter context (B)** – where interactions between providers and consumers occur.
3. **Customer context (*C*)** – where value is ultimately shaped through consumers' own activities, memories, experiences, and goals.

While traditional literature conceptualises value through provider-defined touchpoints (pre-, during, and post-service) (Gao and Liu, 2022; Patrício et al., 2011), such views restrict insight into how consumers create meaning and value beyond the firm's visibility or control. While SDL confines value formation to the provider and service encounter contexts, CDL integrates all three contexts, positioning the consumer context (C) as the central site of value creation. This highlights that real value unfolds within the consumer's own ecosystem, beyond the firm's visibility or control. The three-context model visualises CDL's central proposition: value creation is **temporally continuous** and **contextually distributed** across consumers' lived worlds, rather than confined to provider-consumer exchanges.

Adopting CDL posits that service providers should ideally mirror the consumer's experiences and activities occurring in the consumer context (C) across the past, present and future, recognising the entire consumer ecosystem – which includes other providers interacting with the consumer. However, when shifting their mindset from SDL to CDL, service providers face a major challenge in how restrictive their resources, capabilities, business models, or strategies are. This challenge explains the low adoption of CDL among service providers and the predominance of adopting SDL instead.

From the aforementioned and the illustration in **Figure 2**, it can be argued that the service *value-in-use* is only partly influenced by interactions with the service provider and mainly by other factors that occur deep in the consumer world or ecosystem.

Dynamic Consumer Behaviour and Variability

The mechanistic nature of SDL has been criticised for oversimplifying the relationship between consumer behaviour and contextual dynamics, neglecting how environmental variations stimulate new behavioural patterns (Marr, 2009; Mar and Zilio, 2013). This rigidity limits SDL's ability to account for emergent and context-specific adaptations in consumer responses. Recent advances in behavioural and cognitive research, on the other hand, support CDL's *temporal* view of value. Consumers dynamically adapt their decisions and behaviours according to contextual and temporal pressures (Waschke et al., 2021). When placed under pressure, consumers tend to expedite decisions but prioritise choices under low-demanding circumstances (Kelly et al., 2021; O'Connell and Kelly, 2021). Under CDL, consumer decision-making is not seen as a linear process within service encounters but as a *context-dependent*, *adaptive* phenomenon shaped by situational demands, cognitive efforts, and life goals (Zilio, 2019). Such adaptation — referred to as *neural variability* — illustrates how consumers *continuously reconfigure* value formation processes that result in higher probability of success or reward, often beyond the provider's awareness.

Building on this view, Zilio (2019) further explains that consumers' behaviours unfold dynamically across spatial and temporal gaps, often influenced by prior experiences or unrelated activities beyond the immediate service encounter. These contextual contingencies act as black boxes to providers, making consumer logics unpredictable and difficult to frame within structured exchanges. However, it is important to note that consumer logics differ from one consumer to the other, and service providers cannot afford to alter their offerings and services to support all of them (Chalmers Thomas et al., 2013; Heinonen and Strandvik, 2020). CDL therefore recognises that service providers can only influence, but not control, consumer behaviour as each consumer's adaptive reasoning is unique (Bolton et al., 2014). Providers must instead tailor their strategies to resonate with evolving consumer contexts through responsive design and contextual marketing initiatives. This reasoning highlights CDL's strength in capturing the *dynamic*, *non-linear evolution* of consumer behaviour across contexts and time—offering explanatory power beyond the static boundaries of SDL.

Digital technologies have further amplified consumers' autonomy in value formation by enabling self-service, instant access to information, and participation across digital communities (Kannan and Li, 2017; Tueanrat et al., 2021). These developments have enabled consumers' expectations for individually-tailored services on demand.

Consequently, service providers need to understand digital consumers *holistically* – acknowledging that each consumer's behavioural and cognitive processes differ dynamically over time. Such evolving individuality challenges SDL's nested and interdependent systems of exchange, which fail to explain the decentralised and self-regulating nature of consumer behaviour.

Distinction from Service-Dominant Logic (SDL)

While CDL builds upon SDL's recognition of value co-creation, it departs fundamentally in its treatment of value formation, temporality, and visibility. CDL situates value formation within the consumer's own context rather than the dyadic transactional service sphere, recognising that value evolves across time and is largely invisible, experiential, and subjective.

Building on these dimensions, CDL extends the conceptualisation of value by integrating behavioural, temporal, and collective dimensions of consumer experience, highlighting consumer primacy and empowerment beyond the provider's field of vision. Providers under CDL can only influence value *indirectly* through meaningful alignment with consumers' goals and contexts. Given these distinctions, this study adopts a **Consumer-Dominant Logic (CDL)** perspective to better capture the *autonomous*, *context-dependent*, and *temporally* evolving nature of consumer value formation that extends beyond firm-managed service interactions. **Table 4** summarises the key distinctions between SDL and CDL, positioning CDL as the guiding perspective for this study.

Table 4: *Comparative Summary: SDL and CDL*

Dimension	**Service-Dominant Logic (SDL)**	**Consumer-Dominant Logic (CDL)**	**Contribution**
Value locus	Co-created in provider-consumer interactions	Formed within consumers' *lifeworlds*, often *independent* of direct service encounters	Expands value understanding **beyond** provider-managed boundaries
Value Scope	Centered on dyadic provider-consumer value processes	Encompasses both value-shaping *individual* and *collective* (C2C) experiences and interactions	Recognises **relational** and **social** dimensions of consumer value formation

Temporal scope	Limited to discrete service encounters	Extends dynamically across *past*, *present*, and *anticipated* future experiences	Introduces **temporality** as a dynamic construct of value formation
Visibility	Observable and measurable within service exchanges	Largely *invisible*, *experiential*, and *situated* occurring within consumers' meaning-making	Recognises **private** and **subjective** value processes beyond observation
Role of provider	Value facilitator and co-creator within firm boundaries	*Contextual* enabler and *peripheral* influencer within consumers' ecosystems	Redefines provider's role as **supporting** – rather than directing – in value creation
Nature of logic	Systemic and exchange-oriented	*Contextual*, *experiential*, *behavioural*, and *temporal*	Shifts logic toward **lived experiences**, **consumer agency**, and adaptive **meaning-making**

This section positions CDL as a temporal and experiential evolution of SDL, capturing how consumers autonomously form, reform, and interpret value across time and context. By transcending provider- and service- encounter boundaries, CDL situates value creation within the consumer's ongoing life narrative. The comparative summary reinforces CDL's contribution in reframing value as *contextual*, *dynamic*, and *meaning-driven*. This foundation leads to the next section, which examines the mechanisms of value formation – central to understanding how AI-enabled hyper-personalisation can influence what consumers deem valuable within their lifeworlds.

2.2.3 Value Formation

Past research has shown that a consumer's mental and physical participation in a service plays a central role in shaping perceived value (Chen and Wang, 2016; Prebensen and Xie, 2017). Several studies have identified factors influencing value creation outside consumer-provider encounters (Bianchi, 2019; Fan et al., 2020; 2025; Rihova et al., 2018; Malone et al, 2018), challenging the traditional provider-driven view of value (Malone et al., 2018). This perspective aligns with Consumer-Dominant Logic (CDL), which emphasises a consumer-based approach to understanding value creation (Heinonen et al., 2010; Heinonen and Strandvik, 2015;

Heinonen and Lipkin, 2022). Although relatively recent, this new perspective has gained traction for its ability to capture value formation within consumers' own contexts and lifeworlds.

While multiple conceptualisations of consumer value exist (Zeithaml et al., 2020b), CDL distinguishes among three distinct domains: (1) *value-in-exchange,* which denotes the value derived in the provider's domain, (2) *value creation,* which emerges in joint provider-consumer encounters, and (3) *value formation*, which unfolds within the consumer's lifeworld, reflecting lived, contextual experiences (Grönroos and Voima, 2013; Heinonen, 2023; Malone et al., 2018; Schembri, 2006). The *value-in-exchange* can be unidimensional, focusing on tradeoffs between perceived quality and price including non-monetary sacrifices such as time, energy, and effort (Anderson and Narus, 1998; Zeithaml, 1988). It can also be multidimensional with functional, emotional, affective, temporal or spatial aspects of a service (Chang and Dibb, 2012; Grönroos, 1990; Holbrook, 1994). However, it remains controlled by the service provider, reflecting value-creating experiences that form the basis of the value exchange (Holbrook, 2006, p. 715).

On the other hand, CDL shifts attention from *value creation* to *value formation*, focusing on what constitutes value as experienced and interpreted by the consumer – independent of provider facilitation (Heinonen et al., 2020; 2019; 2022). Value formation is dynamic, continuously shaped through consumers' everyday activities, relationships, and interactions with the focal provider or other providers. Contrary to co-creation, consumer value formation is defined as "*customers' emerging behavioral and mental processes of interpreting, experiencing and integrating offerings in their everyday lives/businesses, with either positive or negative outcomes*" (Heinonen and Strandvik, 2020, pp. 479). In contrast, SDL and SL center value within provider-consumer exchanges, whereas CDL recognises value as emerging autonomously within the consumer's world.

By foregrounding this consumer lens, CDL challenges the provider-centric assumption that value is confined to the service encounter. Instead, value formation extends across time – past, present, and future – and across social and contextual settings, reflecting consumers' ongoing adaptation and sense-making (Heinonen et al., 2013; Medberg and Heinonen, 2014; Heinonen and Strandvik, 2020). Hence, understanding value formation requires examining how service offerings integrate into consumer's broader lifeworlds, fulfilling individual goals beyond the provider's field of visibility (Bolton et al., 2014; Heinonen et al, 2019). Value can also emerge independently from firms, shaped by consumers' everyday activities and long-term experiences (Malone et al., 2018; Nakata et al., 2019). Hence, value is not confined to provider-consumer elements but extends to autonomous consumer practices that unfold over time and context (Grönroos and Voima, 2013; Medberg and Heinonen, 2014).

From a CDL perspective, as explained by Heinonen et al. (2013, p. 104), "*the focus of value creation has changed from the company's service processes having involved the customer, to in fact the customer's multi-contextual value formation involving the company*". CDL therefore positions the consumer – not the provider – as the primary actor in value formation, with the provider participating within the consumer's multi-layered lifeworld and ecosystem (Heinonen and Strandvik, 2018). Value formation is embedded in the consumer's evolving reality, encompassing both deliberate and implicit processes that maybe cognitive, emotional, or even unreflective (Grönroos and Voima, 2013; Heinonen and Strandvik, 2018; Sahhar and Loohuis, 2022).

Consumers make sense of value *iteratively*, guided by their own personal logic and prior experiences (Grönroos and Voima, 2013; Heinonen and Strandvik, 2015, 2018). Their meaning-making and problem-solving processes are contextually shaped, positioning *sensemaking* at the core of value formation within CDL (Heinonen and Strandvik, 2022; Heinonen et al., 2013). Existing studies call for service providers to understand how data-driven tools and AI can support consumers' autonomy and integrity in creating value (André et al., 2018; Manser Payne et al., 2021).

However, many marketers still overlook the nuanced role of AI in value formation (Campbell et al., 2020). CDL recognises that while service providers may influence value formation, they cannot control it without understanding the consumer's individual and collective contexts (Heinonen et al., 2019). Consumers may or may not invite service providers into their value processes, meaning much of the consumer value formation remains invisible to the firm (Fournier and Avery, 2011). These hidden elements often hold the highest potential for insight and innovation, as they reveal misalignments between the provider's and the consumer's logic (Heinonen et al., 2019; Strandvik et al., 2019).

Accordingly, this study adopts Consumer-Dominant Logic (CDL) as its theoretical foundation and an alternative to SDL wherein consumers '*dominate and control the value creation*' process (Heinonen and Strandvik, 2015, p. 474). This approach enables a more accurate understanding of how hyper-personalisation interacts with consumers' ongoing value formation across their lifeworlds (*consumer ecosystem*).

The model developed in **Chapter 3** builds on this foundation, exploring how consumers embed services into their daily activities and active life goals through AI-enabled hyper-personalisation. From this perspective, the next section examines how these goals underpin consumer value formation and influence decision-making within their lifeworlds.

2.3 Consumer Goals and Goal Strength

Neisser's (1967) seminal book "Cognitive Psychology" – the manifesto of the cognitive revolution – brought about a major shift from behaviourist interpretations of human action to an understanding grounded in *internal, goal-driven* cognitive processes. While behaviourism viewed higher mental processes as responses to external stimuli (Crews, 2017), Neisser emphasised *top-down* cognitive processing where intentions, expectations, and goal pursuits guide perception and behaviour. This cognitive revolution positioned the conscious mind – rather than the environment – as the central regulator of higher mental functions including attention, choice, and judgement (Baars, 1986; Neisser, 1967). Since its publication, over five decades of research have validated Neisser's proposition regarding the pervasive role of goal pursuit in shaping cognitive processes of the human brain (Bargh, 2021).

Active Consumer Goals

Goal pursuit represents the cognitive process through which individuals continuously engage in behaviours directed toward achieving desired end states (Feather, 1962; Fishback and Dhar, 2005; Moshontz and Hoyle, 2021). *Goals* serve as **mental representations** of preferred outcomes, motivating behaviour that reduces the gap between current and ideal conditions (Fishbach and Woolley, 2022; Milyavskaya and Werner, 2018). Such pursuits may operate *consciously* – through deliberate intention – or *unconsciously*, as part of the consumer's habitual or automatic responses to stimuli (Austin and Vancouver, 1996; Brandstätter and Bernecker, 2022; Bargh, 2021).

A goal is considered "*active*" when it is triggered and remains accessible in memory, influencing perception, evaluation, and behaviour until fulfilled or replaced (Anderson, 1983; Neely, 1977; Rumelhart and Ortony, 1977). An active goal represents a current "*state of affairs or an outcome that people desire to attain through their actions*" (Kruglanski, 1996 in Ajzen and Kruglanski, 2019, p. 777). Once activated, a goal strengthens the longer it remains active, guiding attention and behaviour in a direction consistent with goal attainment (Milyavskaya and Werner, 2025). Active goals exert a powerful influence over other cognitive processes, shaping how individuals interpret information and allocate mental resources (Agrawal and Wan, 2009; Bolos et al., 2022; Bargh, 2021). Goals are believed to significantly impact decision-making and guide consumer choice, behaviour, and one's assessment of risk (Ferguson, 2008; Ferguson and Bargh, 2004; Hill and Durante, 2011).

This influence can alter preferences, evaluations, and attitudes (Huang and Bargh, 2014; Melnikoff and Bailey, 2018; Melnikoff and Strohminger, 2020) in favour of facilitating the current goal progress. Activating a goal means keeping it at the forefront of attention, where it drives motivation to initiate the activity or behaviour supporting its pursuit. It also influences how strongly a person stays committed to the goal, even when facing obstacles (Bolos et al, 2022; Fishbach and Choi, 2012; Shah and Kruglanski, 2003). Thus, consumers' perceptions, preferences, and behavioural choices are *dynamically* oriented toward attainment of their currently active goals.

However, goals are not isolated intentions but form part of a hierarchical cognitive network that connects higher-order aspirations with lower-order actionable sub-goals (Bargh, 1990; Bargh and Gollwitzer, 1994; Kruglanski, 1996). With this structure, higher-order goals represent abstract, desired end states, while lower-level goals serve as actionable means to achieve these broader objectives (Bagozzi and Dholakia, 1999). An individual's behaviour is thought to be guided by a goal positioned at the center of this hierarchy – the *focal goal* – linking abstract motivations with specific behaviour. It represents the immediate objective that directs attention and effort toward goal fulfillment, guiding how individuals prioritise and rationalise their actions to serve that focal goal (Friedman et al., 2018; Lee and Chu, 2022). For example, the higher-order goal of “looking better” may be supported by a focal goal such as “exercising”, which is in turn achieved through lower-level goals like “going to the gym everyday”.

Behavioural Motivational Frameworks

Building on the cognitive and hierarchical understanding of goals, behavioural motivational frameworks explain how individuals translate these internal goal structures into observable actions and decision making processes (Concari et al., 2020; 2022; Geiger et al., 2019; Varotto and Spagnolli, 2017). These frameworks highlight the dynamic interplay between cognition, motivation, and behaviour, clarifying how intentions are formed and sustained in pursuit of consumer goals. Among the most influential frameworks are the **Theory of Reasoned Action (TRA)** (Ajzen and Fishbein, 1970; Fishbein and Ajzen, 1975), the **Theory of Planned Behavior (TPB)** (Ajzen, 1991), and the **Goal Systems Theory (GST)** (Kruglanski et al., 2002). While the Theory of Planned Behaviour (TBP) emphasises the role of attitudes, subjective norms, and perceived behavioural control in shaping intentions, the Goal Systems Theory (GST) focuses on the hierarchical organisation and interconnections of goals that govern behavioural activation and persistence.

In the Theory of Planned Behaviour (TBP), intention – defined as “*the person’s motivation in the sense of his or her conscious plan to exert effort to carry out a behaviour*” (Eagly and Chaiken, 1993, p. 168) – is considered the immediate antecedent of behaviour. It represents ones’ readiness to engage in a specific action, with stronger intentions predicting a higher likelihood of behaviour (Hamilton et al., 2022). Despite its predictive power, TBP has faced criticism for overlooking the influence of unanticipated events, shifting contexts, and unconscious motivations that may alter behavioural execution (Ajzen and Kruglanski, 2019). It falls short of considering the motivation driving engagement in a particular behaviour in the first place. These limitations underscore that attitudes and subjective norms alone are insufficient to fully explain action initiation, as behavioural intention is shaped by dynamic motivational and situational factors (Hagger et al., 2022; Yang-Wallentin et al., 2004). Although individuals may hold positive attitudes or experience social pressure toward a behaviour, these factors alone do not necessarily translate into behavioural intention or action (Hamilton et al., 2022).

To address these limitations, Goal Systems Theory (GST) provides a complementary perspective, viewing behaviour as **goal-driven** and hierarchically organised. Its top-down approach argues that "*initiation presupposes the prior activation of one or more goals for which the behaviour in question serves a means*" (Ajzen and Kruglanski, 2019, p. 777). In this framework, goals are interconnected nodes within a cognitive network, where higher-order goals activate subordinate goals and instrumental behaviours that facilitate attainment (Kopetz et al., 2012; Kruglanski et al., 2002; Fishbach et al., 2022). The activation strength and perceived value of each goal determine its motivational influence, with goal pursuit being influenced by *desirability*, *feasibility*, and *availability* of means (Huang et al., 2023; Kruglanski et al., 2015). Oettingen et al. (2004) emphasise that the more valuable and attainable a goal is perceived to be, the more vigorously individuals will pursue it. GST therefore extends beyond the conscious planning focus of TPB, capturing how multiple goals operate simultaneously — sometimes cooperatively, sometimes competitively — within the individual's cognitive system.

Integrating TPB and GST provides a more comprehensive understanding of consumer behaviour by recognising that goal pursuit can be both deliberate and automatic, shaped by cognitive evaluations and situational cues. This integrated view helps explain why consumers' intentions and actions often diverge, as momentary cues or competing goals can shift focus and modify behavioural persistence.

Motivation and Commitment

Kruglanski et al. (2015, pp. 2) argue that "*attitudes toward objects, even if strong, or toward behaviour, even if highly positive, are insufficient in and of themselves to incite action*", as behaviour is instead driven by goal activation. **Motivation**, therefore, represents the cognitive and emotional drive to achieve an active goal or set of active goals, indicating that active goals serve as powerful motivators of action.

Goal **commitment**, on the other hand, is primarily influenced by two key factors: (1) the *value* of the goal and (2) the *expectancy* of goal attainment (Gollwitzer and Oettingen, 2012; Latham and Locke, 2006; Locke and Latham, 1990, 2019). The value of a goal reflects its perceived importance or desirability, while expectancy represents the perceived likelihood of successfully attaining it. When goals are both desirable (high value) and attainable (high expectancy), individuals exhibit greater focus, effort, and persistence toward their pursuit (Dachler and Mobley, 1973; Kolb and Boyatzis, 1970; Locke et al., 1984). The joint influence of these two dimensions forms the foundation of classic goal pursuit theories (Atkinson, 1957; Vroom, 1966), establishing motivation and commitment as central forces sustaining goal-directed behaviour. The Goal Systems Theory (GST) provides valuable insight into how consumers assess the value of their active goals and the likelihood of achieving them — both of which shape goal commitment. When a particular behaviour or means is uniquely and strongly linked to an active goal, its perceived value is amplified. This reflects the *transfer* principle of GST: the higher the value of the goal, the more instrumental and valuable its associated means becomes.

Building on this foundation, recent research has explored goal pursuit through the lens of reinforcement learning, positing that achieving sub-goals elicits internal reward signals similar to those triggered by external incentives (Juechems and Summerfield, 2019; Mas-Herrero et al., 2019; Ribas-Fernandes et al., 2019). Reinforcement learning frameworks explain how individuals assign value to goals based on both internal cognitive *setpoints* and external environmental stimuli serving as cues guiding behaviour. Within this view, goal pursuit operates as a *feedback control system* composed of *goal setting*, *striving*, and *progress monitoring* (Carver and Scheier, 2001; Miller et al., 1960; Powers et al., 1960; Wiener, 1948). Individuals assess the discrepancy between their current and desired states, using this feedback to guide corrective actions and sustain movement toward goal attainment (Inzlicht et al., 2021; Milyavskaya and Werner, 2025). This iterative process forms the foundation of **adaptive goal regulation**.

From a cognitive perspective, this regulation is bounded by the limitations of human rationality. Goal-directed behaviour operates under finite cognitive capacity, as individuals must manage limited attention and processing resources (Lieder and

Griffiths, 2020). Consequently, consumers rely on *resource-rational heuristics* to make effective decisions within complex and information-rich environments (Callaway et al., 2018). These heuristics enable efficient goal pursuit by focusing on cues and information most relevant to their active goals, rather than evaluating every possible alternative (Lieder et al., 2018). While such bounded rationality promotes cognitive efficiency, it can also generate trade-offs between competing goals. As Prystawski et al. (2022) suggest, individuals prioritise goals that can be achieved efficiently under cognitive constraints, sometimes pursuing one goal at the expense of another (e.g., enhancing social image at the expense of personal health) (Kopetz et al., 2019; 2021). This illustrates how cognitive limitations and motivational priorities jointly shape the dynamics of everyday goal pursuit.

Goal Systems and Means-Ends Configuration

This paradox aligns with the second principle of Goal Systems Theory (GST), which posits that the number of active goals a specific means serves, and the number of available means for a given goal, jointly determine the *strength* of the means–goal association (Kruglanski et al., 2023). For example, if biking serves both commuting and exercising goals, its motivational strength for each diminishes as it becomes less instrumental for either. According to the principle of *attainment maximisation*, individuals prioritise means that most efficiently contribute to goal fulfillment. Thus, a consumer who bikes for exercise may choose to drive instead when convenience outweighs the fitness benefit.

When multiple behaviours can serve the same goal — as in the case of biking for both commuting and exercising — the perceived value of each means diminishes because each becomes a substitutable rather than an essential option (Ajzen and Kruglanski, 2019). In contrast, when only one means exists to achieve a goal, its perceived value heightens, making it more likely to be pursued and reinforcing goal commitment. The likelihood of a behaviour being selected also increases when it serves multiple active goals simultaneously. Thus, behaviours that advance several consumer goals strengthen motivation and persistence toward those actions (Ajzen and Kruglanski, 2019). This insight underscores the strategic potential for service providers to frame their offerings as means that advance multiple consumer goals, thereby enhancing engagement and commitment toward their services.

From this perspective, the selection of a specific behaviour (i.e., the means) depends on the individual's evaluation of both *internal* and *external* information. Internally, this involves the *configuration* of the goal system — how specific means link to specific goals. Externally, it reflects feedback drawn from previous experiences or social observations within similar goal-related contexts (Huang, 2023). These external cues integrate into the internal goal system *dynamically* and *iteratively*, enabling individuals to continuously update how they perceive and evaluate means–goal relationships. When new means become available, they are incorporated into this internal structure, reshaping perceptions of a goal's value and expectancy (Huang, 2023). This dynamic re-evaluation influences how strongly individuals commit to pursuing a given goal, reinforcing the **adaptive** and **context-sensitive** nature of goal pursuit.

Temporal Dynamics of Goal Pursuit

Beyond value and expectancy, the **temporal** dimension plays a vital role in sustaining goal pursuit. Maintaining motivation and commitment over time requires individuals to continuously engage in behaviours that facilitate goal progress (Bolos et al., 2022; Bonezzi et al., 2011; Etkin, 2019). This sustained engagement is captured in the construct of *goal strength*, which reflects the degree of emotional and mental investment in the goal pursuit process. A strong goal strength promotes persistence and focus, even in the face of obstacles, whereas low goal strength is associated with disengagement and goal abandonment (Bélanger-Gravel et al., 2013; Bolos et al., 2022; Kivetz et al., 2006).

Therefore, goal strength functions as a *dynamic* construct, shaped by both initial motivation (value) and perceived feasibility (expectancy), and sustained through continued commitment over time (Bandhu et al., 2024). This highlights that consumer goal pursuit is not static but evolves continuously as motivation and context interact to shape persistence and behavioural engagement. Goal strength, therefore, represents what drives individuals to act in goal-congruent ways, emerging from the interplay between *motivation* (the desire for goal attainment) and *commitment* (persistence despite obstacles). It captures the degree to which individuals remain mentally and emotionally invested in pursuing their active goals over time.

Research shows that individuals with strong goals exhibit greater consistency in their pursuit behaviours, even under conditions of limited progress or rewards (Thomas et al., 2022). Moreover, as goal pursuit resumes and progress accumulates, goal strength itself can increase - creating a *self-reinforcing cycle* in which prior achievements motivate continued engagement (Wallace and Etkins, 2018). The more progress individuals perceive toward goal attainment, the more deeply committed and motivated they become (Bolos et al., 2022). This dynamic interaction between progress and persistence highlights the evolving nature of consumer motivation, where past successes serve as intrinsic feedback that strengthens future goal-directed behaviour.

Dynamic Goal Systems and Contextual Framing

In addition to conceptualising behaviour as *goal-driven*, the Goal Systems Theory (GST) and related perspectives (Bargh, 2022) highlight the dynamic nature of goals, which are not fixed but fluctuate across *time* and *context*. This fluidity implies that consumers' evaluations of behaviours and their associated means are highly sensitive to **temporal** and **situational** conditions. Understanding how individuals perceive the relationship between goals and the behaviours required to attain them is therefore critical, as it directly influences the decision to engage in and sustain particular actions (Fishbach and Ferguson, 2007; Kruglanski and Kopetz, 2009).

By strategically leveraging goal architecture, service providers can shape consumers' perceptions of *means–ends* associations, guiding behavioural choices toward desired outcomes (Fishbach et al., 2022). To do so effectively, service providers must understand the interrelationships among goals-means configurations, which are dependent on both informational and contextual framing (Bolos et al., 2022). These configurations may shift or even appear contradictory due to situational inconsistencies or evolving priorities (Van Osselaer and Janiszewski, 2012). Consequently, by aligning contextual cues with consumers' active life goals, service providers can better facilitate engagement and decision-making during service encounters.

Toward a Theory of Reasoned Goal Pursuit

Recognising the complementary value of both the Theory of Planned Behaviour (TPB) and the Goal Systems Theory (GST), contemporary scholars have proposed integrated or **hybrid** models to bridge conceptual gaps between them (Hagger and Hamilton, 2020). These models acknowledge that no single theory fully explains consumer behaviour, and that combining constructs enhances explanatory power (Hamilton et al., 2022).

The **Theory of Reasoned Goal Pursuit (TRGP)** (Ajzen and Kruglanski, 2019) synthesises TPB and GST by incorporating active goals as central determinants of behaviour — extending, rather than replacing — TPB's foundational structure. In this model, intentions continue to reflect the influence of attitudes, norms, and behavioural beliefs, but they also integrate the individual's currently active goals. From this hybrid perspective, consumers pursue behaviours that advance one or more types of active goals:

1. **Procurement goals**, which relate to personal outcomes and experiential benefits.
2. **Approval goals**, which pertain to social validation from significant others.

When a behaviour effectively satisfies procurement or approval goals, its impact on attitudes and normative beliefs is amplified. Conversely, when behavioural expectations are unlikely to contribute to goal fulfilment, their influence on decision-making diminishes (Hamilton et al., 2022).

Although active goals exert a strong influence on consumer behaviour, research also highlights the role of past experiences, environmental stimuli, and social cues in activating or reactivating goals (Bargh et al., 2001; Chartrand and Bargh, 1996; Chen et al., 2021; Weingarten et al., 2016). These incidental triggers may not always relate directly to current goals but can momentarily stimulate latent motivations. For instance, the aroma of freshly brewed coffee may unconsciously activate the goal of consumption, even if it was not part of the consumer's immediate intentions. Conversely, chronically activated goals — such as those of long-term dieters — may remain stable and unaffected by incidental cues (Köpetz et al., 2011; Van Osselaer and Janiszewski, 2012). Such cues may operate independently or in conjunction with active goals, influencing consumer decisions in real time. The interaction between contextual triggers and cognitive motives underscores the fluid nature of consumer decision-making, where conscious intentions and unconscious impulses dynamically shape behavioural outcomes.

From a broader perspective, while the concept of active goals provides a compelling account of motivation, it does not replace foundational psychological theories. Instead, it extends them by integrating both deliberate and unconscious drivers of behaviour. Building on insights from Freud's emphasis on unconscious impulses and Skinner's behavioural contingencies, contemporary cognitive psychology focuses on how internal mental representations — such as intentions, goals, and expectations — interact with environmental cues. Ultimately, **environmental triggers** and **internal motives** converge within a dynamic cognitive–motivational framework, continuously shaping consumer behaviour and decision-making (Bargh, 2022).

Integrative Motivational Influences in Consumer Behaviour

Ajzen and Kruglanski's (2019) framework identifies three key categories of influence guiding consumer goal pursuit:

1. *Cognitive motivational influences* — these emerge from active or latent goals that shape preferences and decision-making, aligning with *self-to-self* value formation (Melnikoff and Strohminger, 2020).
2. *External stimuli* and *contextual cues* — these include environmental and service-related factors that trigger or redirect goals, reflecting *provider-to-self* value processes.
3. *Post-conscious cognitive processes* — these involve evaluative and memory-based mechanisms, where past experiences and shared interactions influence how consumers assign value over time (*service-in-use* or *consumer-to-consumer* formation).

Together, these mechanisms emphasise that consumer behaviour is *dynamically* shaped by the interplay of internal motives and contextual triggers. For service providers, this suggests that hyper-personalisation should focus on aligning marketing efforts with consumers' *active life goals*, sustaining both motivation and commitment to enhance consumer goal strength — the enduring psychological engagement driving goal-congruent decision-making.

In summary, this section established the theoretical grounding for understanding how consumer goal strength operates as a *dynamic*, *evolving* construct shaped by *motivational*, *contextual*, and *temporal* factors. The present study adopts a **goal-driven** perspective rather intention-driven perspective, emphasising how consumers' active life goals underpin their decision-making in hyper-personalised environments. As such, the study captures how goal pursuit evolves over time. The **temporal** dimension of goal pursuit is reflected through the study's 3-wave longitudinal design examining changes in motivational intensity and commitment, and revealing how *goals–means configurations* adapt to shifting contexts. Together, these insights enables understanding how AI-enabled hyper-personalisation interacts with consumers' evolving goals and sustained engagement over time.

Building on this, the next section explores the role of **privacy framing** as a contextual mechanism that may influence consumers' engagement with hyper-personalised environments and the strength of their ongoing goal pursuit.

2.4 Privacy Framing: Trade-offs and Impact

The increasing reliance on Artificial Intelligence (AI) and algorithmic decision-making in hyper-personalisation raises critical concerns regarding consumer data privacy, inferred preferences, and algorithmic transparency. As AI systems extract increasingly granular user data — often without explicit consumer awareness — the nature of privacy risk has evolved. These systems not only collect volunteered information but also infer sensitive attributes such as preferences, lifestyles, and intentions, amplifying perceptions of surveillance and intrusion (Anica-Popa et al., 2021; Milne et al., 2020; Zhang et al., 2018; Walker and Milne, 2024).

Privacy, therefore, is no longer a fixed boundary or static constraint but a *dynamic*, *psychological* construct that both shapes and is shaped by consumers' perceptions of value. From a Consumer-Dominant Logic (CDL) perspective, privacy is conceptualised as co-created and contextual — emerging through individual interpretation rather than imposed universally. Consumers continuously negotiate what they are willing to disclose, trade, or protect based on situational goals, trust levels, and perceived benefits (Heinonen and Strandvik, 2020). Accordingly, the way privacy is framed — as a potential risk or as part of a value exchange — significantly determines if data sharing is perceived as acceptable, beneficial, or intrusive.

While existing literature explores privacy concerns, trust, and algorithmic transparency in digital and personalised contexts (Shin and Biocca, 2022; Spiekermann et al., 2021), there is insufficient understanding of how these factors evolve over time and interact with longitudinal consumer behaviour. As hyper-personalisation becomes increasingly sophisticated — drawing from multiple streams of behavioural, demographic, contextual, and goal-oriented data — long-term effects of privacy on consumer engagement, motivation, and value perception within hyper-personalised environments remain underexplored (Davenport, 2023). Much of the existing literature treats privacy as a static construct or a singular trust variable, thereby neglecting its dynamic, consumer-specific nature.

Addressing this gap, the present study adopts a longitudinal, consumer-centric perspective to examine privacy framing as a dynamic moderating construct within the broader Consumer-Dominant Logic (CDL) framework. Rather than assuming uniform responses to data practices, this study investigates how individual interpretations of privacy messages and trade-offs dynamically influence goal strength, engagement, and perceived value in AI-enabled hyper-personalised environments. This approach recognises privacy as an evolving boundary — fluidly shaped by emotional, contextual, and motivational factors over time. Through longitudinal analysis, the study captures how privacy-related trade-offs unfold, revealing how consumers balance perceived risks and rewards in shaping sustained engagement.

Together, these insights contribute to a deeper understanding of privacy not merely as a static constraint but as a co-created element of value formation — central to understanding consumers' adaptive engagement and ongoing goal pursuit in hyper-personalised systems.

The following subsections explore this construct across three dimensions:

- **2.4.1** defines and contextualises privacy framing as a **psychological mechanism** influenced by message presentation.
- **2.4.2** explores the **privacy–personalisation** paradox and how CDL framework explains varied consumer trade-offs, including emotional responses such as reactance or empowerment.
- **2.4.3** addresses **ethical responsibilities** of service providers, focusing on explainable AI, transparent design, and value co-creation that preserves consumer autonomy.

2.4.1 Privacy Framing

AI-enabled hyper-personalisation has transformed how consumers experience digital services by tailoring content and recommendations in real time. However, this increased relevance comes at a potential cost: consumers' personal data is continuously collected, processed, and inferred — often in ways that are not fully transparent nor easily understood (Bjørlo et al., 2021; Hoyer et al., 2020). The automation of these processes through Artificial Intelligence introduces new psychological and ethical complexities, including consumer mistrust, surveillance anxieties, and perceived loss of control (Darmody and Zwick, 2020; Lumbreras, 2018).

These concerns are particularly salient when AI-enabled systems rely on inferred behavioural traits such as life goals, values, and preferences that users may not have explicitly shared. As Barth and de Jong (2017) and Jain et al. (2021) highlight, such inference practices intensify perceptions of intrusiveness and raise fears of surveillance capitalism. This is especially problematic in hyper-personalised environments that require continuous access to granular, cross-domain data. While some of this data is voluntarily disclosed (e.g., age, interests), other forms are algorithmically inferred without consumers' full awareness, heightening perceptions of manipulation and control loss.

In digital contexts, the term *privacy* extends beyond the notion of secrecy and increasingly relates to agency and control (Acquisti et al., 2020; Kokolakis, 2017). Information privacy can thus be understood as '*the claim of individuals, groups, or* *institutions to determine for themselves, when, how, and to what extent information about them is communicated to others*' (Westin, 1967, p. 5). Contemporary consumers are less concerned about whether companies possess their data and more about how much autonomy they retain in deciding **when**, **how**, and **for what** purposes it is used. Yet, as AI systems become more opaque, such perceived control often proves illusory, widening the gap between actual and perceived (Waks, 1989).

From a psychological standpoint, privacy framing functions as a key interpretive mechanism that shapes how consumers evaluate these trade-offs. Depending on how data use and value exchange are communicated, privacy messages can frame data sharing as either *empowering* — enhancing relevance and convenience — or as *intrusive*, evoking resistance and distrust. This framing process directly influences *goal-congruent* engagement in hyper-personalised contexts, determining whether consumers view personalisation as value-enhancing or as a threat to autonomy.

Framing, a foundational concept in decision-making and communication theory, refers to how information is presented to shape judgment and behaviour (Tversky and Kahneman, 1981). In the privacy domain, framing effects have been shown to significantly influence users' willingness to disclose data, particularly when decisions involve emotional or uncertain outcomes (Acquisti et al., 2015). Two privacy framing types typically dominate:

- **Gain framing**, which emphasises benefits of disclosure (e.g., "Share your data to receive tailored experiences")
- **Loss framing**, which stresses the drawbacks of withholding data (e.g., "You may receive generic recommendations if you don't share data")

Recent research, however, identifies a third, more diagnostic variant — **risk framing**. Unlike gain or loss frames, which focus on outcomes-based evaluations, risk framing draws attention to the *process* and inherent *uncertainty* of data disclosure. It highlights perceived threats such as algorithmic bias, data misuse, or loss of autonomy. Studies by Zhang et al. (2018; 2022) demonstrate that risk-framed messages elicit stronger affective reactions — including fear, reactance, or vigilance — particularly among privacy-sensitive individuals. Collectively, these framing effects reveal that privacy communication does not merely inform but actively shapes consumer cognition and emotion, influencing perceptions of control, trust, and personal relevance. Understanding these mechanisms is therefore essential for examining how privacy framing affects consumer motivation and engagement within AI-enabled hyper-personalised systems.

In hyper-personalisation, risk-based privacy framing is particularly salient because the effectiveness of personalisation strategies often depends on consumers' **subjective interpretation** of the *value–privacy* trade-off. The same message about sharing life goals or behavioural data can be perceived as empowering by one consumer and invasive by another — a distinction that lies at the heart of the Consumer-Dominant Logic (CDL) perspective. From a CDL lens (Heinonen and Strandvik, 2020), consumer perceptions of value are *contextual*, *experiential*, and *idiosyncratic*. Privacy, therefore, is not a universal barrier but a subjectively constructed stimulus, whose meaning depends on prior experiences, values, perceived vulnerability, and trust.

Privacy framing offers a critical entry point into this value formation process, shaping how consumers interpret not only the service offered but also the very meaning and consequence of data disclosure. Viewed through this lens, risk framing functions not merely as a communication device but as a psychological mechanism that exposes variability in how consumers make sense of hyper-personalisation.

This study integrates risk-based privacy framing into its experimental design as a **moderating variable**, testing whether the presentation of privacy-related information alters the effect of hyper-personalisation on consumer goal strength and engagement. By embedding privacy framing directly within the stimulus design, the study captures **dynamic behavioural trajectories** — not only whether consumers engage, but *how* their engagement evolves when the perceived risk of disclosure is made salient. This approach aligns with recent calls for **longitudinal models of digital trust and privacy sensitivity** (Davenport, 2023; Martin and Murphy, 2022), particularly in the context of AI-driven personalisation.

In this view, privacy framing serves as a **boundary condition** within the model, enabling an examination of whether consumers' reactions to personalisation are fragile, habitual, or genuinely goal-aligned — and whether privacy sensitivity diminishes or amplifies engagement over time.

2.4.2 Privacy-Value Paradox

A long-standing challenge in digital personalisation research is the **privacy–personalisation paradox**, which encapsulates the contradictory behaviour of users who express concern over privacy yet continue to disclose personal information in exchange for convenience or tailored experiences (Awad and Krishnan, 2006; Norberg et al., 2007). While hyper-personalisation enhances value potential by tailoring content to individual goals, it also amplifies privacy risks — such as loss of control, identity exposure, or algorithmic profiling — which can trigger consumer resistance or disengagement (Barth and de Jong, 2017; Martin et al., 2020; Menard and Bott, 2025). This tension manifests through consumers' *cognitive evaluation* of perceived privacy risks versus expected benefits, often referred to as the privacy–value paradox (Chen et al., 2022a; Cloarec et al., 2022; McKee and Peltier, 2023).

This paradox is increasingly examined through the lens of **consumer empowerment**, which posits that individuals are more willing to share data when they feel in control, understand what information is collected, and perceive fairness and transparency in the process (Lutz and Hoffmann, 2017). Empowerment is thus linked to perceived autonomy, trust, and agency — factors that are essential for fostering positive consumer engagement in AI-enabled systems. However, reactions to data sharing remain inherently *contextual* and *idiosyncratic*: while some consumers perceive AI-enabled personalisation as enhancing value, others view it as manipulative or exploitative, associating it with heightened exposure of their personal data.

From a **Consumer-Dominant Logic (CDL)** perspective, value is not objectively embedded within the service but co-created and subjectively experienced by the consumer. What one consumer perceives as a valuable, personalised recommendation, another may interpret as an invasive intrusion (Heinonen and Strandvik, 2020). This reinforces the idea that the boundary between benefits and sacrifices is highly *individualised* and cannot be predetermined by the service provider. Consequently, consumers may simultaneously desire the advantages of personalised content while resisting the data-sharing practices required to deliver it (Awad and Krishnan, 2006; Acquisti et al., 2015).

The paradox is also emotional, rooted in perceptions of fairness, agency, and control. When hyper-personalisation is perceived as opaque or intrusive, it can evoke discomfort, suspicion, or even withdrawal from digital interactions (Barth and de Jong, 2017; Choi et al., 2022; 2023). Studies reveal that individuals often feel confused or anxious when exposed to personalised content without clear disclosure of ***how*** or ***why*** data was used (De Keyzer et al., 2022a; Pfiffelmann et al., 2020). This dissonance arises from a perceived lack of transparency and loss of control, which undermines trust, erodes long-term engagement, and triggers reactance — a defensive psychological state against perceived manipulation (Boerman et al., 2017; Gironda and Korgaonkar, 2018; Shin and Biocca, 2022).

Consumers are especially likely to react negatively when personal data appears to serve organisational interests rather than personal ones, particularly in the absence of meaningful consent or transparent communication (Bjørlo et al., 2021; Cukier, 2020; Hoyer et al., 2020). These tensions are further amplified in AI-driven contexts, where algorithmic logic and data use are often opaque, heightening perceptions of vulnerability and unpredictability.

However, emotional reactance to personalisation is not uniform. It varies across individuals depending on personal traits, perceived risks, and cultural expectations (Spiekermann et al., 2021). Understanding these variations is crucial for designing ethical and effective AI-enabled personalisation systems that recognise privacy not as a fixed boundary but as a **dynamic**, **consumer-specific** construct shaping value perception and behavioural engagement.

2.4.3 Ethical Practices and Empowerment

As the literature continues to evolve, increasing attention is given to the **ethical** and **emotional dimensions** of privacy. While consumers generally appreciate personalised experiences, they may react negatively when personalisation becomes overly intrusive or intimate. Conversely, consumers often expect higher levels of accuracy and relevance in personalisation to compensate for the privacy they relinquish in exchange (Davenport, 2023). As sensitivity to data privacy grows, some consumers may withdraw from personalisation altogether, while others demand greater transparency and precision to mitigate perceived risks. Consequently, service providers face the ongoing challenge of determining the *threshold* at which personalisation's desirability outweighs its perceived invasion of privacy.

As consumers become more empowered and data-savvy, traditional approaches to market research and data management have become increasingly inadequate. Providers must therefore adopt **ethically grounded strategies** that balance value creation with respect for user *agency* and *trust* (Blasco-Arcas et al., 2022; Lamberton and Stephen, 2016; Wedel and Kannan, 2016). This reinforces the need for bridging the gap between value capture and value formation (Blasco-Arcas et al., 2022; Lamberton and Stephen, 2016; Wedel and Kannan, 2016). From a **Consumer-Dominant Logic (CDL)** perspective, ethical personalisation requires understanding how hyper-personalisation aligns with consumers' broader life goals and supports value co-creation within evolving digital ecosystems.

Construal-Level Theory (Liberman and Trope, 1998) provides further insight into how individuals evaluate such trade-offs. When personalisation is processed as an *abstract, goal-aligned benefit* — linked to long-term aspirations rather than immediate gratification — it is more likely to enhance motivation and engagement (Agrawal and Wan, 2009). Accordingly, AI-enabled services can become genuinely transformative when they are grounded in consumers' intrinsic values and life contexts. However, the challenge for service providers lies in navigating hyper-personalisation **ethically** within evolving consumer ecosystems. Despite widespread calls for greater consumer empowerment, empirical work using the CDL lens remains limited. This study addresses that gap by adopting CDL as its theoretical foundation to explore how hyper-personalisation can be *ethically* and *contextually* tailored to influence consumer goal strength and sustained engagement (Lipkin and Heinonen, 2022).

While autonomy and hedonic utility remain strong motivators, consumers are also willing to tolerate certain sacrifices — such as reduced privacy — when AI systems demonstrate *reliability*, *accuracy*, and *fairness* in reflecting their stated preferences (Ameen et al., 2021). This willingness to trade control for convenience becomes especially salient in hyper-personalised systems, where the perceived benefit of personal relevance may outweigh discomfort with underlying algorithmic processes (Anderson and Rainie, 2018). Yet as algorithmic systems become more complex, perceived opacity and unpredictability may erode consumer trust and heighten feelings of vulnerability (Park and Young Yoon, 2025).

The perceived risks of AI are often shaped not by the technology itself, but by **how** service providers communicate its use. Transparency, clear articulation of data practices, and the ethical management of sensitive information are, therefore, critical for sustaining consumer trust (Cukier, 2020). The challenge lies not only in managing technical accuracy but also in upholding explainability and consumer empowerment — two cornerstones of ethical personalisation. Recent literature has emphasised the importance of integrating **ethical AI practices** into hyper-personalisation, particularly in three key areas:

- **Explainable AI (XAI)**: Providing users with understandable justifications for how their data is used and how algorithmic decisions are made (Gunning and Aha, 2019; Sokol and Flach, 2020).
- **Transparent Personalisation**: Offering visibility into personalisation logic and enabling users to adjust settings or opt out entirely (Shin and Biocca, 2022).
- **Autonomy-Preserving Design**: Creating interfaces that promote user control and avoid manipulative or coercive nudging (Susser, 2025).

These practices signify a shift from *data extraction* to *relational accountability*, urging service providers to balance data-driven precision with respect for user dignity and autonomy. This is particularly vital in AI-enabled contexts, where algorithmic opacity and emotional manipulation can undermine trust and engagement. Without careful design, such systems may cross ethical boundaries and undermine the very trust they aim to build.

This study contributes to this evolving conversation by not only examining consumer responses to hyper-personalisation under different **privacy framing conditions**, but also by advocating for **psychological granularity** — recognising that ethical engagement is **not** *one-size-fits-all*. By accounting for variations in values, goals, and contexts, the study helps inform the development of **ethically aligned, psychologically grounded, and context-sensitive** design principles for AI-enabled hyper-personalised systems.

2.5 Integration: A Dynamic, Goal-Aligned Paradigm

The preceding sections have shown that research on hyper-personalisation, privacy trade-offs, goal alignment, and psychological engagement has largely developed in parallel. However, within digital service ecosystems, consumer interactions with AI-enabled personalisation are not fixed but evolve **dynamically**, shaped by ongoing negotiation between perceived value, risk, autonomy, and emotional responses. As such, an integrated paradigm is needed to conceptualise how personalisation systems influence — and are simultaneously influenced by — the dynamic nature of consumer goals and subjective value formation.

Building on Lipkin and Heinonen's (2022) **three-actor ecosystem** model, this study positions AI-enabled hyper-personalisation within a multi-layered service environment comprising the:

- **provider-oriented ecosystem**, where AI-enabled features such as personalisation and privacy framing are designed.
- **individual-oriented ecosystem**, where psychological processes — goal strength, motivation, and emotional response reside.
- **socially constructed ecosystem**, which shapes consumer norms, ethical expectations, and trust perceptions.

These ecosystems interact continuously to co-create service value. Grounded in Consumer-Dominant Logic (CDL), this study emphasises that value is not delivered to consumers but co-created through ongoing interactions that evolve over time. Consequently, consumer goal strength is positioned at the centre of engagement — reflecting not a static trait but a dynamic construct that fluctuates as consumers interpret personalisation experiences in changing contexts. Temporal variation in this process — such as shifts in goal salience, cognitive fatigue, or changing levels of perceived intrusiveness — has remained underexplored (Davenport, 2023).

This perspective underpins the study's *longitudinal* design, which traces how hyper-personalisation impacts consumer goal strength and engagement across time. By capturing *within-person* variation, the research reveals how motivational intensity, trust, and perceived relevance shift as consumers experience different privacy framing conditions. This dynamic, temporal approach responds directly to the lack of empirical research integrating AI-enabled personalisation, CDL, and goal pursuit theories (Ajzen and Kruglanski, 2019; Cao, 2021). The longitudinal design adopted further distinguishes this work by capturing temporal changes in consumer goals and value interpretations — an aspect often overlooked in prior cross-sectional or firm-centric investigations (Teepapal, 2025; Wang et al., 2025a; Zhu et al., 2023).

Traditional views of personalisation often treat consumer behaviour as rational and stable, assuming that algorithmic tailoring will yield uniformly positive results (Teepapal, 2025). Rather than viewing personalisation as a technical output or data-driven efficiency mechanism, this study reframes it as a *psychologically* grounded, *context-sensitive* process that accounts for evolving consumer needs and preferences in real-time. While earlier studies have examined hyper-personalisation primarily through technological perspectives such as machine learning, recommendation systems, and NLP applications (e.g., Flavián et al., 2019; Kannan and Li, 2017), few have investigated how these AI-driven mechanisms reshape consumer value formation within their own lifeworlds.

Meaningful personalisation, therefore, requires *dynamic* alignment with the consumers' situational context – including their self-perceptions, social identities, emotional states, aspirations, and goals (Bolton et al., 2018). This calls for hyper-personalisation strategies that are *adaptive*, *responsive*, *longitudinal*, and *psychologically grounded* – all being essential for fostering sustained engagement and perceived relevance. Within this model, value is not embedded in the service itself but is **framed** through consumers' interpretations of *contextual*, *emotional*, and *temporal* cues — aligning with the principles of Self-Determination Theory and CDL (Albert, 2024; Eletxigerra et al., 2021; Heinonen and Strandvik, 2020; Medberg and

Heinonen, 2014). Hence, the same personalisation experience may enhance engagement for one consumer while triggering reactance in another, depending on factors such as goal clarity, perceived control, and trust.

Importantly, personalisation experiences are **trajectory-based**, not transactional. Consumers' reactions to AI-enabled personalisation evolve as earlier experiences influence future motivation and trust. This study addresses this **temporal** dimension by examining how goal strength evolves across multiple time points, responding to calls for longitudinal behavioural analysis in hyper-personalisation research. By integrating *motivational*, *ethical*, and *contextual* perspectives, the framework moves beyond static models of value exchange. It introduces a **context-sensitive** architecture of value formation, where hyper-personalisation and privacy framing act as interdependent stimuli shaping consumer engagement through dynamic goal alignment.

Despite the core concept of hyper-personalisation being associated with Artificial Intelligence (AI) and its subfields such as machine learning and natural language processing, earlier marketing practices — such as customer relationship management systems, business process modelling, or rule-based engines — have only achieved limited personalisation outcomes (Ramachandran et al., 2025). These techniques relied on structured data and predefined rules, which constrained their ability to detect underlying *behavioural patterns* or *contextual meanings* within *unstructured* data. In contrast, AI-driven systems can uncover hidden, dynamic patterns that enable real-time adaptation and predictive understanding of individual consumers. This capacity makes AI **indispensable** for advancing hyper-personalisation beyond traditional marketing analytics. Similarly, although the Consumer-Dominant Logic (CDL) perspective has been advanced *conceptually* and *qualitatively* (Heinonen and Strandvik, 2015; 2020), its application in digital, data-intensive, or technology-enabled contexts remains limited (Lipkin and Heinonen, 2022; Nguyen and Menezes, 2024). Moreover, to date, no study has examind how hyper-personalisation interacts with consumers' active life goals over time through a Consumer-Dominant Logic (CDL) lens. This gap underscores the need to empirically explore these dynamics.

By integrating CDL with AI-enabled hyper-personalisation and adopting a longitudinal approach, this study contributes a novel theoretical and methodological perspective that captures the **temporal** and **experiential** evolution of consumer value formation within their lifeworlds, examining how value is continuously *formed* and *reformed* as consumers interact with intelligent service systems.

This integrated paradigm therefore lays the theoretical foundation for the conceptual model introduced in **Chapter 3**. It highlights the study's novel contribution: advancing understanding of AI-enabled hyper-personalisation as a **goal-driven**, *multi-dimensional*, *temporally dynamic*, and *ethically grounded* process. By linking CDL, goal strength, and privacy framing through a longitudinal lens, the study bridges a critical gap in existing literature and provides a framework for designing adaptive, trust-oriented, and psychologically sustainable personalisation systems.

2.6 Gaps in Literature

Despite extensive research on hyper-personalisation, significant gaps remain in understanding its **long-term** psychological impact and motivational dynamics. Existing studies primarily focus on short-term behavioural outcomes — such as click-through rates or satisfaction — overlooking how AI-enabled personalisation shapes deeper motivational constructs like consumer goal strength and how these evolve over time, calling for a deeper examination of personalisation particularly in AI-enabled digital contexts (Kumar et al., 2020; Davenport, 2023; Rafieian, 2022).

First, limited attention has been given to how different **intensities** of personalisation and consumers' **subjective goal interpretations** influence motivation *longitudinally* to unravel influence on consumer trajectories. The dynamic nature of goal pursuit — particularly the interaction between motivation, commitment, and contextual triggers — remains underexplored in hyper-personalised settings (Etkin, 2019; Kim and Kim, 2025). Goal strength, as a construct, remains largely unexamined in hyper-personalisation literature, despite its relevance to sustained engagement and behaviour change (Nguyen and Menezes, 2024).

Second, privacy risk is often treated as a *static inhibitor* rather than a **dynamic moderator** that interacts with **contextual** cues and **varying individual perceptions**. While privacy concerns are well-documented (Kokolakis, 2017; Luo et al., 2023; Martin and Murphy, 2017), few studies examine how privacy framing — especially risk-based messaging — affects consumer trust, engagement, and value perceptions over *time* – particularly in AI-enabled service contexts (Zhou and Li, 2024). Moreover, individual differences in how privacy is perceived and negotiated are rarely examined, widening the gap in our understanding of consumer response heterogeneity.

Third, dominant theoretical approaches remain *technocentric*, focusing on system efficiency rather than **consumer-centric** value creation. This study addresses this gap by adopting a Consumer-Dominant Logic (CDL) perspective, repositioning value as continuously *formed* and *re-formed* through consumers' subjective interpretations of relevance, autonomy, and trust – rather than defined universally as a benefit or sacrifice (Heinonen and Strandvik, 2020). This subjective view of value formation, including personalisation and privacy trade-offs, remains underexplored, limiting understanding of how AI-enabled hyper-personalisation may amplify or reduce long-term engagement for different consumer segments (Okur and Saricam, 2025).

Fourth, while privacy framing has received attention in specific domains such as health and digital communications (Zhang et al., 2018; 2022), its use in hyper-personalised services and its interaction with long-term value alignment remains under-developed. Traditional gain/loss framing falls short of capturing the *emotional* and *cognitive* processes involved in privacy decision-making. Existing models either isolate personalisation to static or short-term effects or treat privacy concerns as binary variables, overlooking how these variables interact *over time* and *across individuals*.

Finally, little empirical evidence integrates *hyper-personalisation*, *goal alignment*, and *privacy framing* within a unified, longitudinal framework that reflects real-world consumer complexity.

This study **contributes** to addressing these gaps by:

- Investigating **consumer goal strength** as a *dynamic*, *time-sensitive* construct shaped by AI-enabled personalisation.

- Testing the **moderating role of privacy framing** in influencing motivational and behavioural responses **over time**.
- Employing a **longitudinal, within- and between-person design** to capture *temporal* and *contextual* variations in consumer experience.
- Embedding these dynamics within a **consumer-centric ecosystem model** informed by **Consumer-Dominant Logic (CDL)** and motivational theory.
- Exploring **AI-enabled hyper-personalisation** within a **multi-actor ecosystem,** examining consumer responses across interconnected service providers (Mahadevan and Shainesh, 2024) to capture how value alignment and privacy perceptions evolve in shared digital experiences – a dimension often overlooked in siloed, provider-centric models.

Together, these contributions advance theoretical and methodological understanding of how AI-enabled hyper-personalisation interacts with behavioural and psychological constructs such as goal strength, privacy framing and perceived importance to co-create evolving consumer value over time and across individuals. This integrated perspective addresses both the conceptual and empirical gaps identified in existing literature.

2.7 Chapter Summary

This chapter reviewed the key literature underpinning the study's conceptual framework. **Section 2.1** discussed the evolution of hyper-personalisation, outlining its transformative potential in shaping consumer responses through AI-driven technologies and the implementation challenges faced by service providers.

Section 2.2 examined the Consumer-Dominant Logic (CDL), emphasising value as co-created, contextual, and dynamic, contrasting it with traditional service-dominant approaches. **Section 2.3** linked hyper-personalisation with consumer goal strength, integrating motivational theories and highlighting goal pursuit, motivation, commitment, and behavioural adaptation over time.

Section 2.4 introduced privacy framing as psychological mechanism within hyper-personalised contexts, discussing the personalisation-privacy paradox, and ethical considerations such as transparency, accountability, and explainable AI.
Section 2.5 integrated these insights into a dynamic, goal-aligned model of consumer behaviour — recognising the role of ecosystem interactions, individual variation, and longitudinal processes.

Finally, **Section 2.6** summarised the main research gaps and contributions, identifying the need to explore the temporal evolution of consumer goal strength, These insights collectively inform the conceptual model and hypotheses presented next in **Chapter 3**.

Chapter 3 – Conceptual Model

3. Conceptual Model

This chapter develops the conceptual model underpinning this study and informing the hypotheses guiding its empirical investigation. Building on the theoretical constructs reviewed in **Chapter 2**, the model draws primarily from the Consumer-Dominant Logic (CDL) as a lens for examining value formation within evolving digital consumer ecosystems (Lipkin and Heinonen, 2022). The proposed conceptual model provides a **novel perspective** on how AI-enabled hyper-personalisation interacts with *psychological*, *social*, and *contextual* factors to shape consumers' motivation and commitment – specifically consumer goal strength – toward achieving their active life goals.

Grounded in CDL, the model positions the consumer as a **central agent** embedded within a *dynamic*, *multi-actor* consumer ecosystem, integrating key constructs such as hyper-personalisation, goal alignment, and privacy framing. Addressing recent calls for longitudinal and psychologically grounded research, the model reflects the evolving nature of AI-enabled service interactions, providing a robust basis for **hypothesis development**.

The chapter introduces the theoretical model adapted from Lipkin and Heinonen's (2022) conceptual framework, situating it within the study's empirical context. This is followed by a presentation of the conceptual diagram, highlighting key constructs and inter-relationships. Finally, the chapter outlines the main hypotheses of the study derived from the conceptual model.

3.1 Theoretical Framework: CDL

This study builds upon the evolving concept of *consumer ecosystem* within the **Consumer-Dominant Logic (CDL)** framework, as outlined in *section 2.2*. It adapts and extends the foundational work of Lipkin and Heinonen (2022), who define consumer ecosystems as "*systems of actors, resources, and elements that are relevant to customers and linked to each other through different kinds of relationships*" (Heinonen and Strandvik, 2020, p. 75). This definition inforces the **centrality** of the consumer as an active value creator, surrounded by a dynamic evolving constellation of actors and contextual influences that *directly* or *indirectly* influence their service experiences, expectations, and value formation processes.

With this conceptualisation, the consumer ecosystem encompasses a *dynamic*, *idiosyncratic* elements, services, and actors perceived by the consumer as relevant to their motives, personal values, and life goals (Mickelsson et al., 2022). Actors and services in this ecosystem are not fixed, but continuously shaped by consumers' interpretations of *relevance* and *meaning* within their lifeworlds, emphasising consumer-dependent and context-specific nature of consumer ecosystems. This consumer-centric orientation marks a significant shift from the traditional Service-Dominant Logic (SDL), where value creation is primarily provider-driven.

In CDL, the consumer functions as the *controlling* and *sense-making* unit of value-formation. Heinonen and Strandvik (2018, p. 4) describe the *consumer unit* as "*the unit making choices regarding what to acquire/purchase to achieve its own goals*". The unit of analysis can be an **individual** or a **collective** group - such as a household or family - co-engaging with services. These collective consumer units, increasingly relevant in digitally interconnected ecosystems, have been observed in contexts such as families of consumer units (Gummerus et al., 2021), co-consuming units (Kylkilahti et al., 2016), relational units (Epp and Price, 2011; Price and Epp, 2015; Thomaz et al., 2020), and usage centers (Kleinaltenkamp et al., 2017).

Mickelsson et al. (2022) extend this understanding by defining the consumer unit as "*an interconnected group of people who share goals and directly impact each other in terms of everyday service use, choices, and support*". This highlights that the consumer ecosystem is not confined to a single actor but may comprise multiple individuals who co-experience or co-decide on service usage. Importantly, each consumer unit — whether *individual* or *collective* — interprets its own contexts and life goals, constructing a unique value formation logic. This leads to heterogeneous and parallel consumer ecosystems. For instance, a couple may form one collective consumer unit, where each partner connects with different ecosystem actors and services, shaping their shared and individual experiences.

A defining feature of the consumer ecosystem is its *value-creating function* — how the consumer unit collectively determines what it seeks to achieve or experience through service interactions (Christensen et al., 2016; Heinonen and Strandvik, 2020). This process is inherently ***goal-oriented***, reflecting the consumer's priorities, motives, and life themes. As Woodruff (1997) notes, consumers do not simply use services to meet immediate needs; rather, they actively select, include, or exclude actors and offerings based on their relevance to evolving life goals. In this sense, value is not static but continuously **reconstructed** according to context, preferences, and perceived goal progress.

Moreover, consumers often sustain **multiple overlapping** ecosystems, each aligned with distinct or interrelated life goals. For example, a consumer may participate in one ecosystem oriented toward mental wellbeing and another addressing chronic illness, both contributing to their overall sense of wellbeing (Brodie et al., 2021; Schildmeijer et al., 2019). These overlapping ecosystems are not managed by service providers but are curated by consumers themselves, who navigate, select, or distance themselves from actors and resources according to their goal relevance.

This perspective marks a shift from viewing service encounters as **dyadic exchanges** (between provider and consumer) to recognising them as embedded within broader dynamic, multi-actor constellations. In contemporary complex service contexts, value unfolds not as a one-directional offering but as a multi-actor, co-constructed interaction, evolving through shared interpretation and co-experienced engagement (Alexander et al., 2018; Bolton et al., 2018; McColl-Kennedy et al., 2020). Accordingly, the study adopts a systemic view of value creation, whereby value is *co-formed* among multiple actors through shared experiences (Hartmann et al., 2018; Edvardsson et al., 2018; Patrício et al., 2020; McColl-Kennedy et al., 2020; Vargo and Lusch, 2017).

This transition from a *firm-to-recipient* logic to a *networked value constellation* underscores how service interactions increasingly take place within fluid, evolving ecosystems. These encompass not only providers and consumers but also co-consumers, digital touchpoints, institutional systems, and social groups (Akaka and Vargo, 2015; Čaić et al., 2019; Heinonen and Strandvik, 2015). Within these systems, value is negotiated and meaning is co-created, making it essential to understand how consumer behaviour unfolds within these dynamic social and systemic frames.

This emerging systems view of value challenges traditional models that identify service value as delivered solely by the provider. Instead, value emerges through interdependencies and mutual adaptations among systems of actors, conceptualised as a *service delivery network* (Tax et al., 2013). Within such networks, multiple providers collaborate to co-create a connected, holistic consumer experience. For example, a consumer's interaction with a healthcare provider may also involve coordination with fitness apps, pharmacy services, and informal caregivers — all contributing to an integrated value experience. The primary aim of value constellations is to activate new forms of value creation by reorganising the distinct roles and configurations of actors involved in the service process (Lipkin, 2020).

Patrício et al. (2011) and Teixeira et al. (2012) highlight that consumer experience spans three interconnected layers:

1. The *provider–consumer* service encounter,
2. The *service system*, and
3. The *service constellation* — a networked experience involving multiple service actors enabling consumer activity.

The systemic view of business can be traced back to Alderson and Martin (1965), who introduced the idea of "*value-creating organised behaviour systems*" — recognising that value is not produced for consumers but co-created with them through dynamic constellations of interactions. This laid the groundwork for understanding services as configurations of actors and processes, where value emerges through collaborative and systemic engagement. Normann and Ramirez (1993) further advanced the concept of "*value constellations*", where value creation occurs with complex networks of firms, suppliers, partners, and consumers who co-produce and adapt meaning together.

Building on this, Moore (1993) introduced the concept of "*business ecosystems*" which include not only the focal provider and its value chain but also other firms from related and unrelated industries - such as competitors, complementors, and regulatory bodies. These ecosystems highlight the interdependent nature of modern service environments, where the success or survival of one actor depends on the collective health and innovation capacity of the entire system. The term *ecosystem* has since become foundational in marketing and service literature, especially with the rise of Service-Dominant Logic (SDL) and, more recently, Consumer-Dominant Logic (CDL). These frameworks advance understanding of how value is co-created not only by service providers but also by consumers, co-consumers, and a diverse array of actors within complex socio-technical systems (Strandvik et al., 2018; Voima et al., 2011).

In contrast to SDL, CDL adopts a *consumer-centred* perspective, viewing the ecosystem through the eyes of the focal consumer who selects, curates, and assembles value-relevant actors into a meaningful constellation. This framework situates value creation not at the service-level but at the consumer's lifeworld, acknowledging that consumers actively seek, shape, and embed services into their personal value creation processes (Lipkin, 2020). CDL thus represents a paradigm shift, emphasising that value is *formed* through both inter-consumer and intra-consumer processes – shaped by collective experiences, relationships, and contextual interactions. Ultimately, CDL expands the understanding of value creation beyond provider-controlled mechanisms by positioning the consumer as a **meaning-making agent** who continuously navigates, co-produces, and adjusts value through *self-* and *socially-constructed* pathways.

The growing complexity of service systems and evolving consumer roles call for a systemic reconceptualisation of value creation - one that incorporates multi-actor networks, broader stakeholder constellations, and dynamic value processes (Tax et al., 2013; Jaakkola et al., 2015; Vargo and Lusch, 2016). Central to this shift is the concept of the *service ecosystem*, defined by Vargo and Lusch (2016, p.11) as a "*relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange*".

This perspective marks a critical departure from linear models, recognising value creation as an adaptive process in which providers, consumers, and third-party actors integrate resources through evolving service logics. Service experiences unfold within networks of actors shaped by contextual factors and co-created meanings (Lipkin, 2016, 2020). Depending on the focal actor, these ecosystems can be *provider-*, *consumer-*, or *non-centered*. For example, the value constellation might begin with searching for a home and may extend to decorating it – encompassing multiple encounters and actors beyond the bank itself. In consumer-centered systems, emphasis lies in how individuals construct, interpret, and navigate experiences within their lifeworlds, rather than merely reacting to provider-designed services. Social actors - such as family, co-consumers, online communities, and influencers - also contribute to these meaning-making networks, shaping consumer decision making and engagement (Tax et al., 2013; Heinonen et al., 2010; McColl-Kennedy et al., 2020).

In contrast to traditional dyadic models, ecosystemic approaches recognise value as emerging within distributed and interconnected activities that extend beyond immediate service encounters (Vargo and Lusch, 2016; Kelleher et al., 2010; Helkkula et al., 2012). Actors adopt dynamic roles — consumers may act as co-creators, facilitators, or resource integrators — shaping value not only for themselves but for others (Lipkin, 2020). For example, in collaborative or sharing contexts, consumers engage in peer-to-peer interactions (*consumer-to-consumer*) that contribute to value formation (Heinonen and Strandvik, 2015; Akaka and Vargo, 2015). While the service ecosystem captures macro-level value creation, it has been criticised for overemphasising provider and system networks at the expense of consumers' lived experiences (Heinonen et al., 2010; Heinonen and Strandvik, 2022). CDL addresses this limitation by repositioning the consumer and their ecosystem as the focal point of analysis (Voima et al., 2011), emphasising how value is constructed through personal meanings, goals, and everyday contexts.

This *consumer-oriented* shift is reinforced by the increasing complexity of AI-enabled, data-driven personalisation, which challenges traditional assumptions about how value is produced and delivered. As AI systems autonomously predict preferences, value increasingly emerges through continuous interaction and adaptation between consumers, technologies, and their environment, (Heinonen and Strandvik, 2020). From this perspective, the consumer ecosystem is viewed as a "*system of actors and elements related to the customer and relevant to a specific service*" (Heinonen and Strandvik, 2015, p. 479; Voima et al., 2011), including human and non-human agents such as peers, technologies, or digital assistants (Lipkin and Heinonen, 2022; Heinonen and Strandvik, 2018). Value is *formed* and *reformed*, shaped by consumers' personal goals, contexts, and evolving lifeworlds. CDL positions consumers as active agents, embedding value into their everyday lives based on personal meaning, motivation, and goal alignment (Heinonen and Strandvik, 2015; Voima et al., 2011) — representing the *multi-layered* and *dynamic* nature of consumers' lives.

Lipkin and Heinonen (2022) highlight that within consumer ecosystems, interactions among various actors — including digital platforms and social networks — continuously feed back into consumers' goal-attainment processes. These feedback loops help individuals reassess their situations and pursue actions aligned with evolving goals, making value realisation a dynamic and contextual process rather than a static service exchange. The consumer ecosystem, grounded in Consumer-Dominant Logic (CDL), thus shifts the focus from provider-led exchanges to consumer-led value formation, where meaning and relevance are shaped by personal motivations, experiences, and life contexts (Heinonen and Strandvik, 2015; Lipkin, 2016; 2020).

Consumer ecosystems are *inherently dynamic* and *contextual*, continuously shaped by evolving goals, experiences, and life situations (Čaić et al., 2019). Consumers determine which actors are relevant, *when* and *how* to engage with them, co-creating value through these interactions rather than receiving it from providers. This consumer-led logic departs from fixed service designs, enabling *goal-aligned* personalisation within AI-enabled environments (Lipkin, 2016). As Lipkin and Heinonen (2020) note, the boundaries of consumer ecosystems are fluid — expanding or contracting depending on what consumers perceive as meaningful to their goals. Value experiences therefore extend beyond immediate provider interactions to encompass co-consumer exchanges, digital engagements, and reflections across time (Tynan et al., 2014).

The *temporal dimension* of consumer ecosystems is thus critical: value formation unfolds cumulatively as consumers interpret and reassess their experiences over time (Helkkula and Kelleher, 2010; McColl-Kennedy et al., 2020; Schembri, 2006). AI-enabled hyper-personalisation now amplifies this process, integrating psychological and social dimensions continually reshaping how consumers construct and experience value (Bolton et al., 2018; McColl-Kennedy et al., 2020). The *goal-directed* nature of the consumer journey is central to CDL. Hamilton and Price (2019) emphasise that understanding how consumers pursue their goals requires moving beyond firm-centric views of value creation. Rather than being a transactional outcome, value arises as consumers evaluate their current situation against desired goals and mobilise resources toward bridging that gap (Becker et al., 2020). These collective experiences not only support goal achievement but also guide future behaviour (Čaić et al., 2019; Carver and Scheier, 1998; 2001).

The consumer ecosystem focuses on how consumers select, experience, and embed offerings within their lifeworlds (Lipkin, 2016; Heinonen and Strandvik, 2015). This holistic view underscores consumers as purposeful agents, integrating diverse resources and relationships in pursuit of evolving life goals. In this view, service providers can better understand how their offerings fit into consumers' broader value formation processes and how different elements connect with and beyond their control. A goal-oriented perspective can enable service providers to identify opportunities for innovation and collaboration, developing solutions that help consumers achieve their life goals (Epp and Price, 2011; Hamilton and Price, 2019; Macdonald et al., 2016). The concept of *consumer value constellation* positions consumers at the center of value network, integrating multiple encounters and actors that collectively shape their experience (Patrício et al., 2011).

Expanding this view beyond the narrower service encounter, service providers can recognise how consumers embed, adapt, and modify services across their lifeworld. This approach reveals a richer picture of value creation — one that encompasses functional, emotional, and social dimensions as experienced over time.

3.2 Proposed Conceptual Model

The Consumer-Dominant Logic (CDL) perspective has gained prominence as a framework for understanding value formation within consumer ecosystems. Recent studies have applied CDL across diverse contexts — including leisure (Cerdan Chiscano, 2024), online communities (Heinonen et al, 2019), healthcare (Seppänen et al., 2017), and tourism (Fan et al., 2025) — to explore how consumers co-create value within their everyday lifeworlds (Cheung and To, 2016; Heinonen, 2022; Lipkin and Heinonen, 2022; Zhang et al., 2019). This lens prioritises consumer experiences within social, emotional, and personal contexts, shifting the focus from provider-centric interactions to the subjective and lived realities of consumers.

Within CDL, value is viewed as *individually* experienced and *socially* constructed, evolving across pre-, during-, and post-consumption phases and across both *temporal* and *spatial* contexts (Helkkula et al., 2012; Kuuru, 2022). This approach allows for a more nuanced understanding of how consumers embed value in their lives and highlights the emotional and motivational processes underpinning this formation (Malone et al., 2018).

Building on this foundation, Lipkin and Heinonen (2022) propose a **three-actor constellation** framework that structures value formation around:

1. **Brand-driven** ecosystems (provider-led value creation)
2. **Individual-driven** ecosystems (consumer-led formation shaped by personal goals), and
3. **Social-driven** ecosystems (value emerging through social and contextual interactions)

These constellations are shaped by the consumer's *goal-oriented* logic, determined by personal activities, contexts, and life pursuits. They determine the size, scope, proximity, and influence of the different actor-sets shaping consumer value experiences.

Key to this three-actor constellation framework are its *temporal* and *spatial* dimensions, expanding beyond specific service encounters to reflect how consumer activities, practices, and experiences evolve. Value formation occurs within the intersubjective and collective context of the consumer's lifeworld (Rihova et al., 2018). In this study, these constellations provide a boundary system for understanding how AI-enabled hyper-personalisation and privacy framing influence consumer goal strength over time. By situating these service dynamics across the constellation spectrum, this view explores how value emerges and is *formed* through a network of multi-actors embedded in consumers' everyday lived experiences.

Value Formation Dimensions

Heinonen et al. (2019) identify two dimensions of value formation — **locus** and **scope** — which help contextualise *where* and *how* value emerges within the ecosystem. The *locus* defines whether value develops in the provider or consumer domain, while the *scope* describes whether value formation occurs at an individual or collective level.

At the *provider domain*, value is formed through the provider's service offerings and their attributes — reflecting a **brand-driven ecosystem**. Conversely, in the *consumer domain*, value arises from consumers' transformation of these offerings through their own behaviours, interpretations, and interactions with others — representing an **individual-driven ecosystem**. Value, formed at the consumer domain, is intangible and idiosyncratic based on various processes that are *directly* or *indirectly* related to the service usage. Consumers control and orchestrate the value formed within their own consumer domain, whilst providers can only control value formed within the service itself (Heinonen et al, 2013).

On the other hand, the scope of value formation extends this distinction. At the **individual level**, value formation is personalised and context-specific, shaped by consumers' internal evaluations and lived experiences. At the **collective level**, value emerges through shared meanings and co-experienced interactions among groups of consumers, giving rise to a **social-driven ecosystem**.

Together, these dimensions reveal how value formation *dynamically* shifts between provider-led and consumer-led processes, evolving across individual and collective contexts. This framework offers the foundation for examining how AI-enabled personalisation interacts with these dimensions to shape consumers' motivational and behavioural responses over time.

Individual-Level Value Formation

At the *Individual-level,* value formation occurs in two ways:

1. **Provider domain labeled as *self-to-provider***

   Here, value arises as consumers interact directly with providers and their offerings. It reflects the *brand-driven* ecosystem, where value emerges from the tangible and functional attributes of the service (e.g., quality, usability, and alignment with consumer needs). This value is overt and visible to the provider since it is embedded in service encounters and observable outcomes.

2. **Consumer domain labeled as *self-to-self***

   In this domain, value formation stems from consumers' personal interpretations and lived experiences, *independent* of the provider. It represents the *individual-driven* ecosystem, where value is subjective, evolving from consumers' reflections, emotions, and contextual linkages to other experiences in the past, present and future (across time). This type of value is intangible, fluid, and often invisible to providers, as it is shaped by ongoing meaning-making within the consumer's lifeworld.

Together, these perspectives capture how value co-creation dynamically spans **provider-led** and **consumer-led** processes. They provide a conceptual bridge for understanding how AI-enabled hyper-personalisation interacts with these dimensions to influence motivational and behavioural responses over time.

The **brand-driven consumer ecosystem** (Heinonen et al., 2019) highlights the central role of the focal provider in orchestrating service delivery and managing consumer relationships. Although other actors may be present, they play a secondary role relative to the focal provider. In the context of this study, the AI-enabled hyper-personalisation is coordinated primarily by the Telecommunications provider (focal provider), who manages the infrastructure, data, connectivity, and content delivery. The Entertainment provider, in this scenario, operates behind the scenes partnering with the focal provider to facilitate and fulfill Entertainment content delivery. Subscription to the service and its management across the whole life cycle remains with the focal provider. In this ecosystem, value creation is closely tied to the provider's offering and brand, with consumers focusing on activities and goals aligned to the service experience.

In contrast, the **individual-driven consumer ecosystem** positions the consumer as the dominant actor. Here, value arises from personal contexts, emotions, and performance-related goals, extending beyond the provider's direct influence. Lipkin and Heinonen (2020) note that such value is shaped by the consumer's subjective interpretations — for instance, satisfaction with a wearable tracker depends less on its technical quality and more on how it aligns with the user's self-improvement goals.

Collective-Level Value Formation

At the *collective-level,* value formation reflects shared and community-based processes that extend beyond individual consumers.

1. **Provider domain labeled *collective-to-provider***

   Here, value arises from collaborations between providers and consumer communities. Members collectively influence the provider's value offerings — for example, co-design initiatives or community-driven innovation platforms such as Threadless or Apple's discussion boards. While value remains visible to the provider, it is shaped by collective participation and co-creative feedback, illustrating a semi-managed form of co-creation.

2. **Consumer domain labeled *self-to-collective***

   This form of value emerges within the social-driven ecosystem, where consumers create and share meaning collectively through community interaction. Examples include user-generated content, online reviews, or peer recommendations that shape others' perceptions and behaviours toward a brand. Unlike the provider domain, this value is autonomously formed by the collective, outside the provider's control, highlighting how social influence and shared experiences drive value formation.

Together, these *collective-level* perspectives emphasise how co-created and community-embedded value contributes to the evolving dynamics of AI-enabled ecosystems, reinforcing the interplay between **individual** and **social** dimensions of consumer experience.

The **social-driven consumer ecosystem** encompasses social actors — such as peers, co-consumers, and collectives — who influence the focal consumer's experiences and value perceptions (Lipkin and Heinonen, 2020). Value in this ecosystem emerges through social interactions and shared meanings, often mediated by digital or physical networks. Experiences are shaped by connections to family, friends, and communities, as well as social platforms where consumers seek belonging, recognition, or status. Value emerges in the "*dynamic, collective and shared customer realities*" (Heinonen *et al.*, 2013, p. 112).

Social dynamics may both enhance or hinder value formation, as peer influence and competition shape how consumers interpret and evaluate experiences. Furthermore, research on group dynamics and peer effects found that a consumer might change his/her behaviour when being in a certain social group (Falk and Ichino, 2003; Clasen and Brown, 1985; Lemmink et al., 2019; Renjilian *et al.*, 2001; Nier, *et al.*, 2001). This ecosystem reflects the collective and relational dimension of Consumer-Dominant Logic (CDL), highlighting that value is not solely created in isolation but through consumer-to-consumer (C2C) exchanges (Heinonen et al., 2018; Nguyen and Menezes, 2024). For instance, online travel communities or social media networks illustrate how consumers co-create value collectively through shared insights, emotional support, and recommendations (Fan et al., 2020).

The proposed model integrates Consumer-Dominant Logic (CDL) with AI-enabled hyper-personalisation and privacy framing, adopting a **longitudinal**, **multi-actor** perspective. This approach captures how value is continuously co-created through interactions within consumers' lifeworlds, where *contextual* variations and *temporal* dynamics shape motivation, trust, and engagement over time.

To gain a holistic view of value creation, service providers must consider broader temporal and spatial frames that extend beyond specific encounters to encompass consumers' lived experiences. Grounded in CDL, this study follows the model of Lipkin and Heinonen (2020), recognising the consumer as an active value creator embedded within dynamic service ecosystems. Adopting this model emphasises the *individual* and *collective* shared nature of value as a key premise of value formation (Heinonen and Strandvik, 2015; Heinonen et al., 2018). The relevance of this investigation lies in its response to recent calls for deeper theoretical and empirical exploration of CDL (Anker et al., 2022).

This study **contributes** to the contemporary service and marketing literature by advancing CDL as a conceptual lens for understanding how consumer ecosystems shape value formation within hyper-personalised AI services. While earlier studies have primarily adopted provider-centric perspectives, this research operationalises the consumer's active, goal-oriented role within multi-actor, AI-enabled contexts — bridging conceptual and empirical gaps in current understanding. While prior research started shifting focus from firm-centric to a broader service system perspective, these studies have not yet explicitly operationalised the consumer's active life goals or applied the three-actor constellation within AI-enabled hyper-personalised contexts.

In the context of this study, and as detailed in *section 4.2.2* of **Chapter 4**, the conceptual model incorporates three distinct actor constellations derived from the Consumer-Dominant Logic (CDL) framework — namely, the *brand-oriented*, *individual-oriented*, and *social-oriented* consumer ecosystems.

1. The **brand-oriented consumer ecosystem** is represented by:
   - The partnership between the Telecommunications and Entertainment service providers. As illustrated by the progressively clustered hyper-personalised content, these two brand-oriented actors co-create and govern the delivery of hyper-personalised services through integrating connectivity, consumer data, and AI-enabled technologies, combining tailored digital infrastructure with Entertainment content.

   - Privacy framing contextual cues representing data usage and the Telecommunications service provider's orchestration of data governance and privacy-related practices across its partnership.

2. The **individual-oriented consumer ecosystem** comprises consumers' active life goals and the perceived importance of hyper-personalisation as a psychological foundation for consumer-driven value formation. This

component explains how consumers' internal goal structures and subjective evaluations of hyper-personalisation relevance evolve over time, offering an interpretative lens for post-analysis.

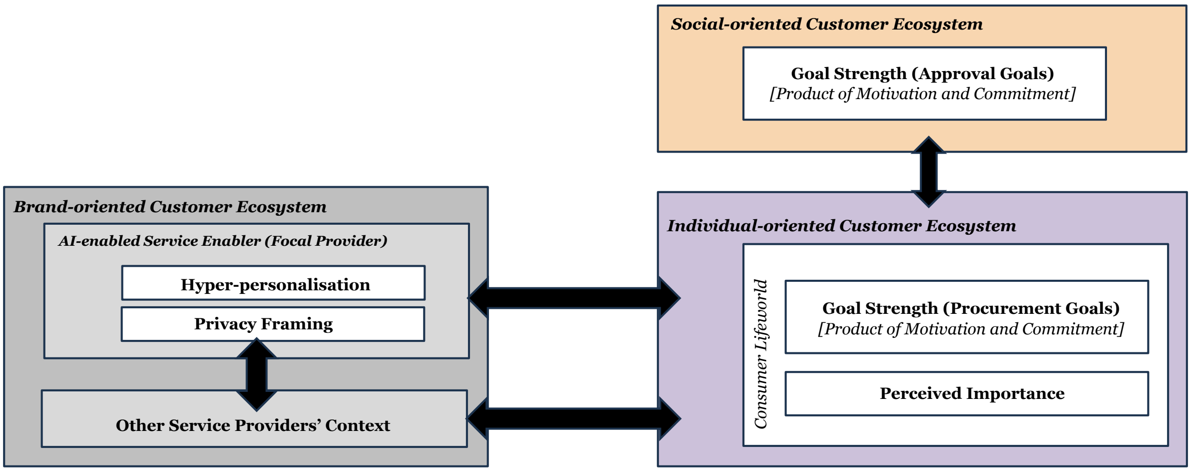
3. The **social-oriented consumer ecosystem** reflects consumer-to-consumer interactions, shared collective experiences, and socially influenced value formation. Within this study, it is *conceptually* integrated through approval-oriented goals (e.g., social recognition or family enjoyment) embedded in participants' self-selected active life goals. While not operationalised as a separate empirical construct, this dimension captures the socially embedded nature of goal pursuit within the CDL framework. Its inclusion complements the *brand-* and *individual-oriented* ecosystems by highlighting the interconnected psychological and contextual foundations of value formation across different goal types.

Figure 2 illustrates the conceptual structure based on these three actor constellations — *brand-oriented*, *individual-oriented*, and *social-oriented* consumer ecosystems — as grounded in CDL. It highlights how AI-enabled service providers drive hyper-personalisation and privacy framing within the brand-oriented domain, how individual goal strength and perceived importance shape value formation in the individual-oriented domain, and how approval-oriented goals in the social-oriented domain embed social influences into consumers' broader lifeworlds.

Figure 3 presents an adapted version of **Figure 2**, replacing the AI-enabled service enabler (*focal provider*) with the Telecommunications service provider and the other service providers with the Entertainment service provider in the context of this study. The direct arrow between the Entertainment provider and the individual-oriented consumer ecosystems is removed to reflect its role as operating behind the scenes.

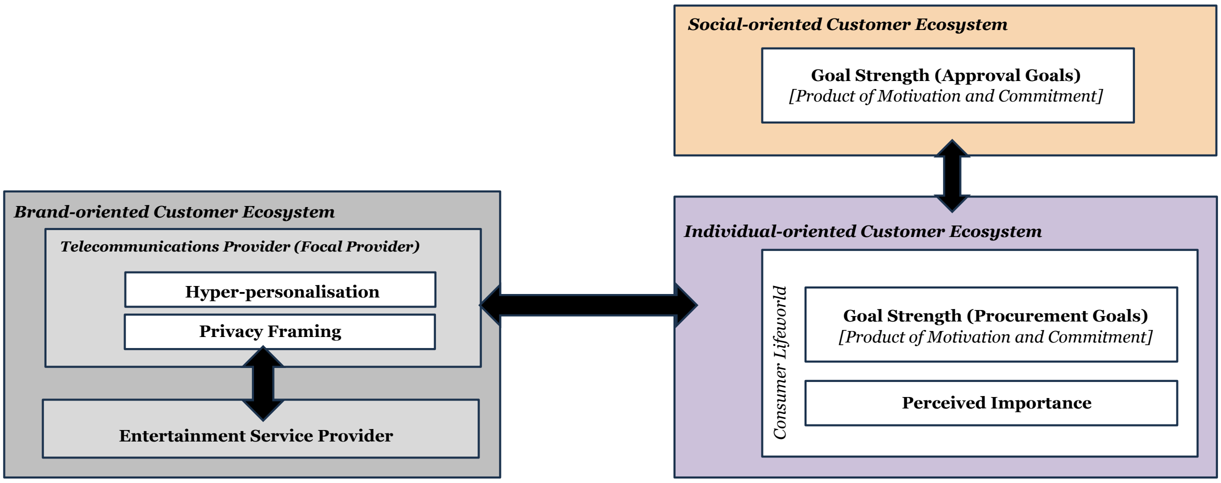
It is important to clarify that the multi-actor AI-enabled ecosystem referred to in the central research question — *How does goal-aligned hyper-personalisation influence consumer goal strength* in AI-enabled, multi-actor consumer ecosystems *over time*? — directly corresponds to the **three-actor constellation** adopted from the Consumer-Dominant Logic (CDL) framework. Within this study, this multi-actor configuration is operationalised through the Telecommunications *(focal provider)* and Entertainment service providers, representing the *brand-oriented* ecosystem, and the consumer ecosystem, encompassing *individual*- and *social-oriented* dimensions of value formation. Accordingly, **Figure 3** depicts how these interconnected actors collectively co-create value within the AI-enabled Telecommunications and Entertainment service context. Hence, the use of “multi-actor ecosystem” in this study reflects the same structural logic as the CDL’s three-actor constellation — where multiple actors interact *dynamically* across brand-, individual-, and social-oriented domains to enable holistic value creation.

The next section builds upon this conceptual framework to develop the study’s **hypotheses**, outlining the proposed relationships among hyper-personalisation, privacy framing, and consumer goal strength within multi-actor AI-enabled service ecosystems.



Note:
1. *Perceived Importance is included as a contextual, non-hypothesized construct reflecting consumers’ internal value perception.*
2. *The social-oriented consumer ecosystem is conceptually represented through approval-oriented goals (e.g., social recognition, family enjoyment) included in the participant’s self-selected active life goals.*
3. *The individual-oriented consumer ecosystem reflects procurement-oriented goals (e.g., peace of mind, professional growth).*
4. *Goal strength, measured as a product of goal commitment and goal motivation, captures the dynamic persistence and intensity of both goal types.*
5. *Although the social-oriented consumer ecosystem was not modelled as a separate empirical construct, its inclusion reflects the multi-dimensional nature of goal pursuit and value formation within the Consumer Dominant Logic (CDL) framework*

Figure 2: *Study's Conceptual Framework: 3-Actor Constellation Consumer Ecosystems Adapted from Lipkin and Heinonen (2022)*



Note:
1. *Perceived Importance is included as a contextual, non-hypothesized construct reflecting consumers' internal value perception.*
2. *The social-oriented consumer ecosystem is conceptually represented through approval-oriented goals (e.g., social recognition, family enjoyment) included in the participant's self-selected active life goals.*
3. *The individual-oriented consumer ecosystem reflects procurement-oriented goals (e.g., peace of mind, professional growth).*
4. *Goal strength, measured as a product of goal commitment and goal motivation, captures the dynamic persistence and intensity of both goal types.*
5. *Although the social-oriented consumer ecosystem was not modelled as a separate empirical construct, its inclusion reflects the multi-dimensional nature of goal pursuit and value formation within the Consumer Dominant Logic (CDL) framework*

Figure 3*: Study's Conceptual Framework within the AI-Enabled Telecommunications Entertainment Service Context (scenario of the 3-wave longitudinal experiment)*

3.3 Study Hypotheses

The rise of Artificial Intelligence (AI)-enabled algorithms and recommender systems has transformed how consumers experience personalised services. These systems analyse vast amounts of user data to predict preferences, tailor communications, and recommend products or content across diverse domains such as entertainment, healthcare, and education – to name just a few (Burr and Floridi, 2020; Sundar, 2020). While customisation is user-initiated, personalisation is largely system-initiated (Arora et al., 2008; Pu and Beam, 2024; Sundar and Marathe, 2010). In such cases, consumers do not actively select content; rather, they are automatically exposed to suggestions shaped by algorithms that adapt to their individual goals, interests, and behaviours (Hutmanen and Appel, 2023; Serino et al., 2005).

This algorithmic adaptation continually reshapes digital environments, tailoring them uniquely to each individual and potentially filtering out content to some while keeping it visible for others. On one hand, personalisation can enhance decision-making and reduce information overload, thereby improving user well-being (Spanakis et al., 2014). On the other hand, challenges persist — such as limited transparency (Storms et al., 2022), loss of user trust (Sallami et al., 2023), and perceived unfairness (Wang et al., 2023). Moreover, researchers caution that personalisation may erode autonomy and create echo chambers, where users are exposed only to content aligned with their existing beliefs, potentially risking intellectual isolation (Areeb et al., 2023; Mejtoft et al., 2020; Newell and Marabelli, 2015; Donkers and Ziegler, 2021).

Recent research seeks to address these concerns by designing more trustworthy and fairness-aware recommender systems (Qi et al., 2022; Wang et al., 2023). Others propose user-centred approaches that incorporate personal traits—such as personality and goal orientation—into recommendation system design (Raza and Ding, 2022; Wieland et al., 2021; Yasmeen and Hashmat, 2025). However, existing studies often overlook the role of goal pursuit, a critical factor influencing how individuals evaluate and engage with personalised systems. Understanding how personalisation interacts with individual goal dynamics could thus provide a more nuanced perspective on user experience.

Overall, the literature reveals that personalisation exerts both positive and negative influences depending on individual motivations and perceived benefits (Amarnath and Jaidev, 2020; Sipos, 2025). Against this background, this study investigates how AI-enabled hyper-personalisation influences value formation and consumer goal strength within service ecosystems, through the two main hypotheses outlined below.

3.3.1 Hypothesis 1: Hyper-Personalisation Impact

Hyper-personalisation, an advanced AI-enabled form of data-driven personalisation, delivers *real-time*, *dynamically* tailored content aligned with individual preferences, behaviours, and situational contexts (Maslowska et al., 2022; Pu and Beam, 2024). Moving beyond transactional views, recent research highlights its psychological implications, particularly in shaping consumer motivation and goal-directed behaviour.

When hyper-personalised experiences align with consumers' intrinsic motivations and personal goals, they foster deeper engagement and persistence, as the interaction is perceived as more meaningful and self-relevant (Ajzen and Kruglanski, 2019; Hutmacher and Appel, 2023). Consumers who identify personalised recommendations as *congruent* with their values are more likely to engage with the platform and pursue related goals (Calder et al., 2016; Maslowska et al., 2022). For example, a consumer engages with a music platform such as Spotify or Pandora when associated with their personal goal of music discovery and enjoyment (Hollebeek et al., 2016). Conversely, irrelevant or intrusive personalisation can lead to *amotivation*, characterised by disengagement and discomfort due to a perceived lack of meaning or control (Maslowska et al., 2022; Viswanathan et al., 2017).

Consumer goals, however, are not static. They shift with *contextual* and *situational* factors such as task urgency, consumer journey stages, and emotional states (Maslowska et al., 2022; Zhang and Bockstedt, 2020). For example, a consumer under time pressure may prefer direct, relevant recommendations, whereas one in a discovery stage might value novelty and exploration. Hence, contextually sensitive hyper-personalisation — adapting to both enduring traits (e.g., personality) and momentary states (e.g., mood) — enhances motivational relevance and goal clarity (Pu and Beam, 2024; Lee and Chu, 2022).

Goal commitment — defined as the strength of one's determination to pursue a goal — varies across contexts and individuals (Ajzen and Kruglanski (2019), explaining why some consumers prefer structured recommendations while others seek exploratory suggestions (Pu and Beam, 2024). Highly committed consumers tend to benefit from targeted recommendations, whereas those with lower commitment engage in broader, information-seeking activities (Naeem and Ozuem, 2025). Thus, AI-driven systems that proactively tailor outputs to users' goal clarity and motivation can enhance goal commitment, engagement, and satisfaction (Liang et al., 2023).

This dynamic aligns with Self-Determination Theory (SDT), which posits that human behaviour is driven by controlled or autonomous motivation (Ryan and Deci, 2020). *Controlled* motivation arises from external pressures or rewards, whereas *autonomous* motivation stems from intrinsic interests and psychological needs such as competence, autonomy, and relatedness. When hyper-personalisation supports these needs — by reducing information overload and aligning experiences with user goals — it strengthens autonomous motivation and engagement (Arnold et al., 2023; Kim and Park, 2025; Pu and Beam, 2024). However, when perceived as intrusive or manipulative, it may hinder intrinsic motivation and satisfaction (Hutmacher and Appel, 2023). Hence, hyper-personalisation can both enhance and impair goal pursuit depending on its alignment with consumers' motivational states and psychological needs. Therefore, this study hypothesises that hyper-personalisation influences consumers' goal strength — defined as the intensity and persistence of motivation toward goal attainment — within AI-enabled service ecosystems.

Recommendation systems should therefore prioritise the dynamic nature of consumer goals by embedding motivational adaptability and contextual sensitivity. Hyper-personalisation systems that align content delivery with users' evolving goals and psychological states can reinforce motivation, commitment, and sustained pursuit (Bolos et al., 2022; Pu and Beam, 2024). Consequently, hyper-personalised systems that incorporate consumer goals within their algorithms can deliver highly tailored, goal-oriented information that can promote both the attainment of goal-directed activities and the motivational processes underpinning goal pursuit.

The **temporal** dimension of goal pursuit also plays a pivotal role in understanding how hyper-personalisation influences consumer goal strength over time. Motivation fluctuates as consumers perceive progress toward their goals — intensifying when goals feel attainable and waning when they seem distant or ambiguous (Etkin, 2019; Wallace and Etkin, 2018). According to self-regulation theory, consumers continuously monitor their progress, adjusting their behaviour to reduce discrepancies between their current and desired goal states (Becker et al., 2020; Carver and Scheier, 1998; Locke and Latham, 1990; Sharif and Woolley, 2020).

Proximity to a goal's starting or end point affects motivation differently. For specific goals, individuals focus on the endpoint, producing a goal-gradient effect, whereas for non-specific goals (having no end points), motivation is stronger near the starting point and declines as distance from it increases (Wallace and Etkin, 2018). That is, when distance from the start increases and motivation is lacking, consumers may disengage. Consequently, service providers must sustain motivational salience across

time to prevent disengagement and drop-out, particularly during extended goal journeys.

Moreover, intervening events during goal pursuit — such as new information or shifts in intentions — can alter consumers' behaviour and weaken the predictive power of initial goals (Ajzen and Kruglanski, 2019). The Theory of Planned Behaviour (TPB) posits that intention–behaviour consistency is highest when both occur in **close temporal proximity**, reducing the influence of external disruptions (Kruglanski et al., 2015). In other words, the behavioural intention at **Time 1** can predict behaviour at **Time 2** if the interval between intention and behaviour is short. However, as the interval between intention and behaviour widens, intervening influences can reshape goals, leading to possible changes in behaviour (Ajzen and Kruglanski, 2019; Fishbein and Ajzen, 2010; Randall and Wolff, 1994). In other words, if intervening events occur at **Time 2** to substantially alter the goal system configuration from that at **Time 1**, the original intention may no longer be applicable, necessitating a re-evaluation.

Thus, the impact of hyper-personalisation on goal strength may vary depending on temporal proximity — remaining stable or diminishing over time. To capture this temporal effect, this study employs a **three-wave longitudinal** design, comparing shorter time intervals between *Wave 1* and *Wave 2* (*10-day*) and longer intervals between *Wave 2* and *Wave 3* (*five-months*), to examine whether proximity sustains or attenuates the influence of hyper-personalisation on consumer goal strength.

By enhancing both motivation and commitment, hyper-personalisation is expected to strengthen consumer goal strength – defined as the combined intensity and persistence of motivation toward goal attainment – while accounting for temporal effects, thereby leading to **Hypothesis 1 (H1)**:

Hypothesis 1 (H1): *Higher levels of hyper-personalisation significantly increase consumer goal strength over time*

3.3.2 Hypothesis 2: Privacy Framing Moderating Role

Hyper-personalisation strategies rely heavily on consumer data — preferences, behaviours, and personal life goals — to tailor offerings. While this data-driven approach has the potential to enhance consumer engagement and goal alignment, its effectiveness is not absolute. Instead, it is contingent on how the data-sharing process is framed and perceived. Framing data disclosure in terms of risk (risk-based privacy framing) can trigger significant psychological responses, particularly when disclosure is perceived as invasive or threatening to autonomy (Zhang et al., 2018; Zhang et al., 2022).

Framing effects suggest that both the content and the presentation of messages influence decision outcomes (Tversky and Kahneman, 1981). Within the context of hyper-personalisation, privacy framing may therefore act as a moderator, altering consumers' psychological and motivational responses to personalised offerings. From a Consumer-Dominant Logic (CDL) perspective (Heinonen and Strandvik, 2020), privacy perception is not static — it is subjectively co-constructed and contextually bound, meaning that the way consumers interpret privacy cues directly shapes their experience of value. Consequently, how consumers interpret data-sharing messages can significantly influence their perceived value of hyper-personalisation and subsequent engagement — particularly when data sharing is framed as sensitive or risky. Consumers exposed to risk-framed messages may interpret personalisation attempts as intrusive, resulting in weaker goal strength and reduced engagement. In contrast, consumers perceiving data disclosures as manageable may maintain motivation and engagement. These variations suggest that framing can create divergent consumer response trajectories.

To empirically investigate this moderating effect, privacy framing was manipulated in this study using a *between-subjects* design. Participants were randomly assigned to either a risk-framed condition (highlighting data exposure or surveillance risk) or a neutral condition (no explicit mention of privacy). This design allows testing whether heightened risk salience weakens the motivational effects of hyper-personalisation on consumer goal strength.

Hypothesis 2 (H2) seeks to examine if privacy framing, as a subjective interpretation construct moderates the relationship between hyper-personalisation and consumer goal strength — such that this relationship becomes weaker when personalisation is presented within a risk-framed privacy disclosure context. This hypothesis addresses a key gap identified by Davenport (2023), who calls for a more dynamic, longitudinal, and context-sensitive view of privacy — not as a static inhibitor — but as a temporal influence on value co-creation over time. Testing this moderation effect provides empirical insight into how privacy framing can either support or undermine the effectiveness of AI-enabled personalisation strategies, especially in longitudinal settings.

Once consumer goals are activated, exposure to positively framed communication can increase commitment and motivation, while negatively framed cues can inhibit or distort these effects (Bolos et al., 2022; Van Osselaer and Janiszewski, 2012). As goals are context-dependent and highly malleable, privacy framing can guide consumers not only in their decisions but also in how they interpret the alignment between personalisation and their own objectives. Because behaviour resulting from goal activation can persist over time (Custers et al., 2019; Qin, 2023), this study explores whether the motivational effects of hyper-personalisation deteriorate — or potentially strengthen — when moderated by privacy concerns.

This relationship is further explained by the personalisation-privacy paradox (Aguirre et al., 2015), which suggests that the benefits of hyper-personalisation maybe offset by the perceived risks of privacy loss (Cloarec et al., 2024; Kim et al., 2019). This paradox shapes consumer reactions to personalisation, influencing whether they increase or decrease engagement with the service provider. Perceived sacrifice (André et al., 2018; Cicek et al., 2025) can reduce engagement when privacy trade-offs are judged to outweigh value. In AI-enabled services, perceived sacrifice can modify the relationship between different factors including convenience, service quality, and personalisation (André et al., 2018; Ameen et al., 2021).

From a goals-means configuration system, service providers can influence the relationship between means (personalised services) and active goals, and in turn decision making, first through efficiently framing contextual factors towards these goals, and second through communicating them effectively during service encounters.

Furthermore, a behaviour resulting from framing goals is believed to remain persistent over time, with the level of motivation and commitment not showing deterioration and should possibly even strengthen over time (Chen et al., 2021; Custers et al., 2019; Crusius and Mussweiler, 2012) - *to be verified from the findings of this study*.

From a consumer-dominant logic (CDL) perspective, this highlights that value is contextual, relative, and co-created, shaped by how consumers assess trade-offs between personalisation and autonomy. Heinonen and Strandvik (2020) argue that such value experiences are inherently subjective — what is considered a benefit by one consumer may be viewed as a loss or threat by another and, hence, cannot be determined beforehand by the service provider. Furthermore, framing effects related to privacy concerns can modulate how personalisation is perceived, though such effects may fade or stabilise as consumers adapt across repeated service interactions (Adjerid et al., 2019; Paliński et al., 2025).

Hence, it is expected that information framing — whether risk-based or neutral —will have a moderating influence on the relationship between hyper-personalisation and consumer goal strength, leading to **Hypothesis 2 (H2)**:

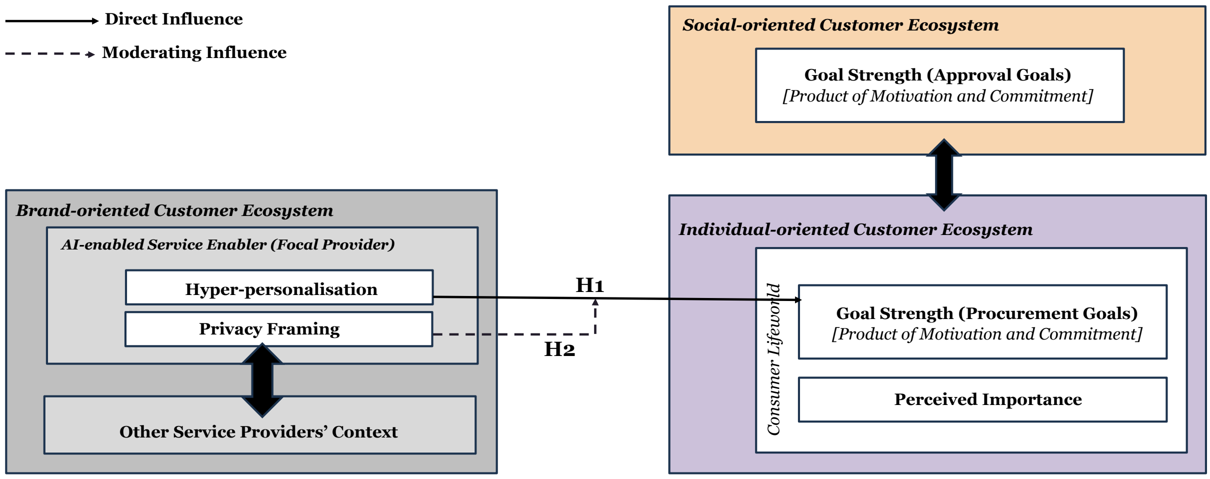
Hypothesis 2 (H2): *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

Table 5 shows the list of the hypotheses forming the basis of this study, based on the underlying literature presented in this section.

Table 5*: List of Study's Hypotheses*

Hypothesis	
Hypothesis 1 (H1)	*Higher levels of hyper-personalisation significantly increase consumer goal strength over time*
Hypothesis 2 (H2)	*Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

The hypothesised conceptual model is shown in **Figure 4**, illustrating the hypothesised relationships between the study's construct within the Telecommunications and Entertainment service context. **Hypothesis 1 (H1)** posits a direct influence between hyper-personalisation and consumer goal strength, while **Hypothesis 2 (H2)** proposes that privacy framing moderates this relationship.



Note:

1. *Perceived Importance is included as a contextual, non-hypothesized construct reflecting consumers' internal value perception.*
2. *The social-oriented consumer ecosystem is conceptually represented through approval-oriented goals (e.g., social recognition, family enjoyment) included in the participant's self-selected active life goals.*
3. *The individual-oriented consumer ecosystem reflects procurement-oriented goals (e.g., peace of mind, professional growth).*
4. *Goal strength, measured as a product of goal commitment and goal motivation, captures the dynamic persistence and intensity of both goal types.*
5. *Although the social-oriented consumer ecosystem was not modelled as a separate empirical construct, its inclusion reflects the multi-dimensional nature of goal pursuit and value formation within the Consumer Dominant Logic (CDL) framework*

***Figure 4**: Study's Hypothesised Conceptual Model with Directional Relationships*

3.4 Chapter Summary

This chapter outlined the conceptual foundation and hypotheses guiding the study. Grounded in the Consumer-Dominant Logic (CDL) framework, it positioned the consumer as a central actor in dynamic, multi-actor ecosystems and highlighted how value formation emerges through evolving psychological, contextual, and social dimensions. Building on this foundation, the chapter introduced the conceptual model, adapting CDL's three-actor constellation — *brand-*, *individual-*, and *social-oriented* consumer ecosystems. It integrates key constructs of hyper-personalisation, privacy framing, and consumer goal strength, emphasising that value unfolds longitudinally through the interplay of individual needs, social context, and service design within multi-actor systems.

Finally, the chapter articulated two hypotheses: **Hypothesis 1 (H1)** examined the direct effect of hyper-personalisation on consumer goal strength, while **Hypothesis 2 (H2)** proposed the moderating role of perceived privacy framing. Together, these hypotheses provide the basis for empirical testing, assessing how AI-enabled hyper-personalisation supports consumers' evolving life goals. The next chapter details the research methodology and experimental design used to test these hypotheses.

Chapter 4 – Methodology

4. Research Methodology

This chapter outlines the methodological framework employed to investigate how varying levels of hyper-personalisation influence consumer goal strength. The study adopts a **quantitative experimental design** grounded in a **positivist paradigm**, enabling empirical testing of the hypotheses through measurable and generalisable outcomes. The research applies a longitudinal analytical design that integrates a simulation-enhanced longitudinal **Discrete Choice Experiment (DCE) with repeated-measures mixed modelling.** This structure enables the investigation of both immediate preference validation and temporal motivational shifts across time and between privacy framing conditions.

The Discrete Choice Experiment (DCE) was estimated using a **Generalised Linear Mixed Model (GLMM)** with a **multinomial logit link** to examine the internal validity of the experimental stimuli and assess systematic variations in choice probabilities over time, across personalisation levels, and privacy framing conditions. The resulting experimental choice data also served as the empirical basis for the three Linear Mixed Models (LMM) used to analyse longitudinal changes in consumer goal strength over three waves.

Within the **Individual Growth Curve Modelling (IGCM)** framework, **three Linear Mixed Models (LMM)** were then applied to capture both *between-person* and *within-person* variations in motivational trajectories. These models tested the study's two main hypotheses and examined the interaction between hyper-personalisation intensity, privacy framing, and consumer goal strength.

A post hoc analysis further examined whether the **perceived importance of hyper-personalisation** moderated the relationship. The hypotheses and analytical design are summarised in **Table 6** below. An **adaptive Learning Automaton algorithm** was incorporated within the DCE to simulate real-time feedback logic of AI-enabled recommendation systems. Together, these methods offer a realistic representation of AI-enabled consumer experiences, enabling the study of sustained behavioural change over time.

The remainder of this chapter outlines the experiment's structure, the pilot study, and the three-wave longitudinal design. It details the consumer profiling strategy, the progressively hyper-personalisation clusters, and the implementation of the adaptive algorithm. It also describes data collection, sampling procedures, data preparation, ethical considerations, and statistical techniques. Key descriptive statistics, variable design, and data distribution metrics are also presented.

Table 6*: Study Hypotheses and Analytical Strategy*

Hypothesis	**Statement**	**Analytical Strategy**
H1	Higher levels of hyper-personalisation significantly increase consumer goal strength over time	Tested in ***Model 2*** Linear Mixed Models (LMM) using grand-mean centered hyper-personalisation (*between-individual*) and person-mean centered hyper-personalisation (*within-individual*) *(refer to section 4.4.4.2)*
H2	*Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*	Tested using ***Model 2*** Linear Mixed Model (LMM) using interaction terms between *Group* (privacy framing) and hyper-personalisation (grand-mean and person-mean centered) *(refer to section 4.4.4.2)*
Post-hoc	-	***Model 3***: Post-hoc exploratory model testing whether perceived importance of hyper-personalisation moderates the effect of hyper-personalisation on consumer goal strength *(refer to section 4.4.4.3)*

4.1 Theoretical Methodological Frameworks

4.1.1 Discrete Choice Models (DCM)

Discrete Choice Modeling (DCM) is a widely known and applied methodological framework used to simulate behavioural decision making in complex service settings. Rooted in Random Utility Theory (RUT), consumers make choices from a set of finite alternatives by selecting the alternative associated with the highest perceived utility or value (Van Cranenburgh et al., 2022; Danaf et al., 2019; Solgaard et al., 2023). Since alternatives are usually modelled as mutually exclusive options, choice modelling can be viewed as a classification task (Van Cranenburgh et al., 2022). DCM applications in personalisation contexts are increasingly used in research and practice (Danaf et al, 2023; Hazrati and Ricci, 2024; Krause and Oosterhuis, 2025; Zhu et al., 2019). Traditional utility models have been expanded to reflect complexities of modern digital environments, incorporating elements such as personalisation, privacy concerns, and framing effects (Adjerid et al., 2019; Paliński et al., 2025). Recent literature emphasises how personal relevance, goal pursuit, and cognitive constraints affect consumer choice behaviour. For example, Ju et al. (2025) found that consumer preferences in chatbot interactions are shaped by personalisation quality and cognitive limitations. Raeside et al. (2024) believe that framing messages can modify utility perceptions. Paliński et al. (2025) found that privacy framing significantly influences consumer responses to digital advertising, suggesting its key role in utility valuation within hyper-personalised service contexts.

Compared to traditional recommendation and personalisation methods that rely primarily on user and item profiling, DCMs resolve several limitations. They are well-suited for recommender systems given their ability to incorporate *user-specific*, *item-specific*, and *contextual* data within a single model to predict individual choices (Danaf et al., 2023; Jiang et al., 2014). Unlike standard personalisation methods, DCMs provide a single unified utility-based framework, integrating and balancing between ***user relevance*** – how well the content matches the user's expressed or inferred preferences - and ***item diversity*** – the degree of novelty and variety across recommended content (Danaf et al, 2023; Jiang et al., 2014). It can recommend new items previously not selected or rated by users. Supporting the inclusion and quantification of consumer preference heterogeneity, DCMs can incorporate observed variables (such as *demographic*) and latent factors (*psychological traits*) to influence consumer choices. For instance, Chen et al. (2025) and Vallarino (2025) found that including consumer demographic data, personality traits, and hidden preference segments can improve the predictive performance of choice models under low-data conditions. Kim et al. (2025) further emphasise that including psychological traits in choice models can better interpret utility structures within personalised contexts.

Recent work highlights how computational models can link observed behaviours to cognitive processes underlying decision making over time (Fernandez et al., 2025; Haines et al., 2024). These models reveal how individuals vary systematically not only in how strongly they weigh different options, but also in when certain factors begin to influence their decisions (Chen et al., 2022b; Lombardi and Hare, 2021). Decisions are not static evaluations but rather unfold as temporally dynamic processes influenced by psychological traits, personality profiles, and risk propensities. This highlights the importance of *moment-to-moment*, *person-level variability* in decision making – especially in adaptive digital environments. Capturing such dynamics is hence essential for understanding how contextual and psychological traits evolve over time, thereby justifying the use of a longitudinal, within-individual design in this study.

DCMs often capture data in discrete choice experiments (DCE), both frequently perceived as a single method (Van Cranenburgh et al., 2022). Based on choice modelling, DCEs are widely used to estimate consumer demand and preferences for hypothetical products, services, and their attributes (Costa et al., 2019; Byun et al., 2018; Lang et al., 2021; Zha et al., 2020). This approach focuses on modelling discrete choices among a set of distinct alternatives to analyse consumer choices related to clearly defined brands, products, services or options. It simulates a hypothetical market in which consumers choose one of several mutually-exclusive alternatives as a set of attributes with one or more levels based on their preferences (Feldman et al., 2022; Lahindah and Sudirman, 2023; Holmes et al., 2017).

Discrete choice modelling assumes that individuals undergo rational decision making by evaluating different alternatives and choosing the one that maximises their utility. Such experiments ask respondents to choose between hypothetical alternatives (for example, different levels of personalisation) described through a set of attributes (e.g., demographic, history usage, life goals) that vary according to pre-defined levels. Researchers can infer individuals' preferences by analysing how they trade off different levels of each attribute when making choices about a product or service they would hypothetically buy (Kim and Park, 2017). This allows researchers to quantify the impact of different factors on consumer choice probabilities, hence, predicting consumer behaviour in response to changes in attributes or external factors.

In a discrete choice experiment, respondents are presented with a series of hypothetical questions or options (i.e., scenarios), often referred to as choice sets, and asked to state their preferences (Akinc et al., 2024). Each hypothetical intervention or alternative has several characteristics (*attributes*) that vary (*attribute levels*). Such experiments use statistical methods to evaluate the importance of different attributes, based on random utility theory, assuming individuals select the option with the highest perceived utility (Galekop et al., 2024). Given their hypothetical nature, discrete choice experiments are particularly suited to study situations that do not yet exist in real-life (Van Cranenburgh et al., 2022; Galekop et al., 2024). They present a very valuable and viable method to adopt when product information is missing, such as in the case of a product or service yet to be launched, or hypothetical offerings not available in real-life. Furthermore, they enable individual-level analysis in case of missing products in market or multiple product offerings (Mariel et al., 2025).

Despite their known limitations including hypothetical bias and strategic behaviour (Haghani et al., 2021), DCEs offer an easy and fast way to set up and implement. Dedicated software packages, such as Ngene and STATA, are available nowadays that facilitate designing such experiments, and online survey platforms like Qualtrics and SurveyMonkey allow swift implementation. Online panel platforms, like Kantar and Amazon MTurk, can be used to gain access to respondents belonging to the target population, making data collection fast and hassle-free. Respondents using these panel platforms have limited privacy concerns regarding their personal data storage and publication as these panels ensure data cannot be traced back to its owner (Van Cranenburgh et al., 2022).

Since its inception, the field of choice modelling has been grounded in theory-driven approaches based on behavioural theories, traced back to Prospect Theory (PT)

(Kahneman and Tversky, 1979), later followed by Regret Theory (RT) (Loomes and Sugden, 1982), and Random Utility Theory (UT) (McFadden, 2001). These theories allow discrete choice models to formalise the psychological and contextual underpinnings of decision-making processes, thereby acting as causal explanatory frameworks (Ben-Akiva and Lerman, 1985). According to Prospect Theory (PT), consumers weigh losses more heavily than gains and are sensitive to framing effects, violating classical utility axioms (Kahneman and Tversky, 1984).

Theory-driven DCMs offer deeper explanatory power compared to black-box algorithmic methods (Van Cranenburgh et al., 2022; Hensher et al., 2016). They incorporate not just utility maximisation, but also psychological distortions and contextual framing effects – hence increasing their explanatory insight. This makes them well-suited to study digital contexts such as hyper-personalised recommender systems, where psychological cues and contextual triggers can significantly alter preference structures (Danaf et al., 2023). This foundational insight enables them to hold value in environments where understanding rather than predicting behaviour remains critical.

Despite the flexibility and wide adoption of discrete choice modelling, there is growing interest in shifting towards **data-driven machine learning** approaches. Unlike theory-driven models, involving an adhoc and time-consuming variable selection process (Paz et al., 2019; Rodrigues et al., 2022), machine learning methods such as deep learning have demonstrated strong performance in accurately modelling personalised preferences given their underlying estimation techniques (Lederrey et al., 2021; Sifringer et al., 2020; Wong et al., 2017). However, their use of latent variables may limit interpretability compared to traditional models (Mariel et al., 2025). Integrating machine learning techniques into discrete choice models helps address challenges in model specification and enhances their flexibility in capturing expanding diverse patterns of choice behaviour (Van Cranenburgh et al., 2022).

By learning patterns directly from data rather than relying solely on theoretical assumptions, this *hybrid* approach reduces subjective bias, improves model efficiency, and scales effectively for large or continuous datasets. It also supports robust and behaviourally meaningful insights, enabling discrete choice models to dynamically adapt to evolving consumer data streams (Danaf et al., 2019; 2023; Nguyen et al., 2021). For instance, Danaf et al. (2019) introduced a hierarchical Bayes framework to enhance the performance of App-based recommender systems by estimating and updating user preferences in real time. Their model included three sets of preference parameters: (1) general *population-level* preferences, (2) *individual-specific* preferences, and (3) *decision-context* preferences. This approach enabled real-time updates of individual parameters as users make choices, feeding new data back to the model. Such hybrid frameworks combine the explanatory strength of discrete choice modelling with the adaptive, data-driven learning power of machine learning, grounded in reinforcement-based pattern recognition (Van Cranenburgh et al., 2022; Sfeir et al., 2022; Sifringer et al., 2020).

Building on this foundation, the present study employs a **hybrid model** that integrates a discrete choice experiment with a simulation-based **learning automaton** as the underlying estimation technique. This simulation approach mathematically represents the adaptive dynamics of hyper-personalisation in real-world settings, making it suitable for evaluating the study's hypotheses. Section 4.1.2 reviews the theoretical foundations of learning automata, while section 4.2 outlines the design and implementation of both the discrete choice experiment and learning automaton.

4.1.2 Learning Algorithms

Related Work

Personalisation and recommendation systems deliver services based on user preferences stored in individual user profiles. Their effectiveness depends on how accurately and completely this information reflects each user's behaviour (Farahani et al., 2022). Two main challenges arise when designing such systems:

1. Establishing an initial user profile for new users
2. Continuously updating the user profile information to reflect changing needs, interests, and preferences (Micu et al., 2022).

To address these challenges, three main categories of algorithms are commonly used in personalised recommendation systems:

1. Content-based filtering,
2. Collaborative filtering, and
3. Hybrid filtering

With a *content-based filtering* approach, recommendations are generated based on item similarity and user's past behaviour. The system predicts what a user might prefer by analysing previously selected content, assuming similar items will also be liked (Mu and Wu, 2023). For example, movie recommendation systems often group movies by shared attributes such as genre, actors and directors, and use these similarities (*user-annotated metadata*) to suggest new titles. However, content-based filtering algorithm has several limitations. Because it relies on individual user data and ignores similarities across broader user community, it often results in low accuracy, narrow applicability, and lack of novelty (Fang and Fan, 2022). When users have rated only a few items, the system cannot accurately capture their preferences, leading to less personalised recommendations even with improved prediction models (Mu and Wu, 2023). This approach struggles to recommend new or diverse content, performing poorly for new users with limited rating histories (Liu et al., 2024).

In the *collaborative filtering* algorithm, recommendations are generated based on user similarities. Items with a high probability of preference for one user are suggested to other users with comparable tastes, relying on collective user intelligence (Fang and Fan, 2022). This algorithm has two main variants: *item-based*, which predicts preferences based on item similarities, and *user-based*, which relies on user rating patterns. While collaborative filtering effectively utilises community behaviour, its performance depends on the sample size and diversity of the user base. The algorithm often struggles when new users or items are introduced – referred to the *cold-start problem* (Farahani et al., 2022). Moreover, variations in information quality and quantity, environmental context, and users' psychological states can further reduce accuracy (Mu and Wu, 2023). Consequently, collaborative filtering systems may fail to provide sufficiently personalised or novel recommendations, particularly for new or infrequent users.

To address the data sparsity and the cold-start problems, *model-based* collaborative filtering techniques have increasingly incorporated machine and deep learning

(Movafegh and Rezapour, 2023). In movie personalisation systems, for example, matrix factorisation integrates users and items within a shared latent factor space, allowing more efficient computation and better prediction accuracy (Farahani et al., 2022). This approach reduces dimensionality and improves training speed and space efficiency, while helping to avoid overfitting. Despite these advantages, matrix factorization still struggles in data-sparse environments, especially as the rating matrix grows (Duan et al., 2022). To overcome this, *deep learning* has been applied to discover complex, non-linear relationships between users and items, improving prediction performance (Hussein et al., 2022). Convolutional neural networks (CNN), and other neural architectures have shown strong capability in identifying hidden produced user features in datasets and enhancing learning accuracy (Chavare et al., 2021; Qin and Zhang, 2021). Nassar et al. (2020) proposed a multi-criteria collaborative filtering model using deep learning, capturing user and item features and then predicting overall ratings, resulting in higher accuracy and improved handling of cold-start scenarios. Recent studies highlight the growing importance of deep learning-based hybrid models in enhancing user satisfaction and adaptability (Iyelolu et al., 2024).

The third category of personalised recommendation algorithms is *hybrid filtering,* combining *collaborative filtering* with *content-based filtering* to overcome the limitations of each individual method (Farahani et al., 2022; Hussein et al., 2022). Hybrid filtering often employs an *item clustering* technique that groups data based on user ratings or item selections. Items with the same cluster are highly similar, while those in different clusters show minimal similarity (Jaaz et al., 2022). Clustering has been long been used across domains such as image analysis, information retrieval, and pattern recognition for its ability to detect structural relationships in data (Movafegh and Rezapour, 2023). In recommendation systems, clustering enhances both efficiency and prediction accuracy by identifying latent associations between items. Jadhav et al. (2016) proposed a two-step hybrid filtering approach, where movies are first clustered using item features, followed by a user-based collaborative algorithm to generate tailored recommendations.

Similarly, Frémal and Lecron (2017) proposed a hybrid recommendation system designed to enhance personalisation efficiency by grouping items based on shared metadata. Movies with similar genres or themes are clustered into sub-groups to manage diversity and treat related items collectively. The system predicts user preferences by assigning adaptive weights to each prediction, dynamically updated using either direct user actions (such as selections or ratings) or indirect signals such as browsing behaviour. Katarya (2018) developed a hybrid model that combines *k-means* clustering with an artificial bee colony (*ABC*) optimisation technique, inspired by behaviour of bees in searching for optimal food sources. Tested on the MovieLens data set, the model achieved higher scalability, accuracy, and personalisation quality while mitigating the common "cold-start" problem. Khurana and Dhingra (2021) enhanced hybrid recommender systems by integrating clustering with content-based filtering and classification methods. Their fuzzy clustering approach effectively tackled both scalability and sparsity challenges, achieving improved accuracy and lower error rates on the same dataset.

Farahani et al. (2022) proposed a hybrid modelling approach that operates at the feature level, combining collaborative and content-based filtering. Instead of sharing items among users, their model shares item feature, integrating feature ratings into the final prediction. Their approach helps address the cold-start problem, enabling recommendations for new items without prior ratings. Their model focuses on **temporal adaptability** – the ability to account for changes in user preferences over time. They argue that traditional collaborative and content-based filtering methods lack sufficient accuracy as they miss to automatically track evolving user interests over time or periodically update profiles. Conversely, their system employs two-phased hybrid filtering approach: clustering movies in an offline phase, followed by updating user profiles in an online phase using a **learning automaton** algorithm. By integrating Learning automata into the recommendation process, their system continuously refines user profiles in real-time, enabling adaptive and self-corrected personalisation. Incorporating learning automata within hybrid filtering demonstrates how machine learning simulation methods can enhance choice modelling with dynamic preference estimation (Van Cranenburgh et al., 2022). This adaptive learning foundation is elaborated in sub-section 4.1.1.

The discrete choice experiment research methodology typically employs mathematical models such as the Multinomial Logit Model (MNL) or machine learning-based estimation strategies to predict the probability of a consumer choosing among alternative options based on both alternative-specific and individual-specific factors. Recent studies have shown that machine learning strategies can outperform traditional MNL models in terms of accuracy and efficiency when predicting consumers' preferences and estimating choice probabilities (Feldman et al., 2022). Among these strategies, the Learning Automaton - a reinforcement-based machine learning method - enhances model performance by iteratively learning to select the optimal action from a finite set of possible choices through continuous interaction with a stochastic environment (Taghipour et al., 2022). The probability distribution of potential actions serves as the input for the learning automaton, which adjusts its selection probabilities based on environmental feedback. Through repeated reinforcement signals, the automaton gradually identifies the action that yields the most favourable outcome while minimising penalties from less optimal choices. In dynamic, complex, and uncertain environments - such as adaptive recommendation systems – this self-learning mechanism enables the model to continuously refine decision probabilities and adapt to evolving user behaviour (Farahani et al., 2022).

Accordingly, this study adopts Learning Automata as the underlying adaptive estimation model within the Discrete Choice Experiment, allowing the simulation to capture how consumers progressively update preferences across waves.

Learning Automaton

The learning automaton is one of the earliest and widely applied machine learning algorithms, extensively studied since the 1970s for its capacity to identify optimal actions through interaction with a stochastic environment (Sangaiah et al., 2023). The automaton continuously learns from environmental feedback to determine the best action from a set of available alternatives (Di et al., 2023). The term "*automaton*" reflects the algorithm's ability to autonomously update and refine its decision-making process through iterative learning without manual intervention. This allows the model to simulate adaptive, intelligent behaviour by *dynamically* responding to environmental changes in *real-time*. The learning automaton selects an action from a finite set, each associated with a certain probability of success. Based on the environment's feedback, it adjusts these probabilities to reinforce optimal actions and penalise sub-optimal ones. Unlike fixed or pre-determined models, learning automata react *dynamically* to feedback, ensuring the system continually adapts to *contextual* variations (Zhang et al., 2024).

When the learning automaton interacts with a random environment, it progressively improves its own performance through iterative learning. At each iteration, the automaton selects the best action out of a finite set of possible actions - referred to as the action set – based on their associated probabilities (Di et al, 2023). The selected action serves as input to the environment, providing a reinforcement signal (*reward* or *penalty*) in response to that choice. The automaton updates the probability distribution of its action set using this feedback, strengthening the likelihood of optimal actions whilst reducing that of sub-optimal ones. This iterative process is simulated using the *linear reward-penalty* algorithm, incrementally adjusting decision probabilities according to revised feedback (Sangaiah et al, 2023). Through repeated cycles of selection and reinforcement, the automaton converges toward the optimal decision strategy – the action that minimises average penalties or maximises rewards in uncertain environments (Billard and Lakshmivarahan, 1999).

Using the action probability vector, the learning automaton effectively addresses the cold-start problem by adapting to new inputs without exhaustive evaluation of all possible actions. A form of Reinforcement Learning (RL), the automaton learns from feedback received from the environment to progressively refine its action probabilities based on the action associated with the highest expected reward (Di et al., 2023). This adaptability makes learning automata especially valuable in dynamic and uncertain environments where complete information is rarely available (Farahani et al., 2022). Empirical applications in adaptive testing and personalised systems (Jin and Pan, 2025) illustrate how learning automaton's trial-and-error learning mirrors human decision making. Isayama et al. (2016) illustrated this interactive adaptability through the Automata Puzzle Game – a system that dynamically refines feedback in response to user inputs reflecting the reinforcement principles central to learning automata.

Learning Automata Process

The learning process in a random environment involves two entities: the learning automaton and the environment itself. The environment is considered *stationary* if the penalty probabilities remain constant over time, and *non-stationary* if the penalty probabilities change (Farahani et al., 2022). Based on how reinforcement feedback is provided, the environment can be categorised into three types: **P-models**, **Q-models**, and **S-models** (Di et al., 2023):

- In a **P-model**, the environment is characterised by two binary reinforcement signals – typically a value of 0 (un*selected)* or a value of 1 *(selected*).

- In a **Q-model**, the reinforcement signal can take on a finite number of discrete values, allowing for a more nuanced feedback system.

- In an **S-model**, the environment allows an infinite range of possible feedback values, making it suitable for highly dynamic or continuous response settings.

These models differ in how flexible and granular the feedback mechanism is, with S-models offering the highest level of adaptability. In practical term, the learning automaton resembles a restaurant testing a set of recipes. Each recipe (action) is tried, and restaurant diners give feedback. Recipes that are highly rated are cooked more often, while those poorly rated are cooked less frequently. Over time, the restaurant refines the menu based on this reinforcement.

The learning automaton process can be represented as an adaptive feedback loop between three main components – Action (A), Feedback (B), and Reward Matrix (C) – within an environment represented as a ternary $\langle \boldsymbol{A}, \boldsymbol{B}, \mathbf{C} \rangle$ structure (Di et al., 2023). This process defines how the automaton learns to select the optimal action in response to environmental feedback through probabilistic updating. The description of each component is highlighted in **Table 7** below.

***Table 7**: Main Components of Learning Automaton Process*

Component	Definition / Function	Mathematical Representation	Interpretation in This Study
Action (A)	Represents all available choices (e.g., personalised recommendations shown to a user). At any moment in time n, the automaton selects one action denoted by = α(n) from the action set A = { α1, α2, ..., αr, ..., α$_R$}. The action set acts as the input of the environment (choices offered to users) and the output of the learning automaton representing the set of personalised recommendations	a(n) ∈ A = {α1, α2, ..., αr, ..., α$_R$}.	Set of hyper-personalised recommendation options presented to the participants.
Feedback (B)	Represents reinforcement signals (penalty/reward) received from the environment in response to each selected action. Feedback guides learning by adjusting action probabilities. Higher values in this set represent greater rewards. Specifically, β0 = 0 represents a penalty, while βQ = 1 corresponds to the largest reward. The environment is a P-model when Q = 1, a Q-model when 1 < Q < ∞, and an S-model when $Q \to \infty$. At time indexed by n, the feedback from the environment is denoted by β(n).	B = {β0, β1, ..., βq, ..., βQ} ($Q \geq 1$)	Reflects user engagement (clicks, selections) indicating positive or negative response to recommendation.

Reward Matrix (C)	Stores expected performance or "rewards" for each action and updates probabilities based on feedback. This update rule ensures that the selected action's probability increases if it receives positive feedback (reward), while all other actions are slightly penalised – allowing the model to gradually "learn" which actions are most effective. The more rewards an action (choice) receives, the higher the probability that it will be selected by the user in subsequent iterations.	C = [$\mathbf{c}1$, $\mathbf{c}2$, ..., $\mathbf{c}r$, ..., $\mathbf{c}_R$]	Represents cumulative reinforcement history used to refine recommendation priorities.

As illustrated in **Table 3** above, for every $\boldsymbol{\alpha}r \in A$ (action set), the corresponding reward vector is $\mathbf{c}r$ = [cr,0, cr,1, ..., cr, q, ..., cr, Q], where $\sum q\ cr, q = 1$. At any time n, when the learning automaton selects action $\boldsymbol{\alpha}r$, the probability of receiving feedback $\boldsymbol{\beta}q$ is $\boldsymbol{c}r$, q, as given by:

$\boldsymbol{c}r$, q = Pr {b(n) = $\boldsymbol{\beta}q$ |$\boldsymbol{\alpha}$(n) = αr}, Pr refers to probability of action r

In a recurrence relation, the learning automaton algorithm can be employed to modify the vector of action probability. In a random environment represented by the ternary ⟨$\boldsymbol{A}$, $\boldsymbol{B}$, $\mathbf{C}$⟩, assume that $\boldsymbol{\alpha}$i(n) ∈ α signify the action chosen by the learning automaton (choice presented to the user at iteration n), and p(n) signify the probability vector defined over the action set A at iteration n. Let a and b signify the reward (*pwenalty decrease*) and the penalty (*penalty increase*) parameters of the action probabilities. If r is the number of actions in the action set that may be adopted by the learning automaton, the vector of action at time n, probability p(n), is updated by the linear learning algorithm provided in (1) below rewarding the ***selected*** action $\boldsymbol{\alpha}$i(n) and penalising all other ***unselected*** actions provided in (2) below.

$P_i(n+1) = P_i(n) + a * (1 - P_i(n))$ *(1) i <= r refers to the selected action*

$P_j(n+1) = (1 - a)\, P_j(n)$ (2) $j <= r$ and $j \neq i$ *refers to the unselected action*

The actions with relatively higher expected rewards are repeatedly evaluated by the learning automaton to crowd out the optimal one, supporting it in enhancing its future recommendations (Mu and Wu, 2023). Within the current study, this framework enables the dynamic simulation of user learning and preference evolution, providing a robust methodological foundation for the discrete choice experiment presented in the next section.

4.2 Materials and Methods

This study followed the recommendations of Van Cranenburgh et al. (2022) for integrating machine learning techniques with discrete choice models (refer to *section 4.1*). In line with Farahani et al.'s (2022) approach, this study uses a hybrid experimental design that combines a **longitudinal Discrete Choice Experiment (DCE)** with a **simulation-based** learning model to study consumer preferences for different levels of hyper-personalisation in the context of Telecommunications and Entertainment service.

The DCE was designed to estimate the probability that consumers would choose specific types of hyper-personalised content. A learning automaton was used to simulate how consumers adapt their choices over time, reflecting real-world personalisation processes based on Artificial Intelligence. This simulation framework models user adaptation by identifying the most likely level of hyper-personalisation preferred, optimising choices that maximise rewards and minimize penalties.

Each participant was presented with a set of initial questions capturing personal data and service preferences to create an individual profile. During the first wave, participants selected one preferred option from four progressively goal-aligned hyper-personalised content (V1 – V4). These levels represented increasingly advanced combinations of data types and personalisation depth. By selecting their preferred option, participants effectively indicated the degree of personalisation they would most like in a real-world service.

The learning automaton updated the system's recommendations in real-time based on participants' choices, assigning probabilities (*cluster weights*) to each personalisation level. Goal strength was then measured at the end of the first wave. The second wave followed ten days later, and the third wave was conducted five months after the first wave, allowing the study to assess *short-term* and *long-term* effects of hyper-personalisation on consumer motivation and commitment (goal strength).

4.2.1 Pilot Study

The pilot study aimed to validate the design of user profile attributes and refine the discrete choice experiment (DCE) structure. As noted in literature, pilot testing is an essential stage in experimental research, helping to identify potential issues, uncover ambiguities, improve measurement validity, and enhance data quality before the main study (Poku-Boansi et al., 2023; Truong, 2017). The term "*pilot study*" refers to informal or small-scale pre-evaluations of prototypical or main study solutions (Janaka et al., 2024).

Truong (2017) highlights that pilot testing helps prevent wasted efforts by identifying and eliminating design flaws before the main study. Janaka et al. (2024) notes that pilot studies can help refine hypotheses and procedures and simulate real-world usage scenarios, especially in human-computer interaction (HCI) research. These simulations improve experimental robustness by confirming the study's timing, feasibility, and overall design suitability.

A total of **105** participants from different regions took part in the pilot study. The focus was on validating the relevance and clarity of the user profile attributes used in the DCE. The choice set was constructed based on attributes and attribute levels of hyper-personalisation, with user profile tags updated in *real-time* to reflect personalised content. Participants were presented with the hypothetical choice options and asked to select the option that best matched their preferences, with each choice indicating their preferred level of hyper-personalisation.
Data were collected in the pilot phase to create the user profile using four sources:

(1) Demographic data (*gender, age, and location*)

(2) Telecommunications data (*frequent browsed content and roaming usage*)

(3) Partner (non-Telecommunications) data (*preferred movie genres*)

(4) Consumer-dominant data (*set of active life goals*)

The pilot study helped verify the contextual relevance of the attribute values. Through enabling participants to enter their own value in the "*Other*" field, new attribute values were identified and added to the list of attribute values in the main study. For example, "*Disney+*" and "*HBO*" were captured as missing attribute values of the entertainment service options. These values were then integrated into the final attribute set to better reflect participants' real-life usage. This contextual enrichment strategy is recommended in Discrete Choice Experiment (DCE) design, as it ensures simulated choices align closely with user expectations (Mangham et al., 2009).

Furthermore, feedback from the pilot study revealed necessary adjustments of mandatory attribute value constraints. For example, the constraint requiring participants to enter exactly three travel destinations visited in the past 24 months was revised from a "***mandatory three***" to a "***minimum* of one**" to improve inclusivity. Specifically, four participants reported they had not travelled to three destinations within the specified timeframe – underscoring the restrictive nature of the original condition. This mandatory restriction was removed in the main study, improving inclusivity and flexibility in participant input.

By enabling a low-risk, cost-effective evaluation, the pilot phase contributed meaningfully to enhance the experiment's precision, clarity, and adaptability, ensuring it was grounded in realistic user preferences while reducing the likelihood of data loss or user disengagement due to design flaws (Janaka et al., 2024).

4.2.2 Experimental Timeline

The main study was conducted across three waves - *Wave 1*, *Wave 2 and Wave 3* - with a **10-day interval** between *Wave 1* and *Wave 2*, and **a five-month interval** between *Wave 2* and *Wave 3* (see **Figure 5**). The shorter gap between *Wave 1* and *Wave 2* allowed the assessment of immediate and short-term effects of hyper-personalisation, while the longer five-month gap between *Wave 1* and *Wave 3* enabled observation of sustained behavioural and motivational changes over extended periods. The adjusted timing followed early batch results showing little variation between the first two waves when only short intervals were used. This timing structure aligns with the theoretical rationale outlined in **Chapter 3** (*Section 3.3.1*), which draws on **temporal goal theory** (Ajzen and Kruglanski, 2019). It supports examining how variations in temporal proximity and intervening events can influence the stability of behavioural intentions and consumer goal strength.

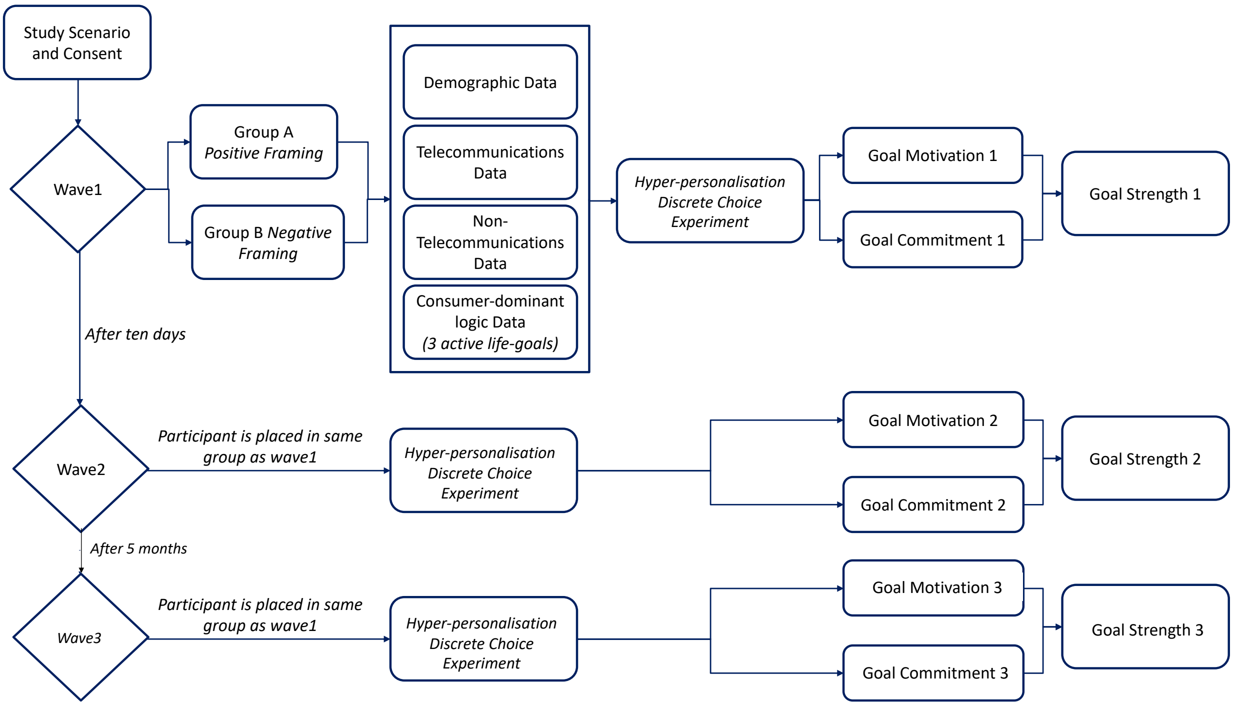


Figure 5*: Discrete Choice Experiment 3-Wave Flow*

4.2.3 Screening and Recruitment

Data were collected in batches targeting 200 participants in *Wave 1* and targeting participants in each batch during *Wave 2*. *Wave 3* batches targeted participants who only completed both *Wave 1* and *Wave 2*. Recruitment was conducted through **Amazon Mechanical Turk (MTurk)** platform between **May 2024** and **September 2024** for *Wave 1* and *Wave 2* and between **October 2024** and **February 2025** for *Wave 3*. To ensure data quality, MTurk participants were screened using two qualifications, as recommended by Peer et al. (2014):

1. An approval rate above **95%** and
2. A minimum of 100 completed approved tasks

These criteria helped ensure participant reliability and consistency across waves. No restrictions were placed on gender, age, or location to maintain diversity.

In *Wave 1*, a total of **1,434** participants took part (**1,358** participants recruited via MTurk and **76** via direct targeting). Of these, **1,235** participants joined *Wave 2* (**86.1%**) and **847** (**68.6%**) participants completed *Wave 3*. In total, **847** participants successfully completed all three waves of the study. A small number of observations (n = 91) were removed due to missing or incomplete data across waves. These missing cases were primarily due to technical or connectivity issues, as they were not recorded in the study's underlying database. Descriptive statistics for the final sample are presented in *Section 4.3.3* (Data Collection).

MTurk Justification and Limitations

Data for this study were collected via Amazon Mechanical Turk (MTurk), a well-established online crowdsourcing platform commonly used in behavioural and experimental research. MTurk was selected for its ability to provide fast, cost-effective access to a broad and diverse participant pool, enabling timely data collection across multiple experimental waves. Prior research indicates that MTurk comprises a relatively stable worker population of approximately 100,000 to 200,000 active global users, facilitating multi-wave research designs (Difallah et al., 2018). Its support for qualification filters and attention checks also help ensure data reliability.

However, several limitations were acknowledged. Despite its large user base, not all workers are concurrently active, making longitudinal retention challenging—reflected in the attrition observed during *Wave 3*. While MTurk's population is generally gender-balanced (Difallah et al., 2018; Qureshi et al., 2022), this study recorded a higher proportion of male participants (over **70%**) and a younger age concentration (**25–34 years**), limiting balanced representation of the broader consumer population. Both **age** and **gender** distributions limited the ability of the study to have a balanced representation of the wider consumer population, restricting use of these demographics as predictors in the study.

In addition, MTurk samples often over-represent participants from the United States and India (Difallah et al., 2018), contributing to a geographically skewed sample (see *Section 4.3.3*). However, the study's sample still includes global representations from other regions of the world, reinforcing the validity and reliability of the findings. Moreover, while monetary incentives enhance participation, they can sometimes influence attentiveness, necessitating robust screening checks.

Despite these limitations, MTurk was deemed appropriate for this study as it enabled efficient multi-wave large data collection from a global, adult population aligned with the study's experimental and cross-contextual aims.

4.2.4 Privacy Framing Design

To examine the moderating effect of privacy framing, participants were randomly assigned during *Wave 1* to either **Group A** (neutral group) or **Group B** (negative framing). Group A displayed positively framed information suggesting no loss of data privacy, while Group B presented negatively framed information highlighting potential loss of data privacy – i.e., perceived privacy concerns were accentuated. This design aimed to test how different privacy framings influence responses to hyper-personalisation.

Random assignment ensured that participants were almost equally distributed across both groups, reducing systematic bias, increasing result reliability, and minimising confounding variable effect (privacy framing) by confining it in one group, therefore allowing for comparison.

Specifically, **755 participants (~ 53%**) were randomly assigned to positively framed information (Group A) and **679 participants (~ 47%)** were randomly assigned to negative framing (Group B) in *Wave 1*. This approach follows prior work on gain-loss message framing (White et al., 2011; Tversky and Kahneman, 1981), which demonstrates that people respond differently depending on whether information is framed as a potential gain or loss – where framing refers to the way information is presented to influence decision-making and perception. In privacy contexts, negatively framed (loss-based) messages often trigger greater caution and risk aversion compared to positively framed messages (Zhang et al., 2018). Refer to *Section 2.4* in **Chapter 2** for literature on privacy framing.

In both groups, the privacy framing text was presented at the beginning of *Wave 1*, alongside a short scenario explaining the study context. The text was designed to activate realistic decision-making by helping participants imagine interacting with a personalised service. Ky phrases related to privacy were **bolded** in both framings to direct participants' attention to intended messages. A graphical illustration was shown to both groups, intended to make the scenario more imaginable in participants' minds.

Participants remained in the same framing group throughout all waves and were not reminded of the group they are in, maintaining experimental consistency and capturing framing effects over time. This approach aligns with recommendations for minimal intervention post the baseline avoiding confounding due to repeated exposure (Shen and Li, 2023; Hagger et al., 2022). Refer to *section 4.3.3* (Data Collection).

For readability purposes, each text (scenario and framing text) was split over two user interfaces to ensure participants did not skip through when seeing a long text (refer to **Figures 6 – 9**).

<u>Scenario of the Study</u> *(shown to all participants in both groups)*
In this study, we will consider a scenario where you are subscribed to an entertainment content service through your Telecommunications service provider. This means that the same company that provides your mobile connectivity for calls, messages, and internet access also offers a partnership with an entertainment provider, allowing you to access and watch content on your TV set. This arrangement enables you to enjoy entertainment content either by yourself or with your family. **Assume** that you are subscribed to the service through your Telecommunications service provider.

<u>Text 1</u>*: Positive information framing (Group A) –* ***Figures 6*** *and 7 below*

The entertainment content you receive can be customised and personalised based on your specific demographic data, historical Telecommunication transactions and usage data, real-time data

captured from your usage of the entertainment service itself and your set of active personal goals. *This hyper-personalised content utilises the data currently captured about you and is designed to enhance your viewing experience and* ***without affecting your data privacy****. An example of this personalisation is the entertainment content you are currently watching.*

Now please imagine you are watching your TV set now, either alone or with your family. Think about your current active personal goal (or set of goals) that you are currently pursuing when subscribing to this service. As a consumer, ***by agreeing to share as much data*** *with the Telecommunication provider and its partnering entertainment provider, you are helping to stay motivated towards achieving your active personal goal (or set of goals) you are committed to when subscribing to this service.*

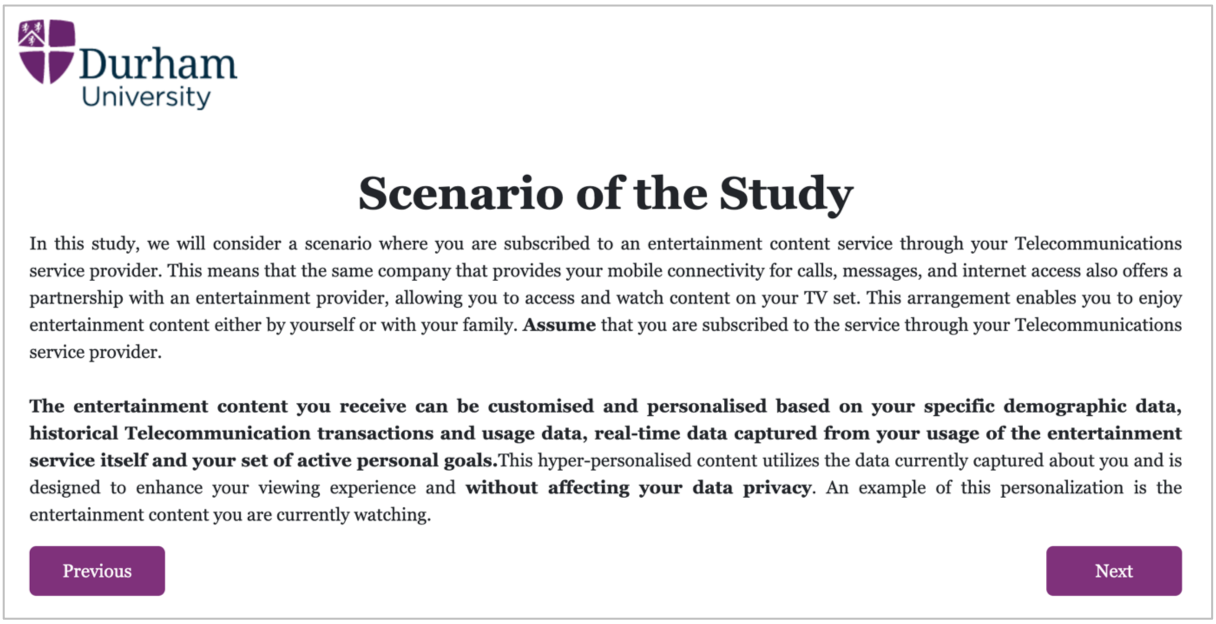


Figure 6*: Scenario of the Study and Positive Framing - Group A (First User Interface)*

Durham University

Scenario of the Study

Now please imagine you are watching your TV set now, either alone or with your family. Think about your current active personal goal (or set of goals) that you are currently pursuing when subscribing to this service. As a consumer, **by agreeing to share as much data** with the Telecommunication provider and its partnering entertainment provider, you are helping to stay motivated towards achieving your active personal goal (or set of goals) you are committed to when subscribing to this service.

Are you currently subscribed to any entertainment service on your TV?
Examples include Netflix, Amazon Prime, OSN, Shahid and the likes

- Yes
- No

Previous | Next

Figure 7*: Scenario of the Study and Positive Framing - Group A (Second User Interface)*

<u>Text 2</u>*: Negative information framing (Group B) –* ***Figures 8*** *and* ***9*** *below*

The entertainment content you receive can be customised and personalised based on your specific demographic data, historical Telecommunication transactions and usage data, real-time data captured from your usage of the entertainment service itself and your set of active personal goals. *This hyper-personalised content utilises the data currently captured about you and is designed to enhance your viewing experience based on* ***how much data you are willing to share****. An example of this personalisation is the entertainment content you are currently watching.*

Now please imagine you are watching your TV set now, either alone or with your family. Think about your current active personal goal (or set of goals) that you are currently pursuing when subscribing to this service. As a consumer, ***by agreeing to disclose your private data*** *with the Telecommunication provider and its partnering entertainment provider, you are helping to stay motivated towards* *achieving your active personal goal (or set of goals) you are committed to when subscribing to this service.*

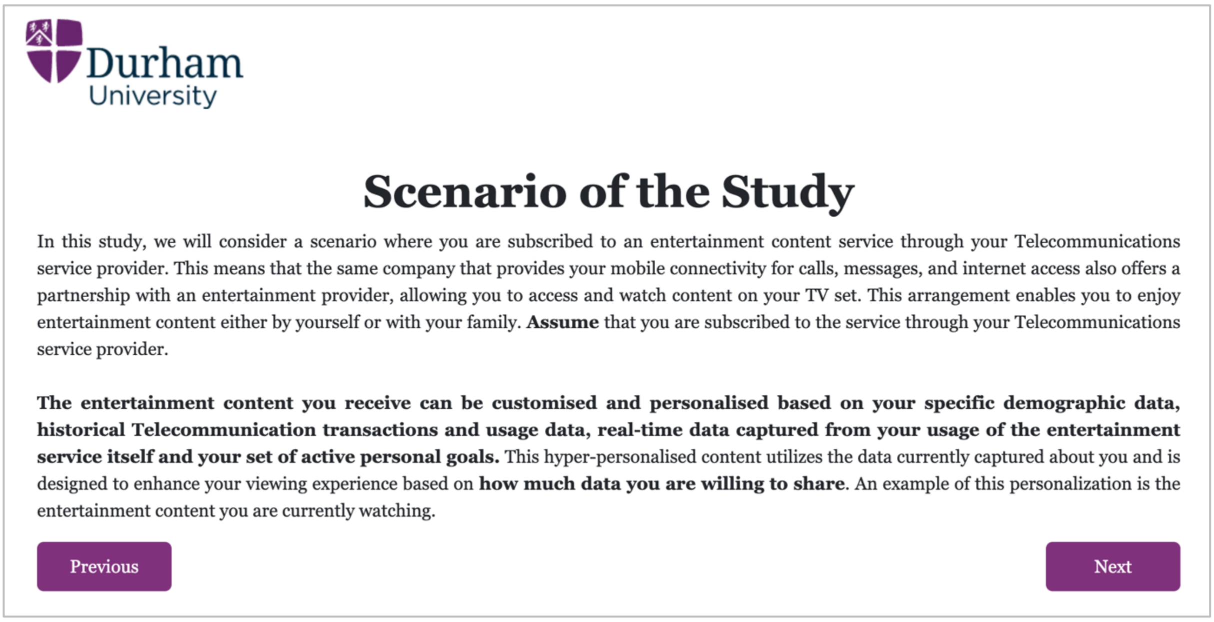


***Figure 8**: Scenario of the Study and Negative Framing - Group B (First User Interface)*

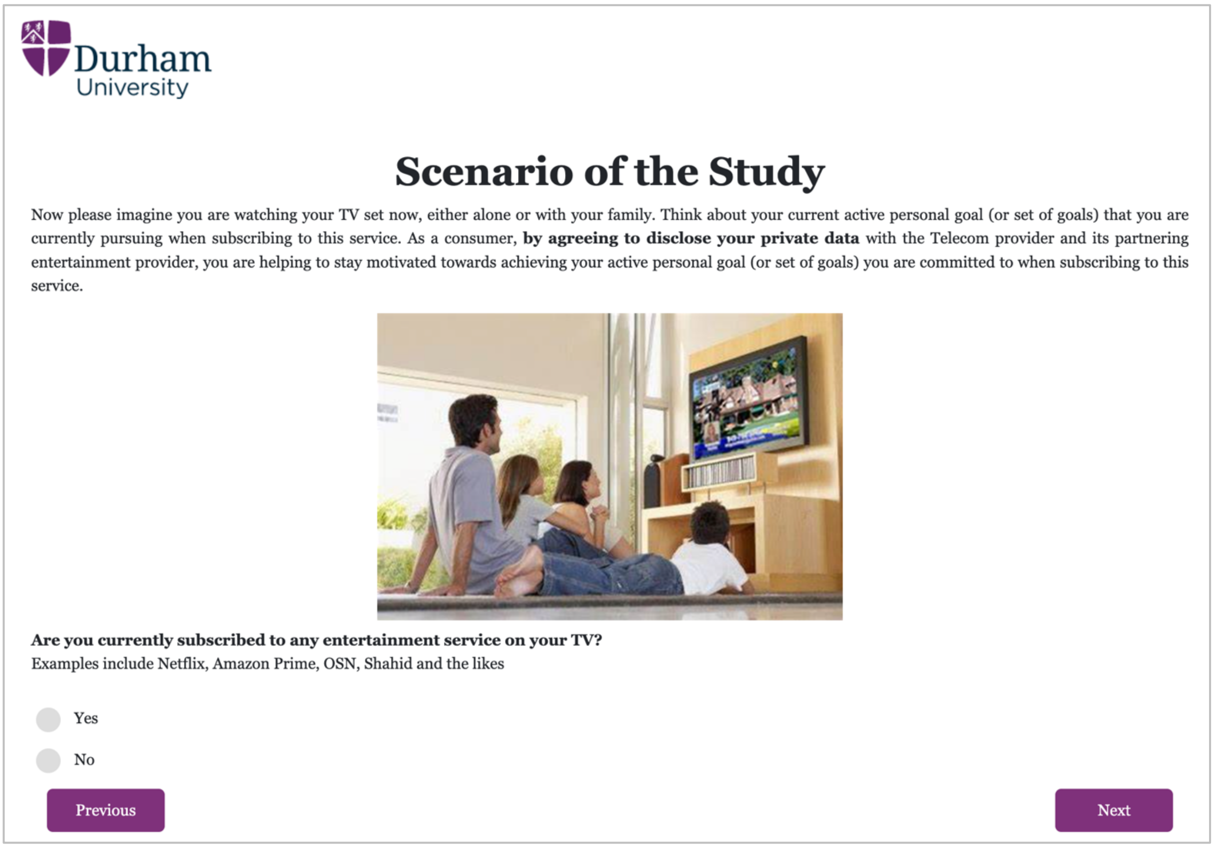


***Figure 9**: Scenario of the Study and Negative Framing - Group B (Second User Interface)*

4.2.5 User Profile Design

During *Wave 1*, participants in both groups were presented with the same set of questions to capture their preferences and interests to create their user profiles. The scenario of the study was first explained, and participants were asked whether they were already subscribed to a similar hyper-personalised service (refer to *Appendix A* for the experiment's screenshots). This question, though not used in data analysis, helped participants better visualise the service being simulated. Participants already subscribed to a similar service were asked to name the service from a list or provide it as an open-ended response.

Two follow-up questions were then presented (*refer to Appendix A*):

1. Whether the participant is currently receiving any personalised content, and
2. How important they consider receiving content personalised to their needs and preferences.

The second question captures the **perceived importance of hyper-personalisation**, which was later analysed as a post-hoc exploratory variable (refer to *Model 3* in *4.4.3.3* and findings in *section 5.1.3*). The remaining questions were used to generate participants' initial user profiles, covering the following four data categories:

(1) **Demographic data**, including user age, gender, and location
(2) **Telecommunications data**, including frequently used Apps (preferred content) and roaming history (up to three most frequent travel destinations).
(3) **Non-Telecommunications data**, including top three preferred movie genres.
(4) **Consumer-dominant logic data**, including top three active life goals.

Demographic Data

Demographic data – specifically *age*, *gender* and *location* – was collected as the foundational layer of hyper-personalisation (refer to *Appendix A*). these variables are widely used in market segmentation and personalised advertising (Kotler and Keller, 2006). Prior studies have shown that demographic factors enhance perceived personalisation when used along or in combination with other elements. For example, *gender* has been linked to higher user engagement and click-through rates when paired with personalised content (Higgins et al., 2018; Kaspar et al., 2019). Similarly, *age* in combination with *gender* and other personalisation elements such as *location* provide contextual cues that strengthen perceptions of relevance and service fit (Walrave et al., 2016; Zarouali et al., 2018). De Keyzer et al. (2022b) further highlight that these three demographic dimensions – interests, age, and location – are among the most important for eliciting perceived personalisation. While the manipulations in their study successfully increased perceived personalisation, it was not possible to disentangle the effect of location on perceived personalisation from other factors. Similarly, it was unclear if gender alone can achieve the same result. Accordingly, this study includes *age, gender, and location* to construct the first and lowest level of personalised content (see **Cluster 1** in **Table 9** in next section).

Telecommunications Data

Beyond demographic data, Telecommunications data – such as app usage, location data, and behavioural interaction patterns – are increasingly used to improve targeting and personalise digital experiences. Leveraging Artificial Intelligence (AI) technologies, such as big data and machine learning, hyper-personalisation draws on consumers' preferences, historical behaviour, and contextual data captured from connected service platforms and mobile devices (Puneet, 2023). Telecommunications service providers play a central role in this process as they own the infrastructure that enables network connectivity and access to large volumes of behavioural and contextual information that inform data-driven hyper-personalisation strategies (Khalik et al., 2023). Studies show that consumers' prior experiences, browsing histories, and app usage significantly shape perceived service relevance and satisfaction (Schwipper et al., 2020).

AI-driven features – such as dynamic recommendations, predictive analytics, and chatbots – further enhance both operational efficiency and consumers' perceived relevance of delivered services (Puneet, 2023; Schwipper et al., 2020). Location-based Services (LBS) have also emerged as a central capability in Telecommunications personalisation, enabling providers to tailor their services individually, such as recommending content based on user's location or travel history. For instance, service providers can recommend customised plans or products using AI to interpret consumers' usage patterns and prior interactions. By integrating multiple data sources – including location, usage patterns, or social media interactions – Telecommunications service providers deliver highly contextual and real-time recommendations. Emerging technologies such as AI, sentiment analysis, and wearable data allow providers to move beyond traditional reactive personalisation, enabling proactive and adaptive service experiences (Puneet, 2023).

In this study, the Telecommunications data category was operationalised using two main inputs:

1. Participants' three most frequently used content categories (representing historical browsing or app usage), and
2. Up to three travel destinations visited in the past two years (representing location-based data).

These variables were captured to reflect real-world behavioural data and were incorporated into user profiles to enhance the personal and contextual relevance of personalised content – particularly in constructing **Cluster 2**, **Cluster 3**, and **Cluster 4** (progressively more personalised levels) within the overall hyper-personalisation framework (refer to *Appendix A*).

Non-Telecommunications Data

The third category captured non-Telecommunications entertainment-related preferences, specifically participants' preferred movie genre selections (e.g., action, comedy, animation). Participants selected their top three preferred movie genres using the MovieLens profiling system (*refer to Appendix A*), which simulated real-world content selection within an Entertainment service context.

MovieLens, developed by GroupLens Research at the University of Minnesota, is a well-established public platform for movie genre categorisation and collaborative filtering. It has been widely applied in personalisation and recommendation system research (Katarya et al., 2018; Khurana and Dhingra, 2021; Farahani et al., 2022). In this study, the MovieLens framework was used to simulate adaptive user profiling based on entertainment preferences. By capturing what consumers choose to watch, MovieLens data reflect behaviour embedded in users' everyday contexts. These preferences captured through partnerships with Entertainment providers, are used to enhance the contextual relevance and personal meaning of hyper-personalised content, contributing to sustained engagement and goal strength. Non-Telecommunications preferences were, therefore, applied to dynamically construct personalised content through real-time metadata tags derived from participants' selections (see **Cluster 3** in **Table 9**). *Appendix A* illustrates the adapted MovieLens interface presented to participants when selecting their preferred entertainment content.

Consumer-dominant logic Data

The fourth category used to build user profiles reflects consumer-dominant ecosystems, capturing participants' top three active life goals. Participants were shown a list of goals and asked to select the three that best represented their current life goals. The Consumer Motivational Scale (CMS) (Barbopoulos and Johansson, 2017) provided the theoretical base for defining these goals. The CMS includes life goals reflecting **gain** (quality, value for money, safety), **hedonic** (comfort, convenience), and **normative** (ethics, social contribution) motivations. This scale was expanded by picking up from Chulef et al.'s (2001) hierarchical taxonomy of human goals, which compiled one of the most comprehensive lists of human goals comprising 135 in total across three broad clusters:

1. *Family-related* including goals of marriage, romance, spending quality time with family
2. *Interpersonal goals* including those related to having a Social life, Friends, Support, Social Recognition, Social Approval, and the opportunity to Give to others and Lead others, and
3. *Intrapersonal goals*, which included (but not limited to) goals related to Career and Education (Personal and Professional Growth), Easy life (Comfort and Convenience), Well-being and Mental Health, Peace of Mind, Happiness, Freedom and Social Awareness, Stability and Safety, Personal Care, Idealism, Ethics, Entertainment, Finances.

As it was not feasible to present all possible goals, a subset of all these goals were selected from all three clusters in Chulef et al's (2001) and covering gain, hedonic and normative goals of the Consumer Motivational Scale (Barbopoulos and Johansson, 2017) - as fitting in the context of the Telecommunications and Entertainment service being studied. The final list of goals presented to the participants included: *Peace of Mind, Quality of Life, Professional Growth, Education and Knowledge, Value for Money, Social Recognition, Well-being and mental health, Comfort and convenience, Happiness, and Enjoying time with family* (refer to *Appendix A*). participants could also select up to three open-ended goals (formulation of own goals) if none of the listed options matched their current life goals.

4.2.5 Discrete Choice Design

The experiment employed a **longitudinal, repeated-measures, stated-preference** Discrete Choice Experiment (DCE) design to simulate consumer decision-making in a controlled, hypothetical setting. It followed a **single-attribute**, **multi-level structure**, where the attribute of interest — *hyper-personalisation* — was represented by four progressively advanced levels (V1 – V4). As the study focused on a single attribute rather than multiple attributes, neither full factorial nor fractional factorial structures were applicable. Instead, all four levels of the attribute were presented within a repeated-measures framework. Conducted across three longitudinal waves, the DCE generated experimental choice data that reflected participants' preferences for varying levels of personalisation. This data enabled the assessment of **internal validity** of the experiment and the **systematic variations** in choice probabilities across the three waves. Furthermore, the experimental choice data served as the empirical foundation for subsequent longitudinal analysis using **Linear Mixed Models (LMMs),** which examined short-term and sustained changes in consumer goal strength over time. This three-wave longitudinal setup enabled the controlled collection of repeated choice data, providing a robust foundation for analysing behavioural stability and adaptive shifts in preferences.

To ensure statistical efficiency and control for attribute-level balance across alternatives, the single-attribute structure (*hyper-personalisation)* was operationalised through four progressively advanced levels (V1–V4). Each level represents a distinct stage of AI-enabled personalisation intensity, ranging from basic demographic customisation to adaptive goal-aligned recommendations. These structured levels were designed to simulate realistic stages of how AI-enabled recommendations evolve within Telecommunications and Entertainment service contexts. This design ensured statistical efficiency while minimising the number of choice tasks presented to participants, avoiding fatigue and reducing cognitive load. By maintaining orthogonality and minimal overlap, the DCE achieved a balanced and efficient experimental structure that preserved internal validity and respondent efficiency, enabling the reliable estimation of main effects across the progressively higher levels of hyper-personalisation.

Table 8 summarises the attribute and its corresponding levels used in the experiment.

Table 8*: Experimental Attributes and Levels of Hyper-personalisation*

Attribute	Level Code	Description
Hyper-personalisation	**V1** – Demographic Personalisation (*Basic*)	Content tailored based on demographic data only (age, gender, location).
	V2 – Telecom Personalisation (*Behavioural*)	Includes Telecommunications data such as frequently used apps and browsing activity.
	V3 – Partner Personalisation (*Contextual*)	Incorporates Non-Telecommunications data such as entertainment preferences (e.g., movie genres).
	V4 – Adaptive Goal-Aligned Personalisation	Integrates Consumer-Dominant Logic data (top three active life goals) for fully adaptive, goal-based recommendations.

The discrete choice experiment focuses on eliciting stated preferences from participants by exposing them to multiple personalised service scenarios. Each scenario presented a set of four alternatives within a pre-defined hyper-personalisation cluster. Each alternative represented a unique combination of embedded personalisation elements. Participants completed three sequential choice tasks per wave, selecting one preferred option in each task.

After providing demographic details, preferences, and their top three active life goals in *Wave 1*, participants completed the Discrete Choice Experiment (DCE) across *three* rounds of selection. Each round presented four alternative service options, each corresponding to one of the four hyper-personalisation levels (V1–V4) – refer to **Table 8**. Each option represented a different intensity of AI-enabled personalisation, allowing participants to choose the version they preferred most. After completing their three selections, goal motivation and goal commitment were measured.

The second wave (*Wave 2*) was conducted ten days later, using a follow-up link matched to each participant's unique ID. This ensured continuity of user profiles without re-capturing preferences, while incorporating the *time* aspect. Participants repeated the same DCE task, remaining in the same privacy framing group (A or B) assigned in the first wave. *Wave 2* also included a repeated measurement of goal motivation and goal commitment, assuming the same goals chosen during the first wave. A third wave (*Wave 3*) followed five months later which was initiated to participants who took part in *Wave 1* and *Wave 2*, repeating the same process to capture *long-term* motivational and commitment changes. Refer to **Figure 5** in *section 4.2.2* for the 3-wave flow.

The personalised service alternatives presented to participants were generated using a simulation-based recommendation framework. This framework was designed to ensure that each choice option reflected a specific level of hyper-personalisation. To operationalise this structure, the experiment employed a **two-step hybrid filtering** approach, combining traditional choice modelling with a simulation-based learning automaton. This hybrid design enabled estimation of user preferences while simultaneously modelling adaptive recommendation behaviour based on participants' prior selections.

The two steps of this hybrid approach were:

1. **Clustering content** based on meta-data derived from captured user profiles to group similar items, and
2. **Extending user profiles** through a collaborative algorithm powered by a learning automaton, which calculated the probability of interest in each recommended hyper-personalised content option.

Step 1: Clustering Content

Recommended content was initially created and uploaded in the database with a cluster category. Each cluster identifies the level of hyper-personalised content. Content in **Cluster 1**, for instance, includes the set of movies personalised based on user demographics while content in **Cluster 2** is personalised based on demographics as well as historical Telecommunications transactions and roaming history (captured Telecommunications data). As illustrated in section 2.1.4, the hyper-personalised value of Cluster 2 is considered higher than that of Cluster 1. There are four movie clusters, categorised based on the four *progressive* levels of hyper-personalisation. The four clusters are presented to each participant based on user preferences populated using the profile captured during *Wave 1* of the study. **Table 9** below shows the four clusters, their description and metadata, with the value of each cluster increasing as more metadata is added. That is, C = {C1, C2, C3, C4} denotes the number of movie clusters. Because user interests and preferences change over time, the purpose of the experiment is to find the interest degree of the active user in each cluster. The value of hyper-personalisation increases as **n** increases, **n <= 4**.

Table 9: *Movie Cluster Descriptions and Tags*

Cluster	Cluster Description	Cluster Metadata (Tags)
Cluster 1 (C1)	*Demographic hyper-personalisation*: content belonging to this cluster is based on the user's captured demographic data (**Figure 2** above)	**Demographic metadata** *(age, gender, and location)*
Cluster 2 (C2)	*Demographic Telecom hyper-personalisation:* content belonging to this cluster is based on the user's captured demographic data and his/her captured Telecommunications transactions (frequent used Apps) and travel history (**Figure 3** above)	**Demographic metadata** *(age, gender, and location)* **Telecom metadata** *(frequent used Apps, travel history)*

Cluster 3 (C3)	*Demographic Telecom, and non-Telecom hyper-personalisation:* content belonging to this cluster is based on the user's captured demographic data, his/her captured Telecommunications transactions (frequent used Apps) and travel history, and non-Telecommunications preferences (**Figures 4** and **5** above)	**Demographic metadata** *(age, gender, and location)* **Telecom metadata** *(frequent used Apps, travel history)* **Non-Telecom metadata** *(preferred movie genres)*
Cluster 4 (C4)	*Demographic Telecom non-Telecom and active goals hyper-personalisation:* content belonging to this cluster is based on the user's captured demographic data, his/her captured Telecommunications transactions (frequent used Apps) and travel history, non-Telecom preferences, and set of active life goals *(3 top selected active goals)* (**Figure 6** above)	**Demographic metadata** *(age, gender, and location)* **Telecom metadata** *(frequent used Apps, travel history)* **Non-Telecom metadata** *(preferred movie genres)* **Consumer-dominant metadata** *(3 top selected active goals)*

Each movie in the experiment's underlying database belongs to only one cluster and has a description associated with it. Each cluster is represented with an image showing the number of the cluster. All four cluster images were designed to look the same except for a number denoting the cluster number to ensure no bias occurs during selection. The user is shown one movie from every cluster **randomly**, but in such a way that it is *not* shown to the user again. The movie description (metadata) has a set of tags that describe the content which is then populated in **real-time** with tag values from the active user profile. The content tags are replaced in real-time to match those of the active user. Each tag is enclosed in the database between hyphens (#) that are replaced in real-time with profile data of the participant, denoting personalisation (see **Table 10**). This replacement is intended to denote personalising the metadata of each movie according to the user participating in the study **dynamically** and in **real-time**. These tags ensure that the participant only sees content that is relevant to them, hence resembling how hyper-personalisation works in real-life. **Table 10** shows an example of how the movie content description in each cluster was designed using the corresponding metadata tags and how each tag was replaced dynamically in real-time based on the active user profile, representing how hyper-personalisation works.

Table 10: *Mapping of the Four Cluster Metatags to Active User Profile*

Cluster	Movie Content in database	Populated Content in real-time
Cluster 1 (C1)	Rising Dunes explores the life of **#random gender name#**, a **#age ID# #gender ID#** navigating the destination of **#user Location#**.	Rising Dunes explores the life of **Ryan**, a **young Male** navigating the destination of **North America**.
Cluster 2 (C2)	Trending Trails follows the journey of **#random gender name#**, a **#age ID# #gender ID#** living in **#User Location#**, exploring **#User content1 ID#** across **#User destination1#**.	Trending Trails follows the journey of **Ryan**, a **young Male** living in **North America** exploring **Cars and Motorbikes** across **United Kingdom**.
Cluster 3 (C3)	Sound of Water follows the storyline about **#random gender name#**, a **#age ID# #gender ID#** from **#user Location#**, in a **#entertainment ID2#** journey in **#user destination1#** exploring **#User content1 ID#**.	Sound of Water follows the storyline about **Ryan**, a **young Male** living in **North America**, in a **classic, masterpiece, quotable** journey in **United Kingdom** exploring **Cars and Motorbikes**.
Cluster 4 (C4)	Leaf follows **#random gender name#**, a **#age ID# #gender ID#** from **#user Location#**, in an **#entertainment ID1#** movie in **#user destination1#** exploring **#User content1 ID#**. As the movie unfolds, **#goal ID1#** and **#goal ID3#** life goals are achieved.	Leaf follows **Ryan,** a **young Male** from **North America**, in an **action, fun movie, special effects** movie in **United Kingdom** exploring **Cars and Motorbikes**. As the movie unfolds, **Peace of Mind** and **Value for Money** life goals are achieved.

It is worth mentioning that not all metadata tags are included in each movie content as this will take away from the realism of hyper-personalisation. Although large volumes of data can be captured representing user interests and preferences, hyper-personalisation might not necessarily include all of them. One of the shortcomings of discrete choice experiments reported in literature, in general, is that it is rarely possible to have all different combinations of attributes and levels included. This means that results can be contingent upon selecting the most important attributes of user choice. Even well-designed discrete choice experiments can only predict up to **91%** of individual choices in real-life (de Bekker-Grob et al., 2020 cited in Galekop et al., 2024).

Figure 10 shows the four clustered hyper-personalised content shown to participants, *dynamically* constructed in *real-time* based on the active user's captured profile. The only distinction between the content thumbnails is a numerical identifier placed on each thumbnail, allowing participants to focus on the content description rather than being influenced by aesthetic differences. The provision and quality of visual cues in recommender systems can significantly influence user choices, making one choice more attractive than the other (Jesse and Jannach, 2021), resulting in perceptual or attentional bias. To avoid any unintended bias, the same visual thumbnail is shown next to each cluster, ensuring consistency across all options. The use of visual thumbnails helped simulate real-world entertainment and streaming services such as Netflix and YouTube, deliberately using the same visual to avoid any attentional bias (Neglur and PS, 2024).

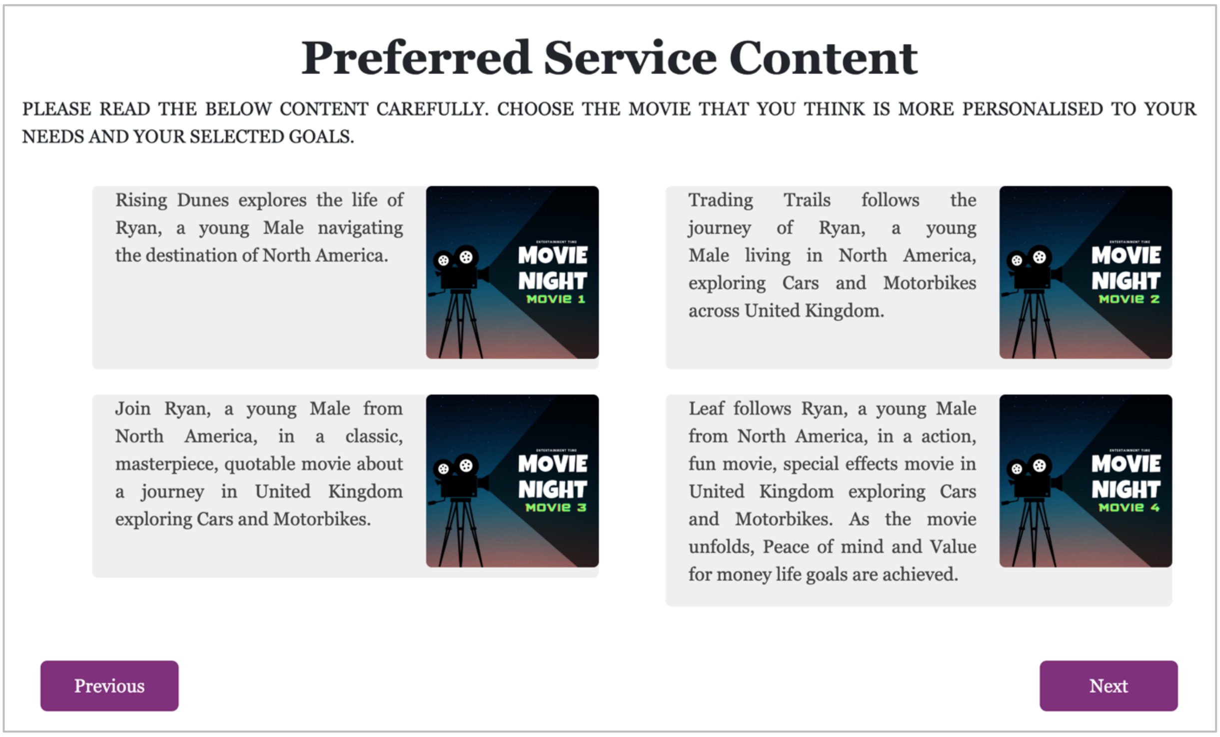


Figure 10*: Participant Selection of the Four-Clustered Hyper-personalised Content*

The participant is prompted to select the preferred content that is perceived as more tailored to their needs and their selected goals. To ensure validity of the selection and calculate the probability of selection using the underlying Learning Automaton (presented next), participants select the content three times. **Figures 11 – 13** show the three selections of a participant in one session.

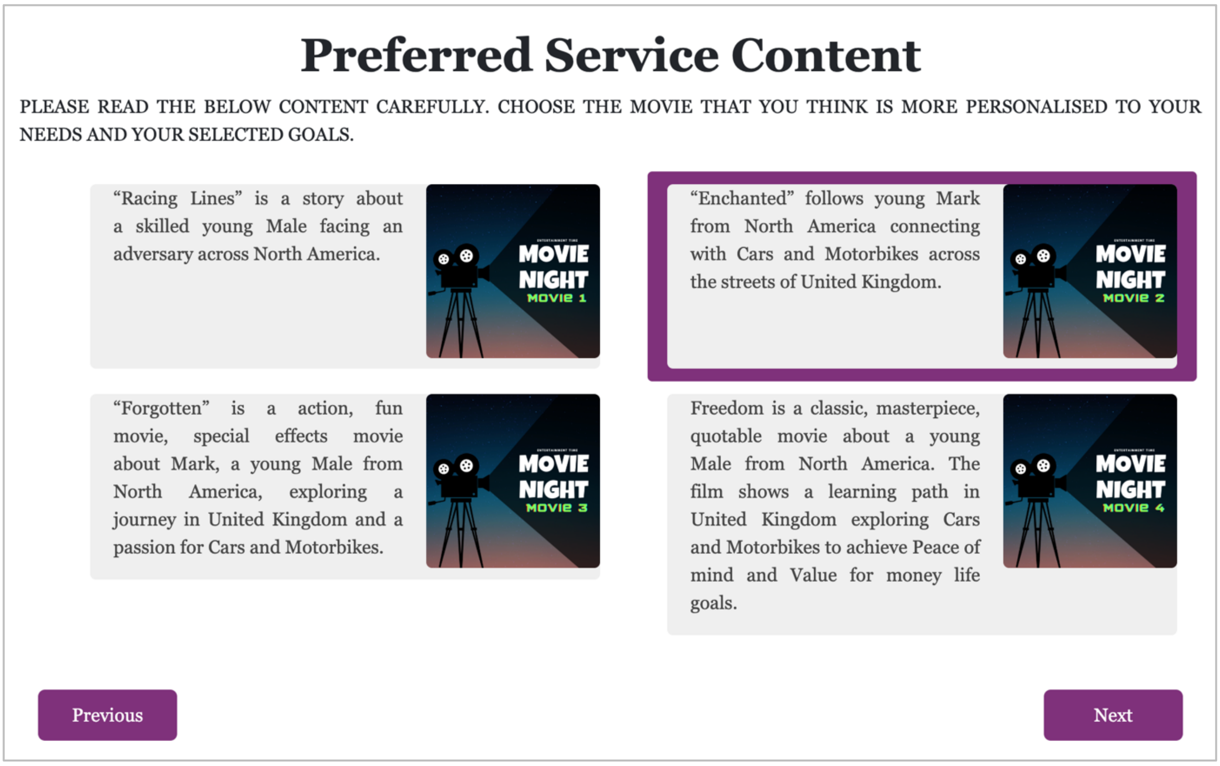


Figure 11: *The first selection of a participant of the Four-Clustered Hyper-personalised Content*

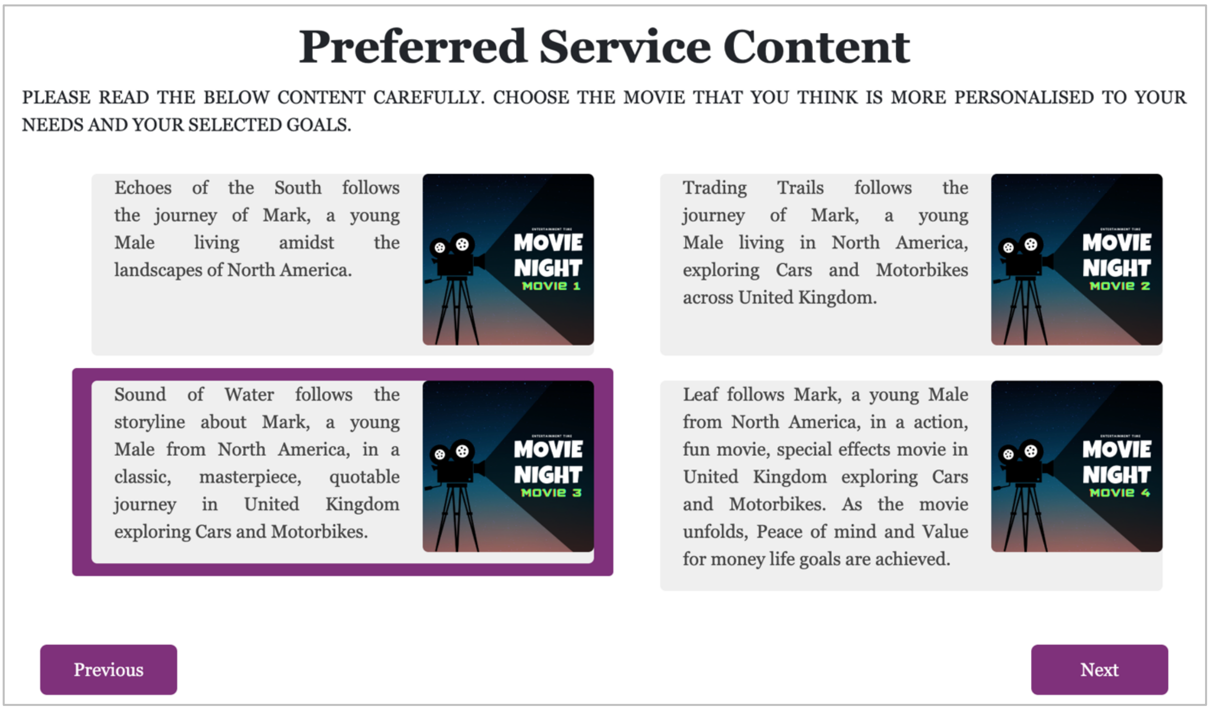


Figure 12: *The second selection of a participant of the Four-Clustered Hyper-personalised Content*

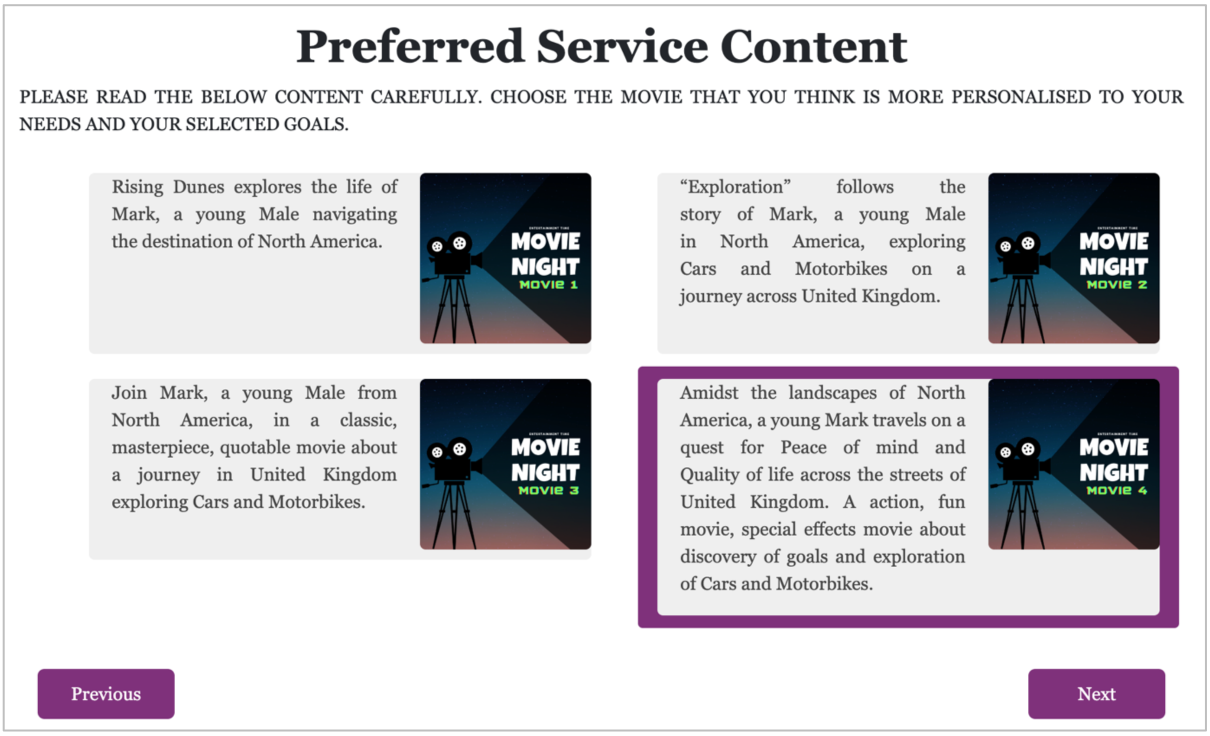


***Figure 13**: The third selection of a participant of the Four-Clustered Hyper-personalised Content*

Step 2: Adaptive Extension of User Profiles

In each selection round, the algorithm used in this study employed a **Learning Automaton** to simulate how hyper-personalisation operate in real-world systems. With every selection, the chosen cluster was rewarded, while the remaining three clusters were penalised. This process dynamically updated the probability of each cluster being selected next. After three rounds, the cluster with the highest probability represented the participant's final selection, capturing how preferences evolved through interaction.

In this experiment (refer to Section 4.1.2), the random environment presented to participants can be described by three variable sets {α, β, γ}:

(1) α - the set of inputs presented to participants

(2) β - the set of actions (or feedback) selected by participants

(3) γ - the learning algorithm governing the adaptive update process

Set of inputs (Action Set)

The finite set of inputs (α) consisted of the four content clusters, each representing one level of hyper-personalisation. These clusters were populated in real-time using the participant's user profile captured during *Wave 1*. The system displayed four recommended content types (see **Tables 9** and **10**), corresponding to clusters C1 to C4. Participants were prompted to select their preferred content, without being shown the cluster labels (refer to **Figures 11 – 13**). Three consecutive rounds of selection were completed per wave, and the algorithm updated probabilities for each cluster based on participant choices. Hence, α ≡ {C1, C2, C3, C4} represents the finite set of four inputs presented to the participant.

Set of actions (Feedback)

The feedback set (β) represented whether a participant selected a recommended content item, using a binary value: 0 = not selected or 1 = selected. Hence, β ≡ {0, 1}. The algorithm interpreted this feedback as reinforcement for adjusting future recommendations. Each participant viewed four movie content types, one from each cluster, and selected their preferred option. After 10 days (*Wave 2*), and again after 5 months (*Wave 3*), participants repeated the same selection process, allowing the model to update their preference probabilities while keeping their original profile data constant.

Learning algorithm (Reward Matrix)

The variable γ represents the reward and penalty probabilities associated with each participant action. The learning automaton algorithm (as described in *Section 4.1.2*) modifies the vector of action probabilities for the input set based on participant selections. In this study, each participant's selection acts as a reinforcement signal for the environment. The algorithm updates the probability weights of the clusters accordingly — rewarding the selected cluster by increasing its probability and penalising the remaining three unselected clusters. During each wave, participants make three selections from the four available clusters. After each round, the algorithm recalculates the probabilities, reinforcing the preferred cluster and reducing the likelihood of the non-selected clusters. The cluster with the highest probability at the end of the third round (in each wave) represents the participant's most preferred level of hyper-personalisation.

To illustrate: Let $\alpha_i(n) \in \alpha$ and $p(n)$ is the probability defined over the action-set at time n. If the user selects $\alpha_i(n)$, where i ≡ {1, 2, 3, 4}, the action probability of the selected input is increased by a = *reward parameter* while all other inputs not selected by the user is penalised by b = *penalty parameter*.

The reward parameter a is calculated as:

$$a = 1 / (\text{the number of inputs i.e., clusters}) = ¼$$

All other non-selected inputs are penalised by decreasing the probability of their occurrence by the same weight of **a**, that is $\boldsymbol{b = a}$. At each instant n, the vector of action probability $p(n)$ is updated by the linear learning algorithm provided in the below formula as the environment rewards the selected action $\alpha_i(n)$ and penalises all non-selected actions.

$P_i(n+1) = P_i(n) + a * (1 - P_i(n))$ *where* P_i *is the probability of the selected cluster*

Before any selection is made, the probability of each cluster is set to **¼** or **25%**.

CLUSTER1	CLUSTER2	CLUSTER3	CLUSTER4
0.25	0.25	0.25	0.25

The user selects one content. The weight of the selected cluster is increased by $a=1/4$ and the weight of all the other three non-selected clusters is decreased by the same weight, where a is equal to 1 divided by the number of clusters i.e., 1/4 (rewarding the selected and penalising the unselected) The new probability of the cluster that is selected by the user is re-calculated as follows:

$P_i(n+1) = P_i(n) + a * (1 - P_i(n))$ *where* P_i *is the probability of the* ***selected*** *cluster*

$$= 0.25 + (0.25) * (1 - 0.25)$$
$$= 0.25 + (0.25 * 0.75) = 0.4375 = 7/16$$

The new probability of the other unselected clusters (**penalised**) is re-calculated as follows:

$P_j(n+1) = (1 - a)\ P_j(n)$ *where* P_j *is the probability of the not selected clusters*

$$= (1 - 0.25) * 0.25$$
$$= 0.1875 = 3/16$$

In other words, the user interest in all action sets (clusters of movies) is assumed to be initially the same (equal distribution). As participants interact with the system, their feedback (selected or unselected) determines how these interests are updated. When a participant selects a movie from a particular cluster, that cluster is treated as preferred and is rewarded, while the others are penalised. During each wave (three interactions per wave), the algorithm increases the probability of selecting the rewarded cluster and decreases the probabilities of the others. Over time, these adjustments cause the choice probabilities to converge toward the participant's actual preferences, reflecting the true level of user interest.

This iterative process updates the weight of each cluster based on feedback, gradually completing the user profile. When a participant selects a cluster *Ci* in iteration *t* (where $i <= 4$ and $t <= 3$), the algorithm rewards that cluster by increasing its selection probability and penalises the remaining clusters equally. The increase and decrease are governed by the learning rate *a*, as described in the probability update equations presented earlier.

Consumer Goal Strength

After three rounds of selection of personalised content, the overall probability of each cluster was added to the user profile, indicating how the learning automaton captured changes in user preferences over time (Farahani et al., 2022). The user profile was therefore *dynamically* updated with each user interaction. Following this, participants answered two questions assessing their perception of how the hyper-personalised content supported their motivation and commitment toward their selected active life goals. These two items were used to measure *goal strength*, calculated as the product of goal motivation and goal commitment for the chosen goals (Bolos et al, 2022; Kopetz et al., 2012). Motivation and commitment were each measured on a seven-point Likert scale ranging from *strongly disagree* to *strongly agree (***Figure 14** below*):*

(1) *Do you think that receiving content personalised to your needs and your selected goals will help you stay MOTIVATED towards these goals?*

(2) *Do you think that receiving content personalised to your needs and your selected goals will help you stay COMMITTED to accomplishing your goals?*

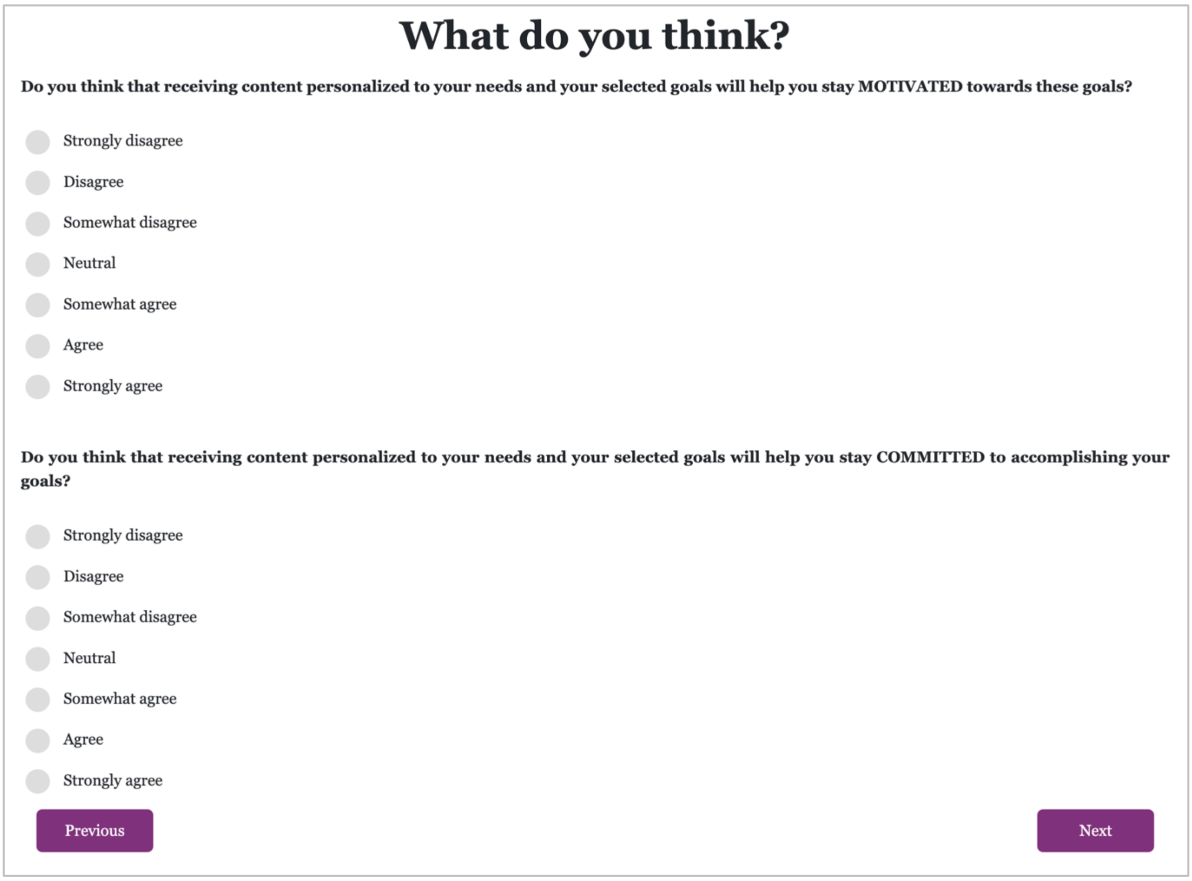


***Figure 14**: Goal Strength Measurement at the end of each wave - product of commitment and motivation*

The second and third waves of the study took place 10 days and 5 months after the first wave. Participant received a follow-up link that matched their unique ID, allowing the system to retrieve their previously captured user profile from *Wave 1*. Since the profile data had already been collected, no additional questions about preferences were asked in *Wave 2* and *3*. During each wave, participants completed the same choice tasks as in *Wave 1*. The learning automaton algorithm updated the probabilities for each selected personalised cluster, rewarding or penalising choices in *real-time*. These probabilities were stored separately to allow comparison across waves. Motivation and commitment were measured again in *Wave 2* and *3* using the same scales as in *Wave 1*, providing a repeated measure of goal strength over time.

4.2.6 Ethical Considerations

This study adhered to the guidelines and principles set and approved by Durham University's Research Ethics Policy. These include safeguarding, informed consent, confidentiality, anonymity, and data protection. Participants were recruited through Amazon Mechanical Turk (MTurk) platform, which automatically restricts access to individuals under 18 years of age. Eligible participants were fully informed about the study's purpose and procedures and were presented with their rights on the consent page (very first page). These rights include the right to withdraw from the study at any time without giving a reason. Informed consent was captured digitally before participation and reaffirmed at the start of each wave (refer to **Figure 15**).

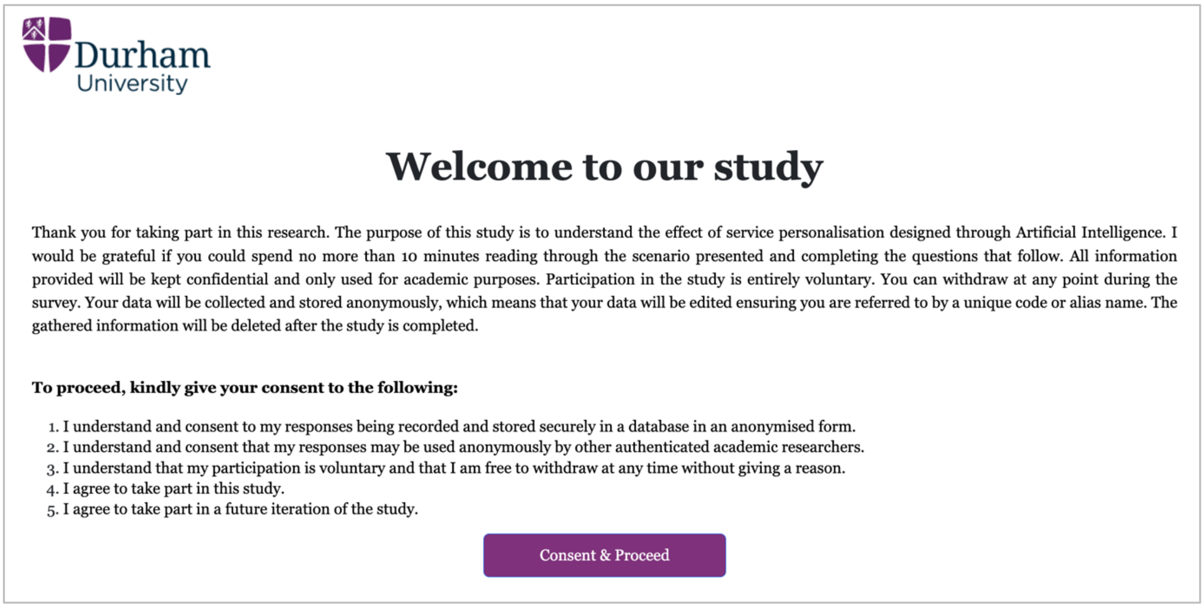


***Figure 15**: Study's Consent Page (First Page) - Displayed in each wave*

No personal identifers (e.g., names or e-mail addresses) were collected at any stage. Data were anonymised through unique numeric or alphanumeric identifiers, generated automatically by MTurk or the study's internal system (see **Figure 16**). For MTurk participants, the platform's alphanumeric *Worker ID* was securely passed to the survey interface to link responses across waves. For direct participants (outside MTurk), a numeric unique identifier was automatically generated by the system. This approach ensured confidentiality and anonymity as key ethical considerations.

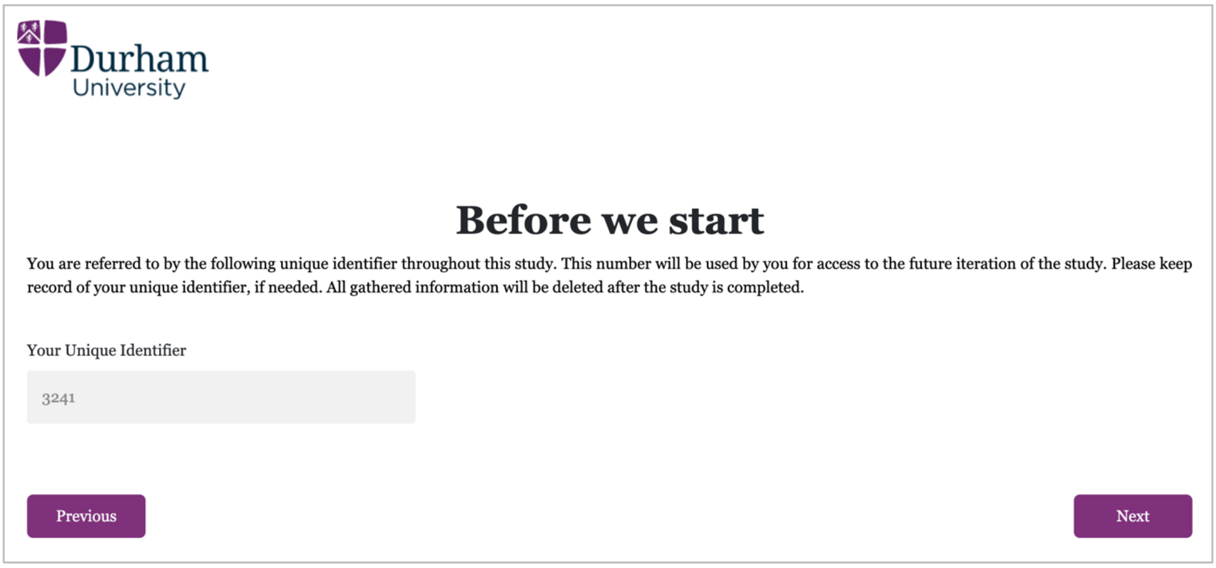


Figure 16: *Unique Identifier of participants used throughout the study*

All data collected at *Wave 1* were securely stored and used solely for academic purposes. Participants were informed that all data would be deleted following completion of the study (refer to *Appendix A*). Participants can freely withdraw from the study at any time. Transparency regarding data use and the study's objectives was maintained throughout, both on MTurk and at the beginning of each wave. Importantly, the privacy framing manipulation (Group A neutral framing, Group B negative framing) was presented purely as as a hypothetical scenario to simulate realistic marketing communication and did not pose any risk of psychological harm to participants.

4.3 Data and Variables

4.3.1 Variable Design

To test **Hypothesis 1 (H1)** – *higher levels of hyper-personalisation significantly increase consumer goal strength over time* – and **Hypothesis 2 (H2)** – *that this relationship is moderated by privacy framing (risk-based versus neutral)*, the following variables were designed to capture the outcome and key predictors.

These variables are used within the linear mixed models of the study, described in *Section 4.4.4*.

Dependent Variable: Consumer Goal Strength

The dependent variable, consumer goal strength (*GoalStrength*) was measured in each wave as a product of **motivation** and **commitment**, each on a 7-point Likert scale, ranging from *Strongly disagree* to *Strongly agree*. The dependent variable was multiplied as a composite score at each wave.

Independent Variable: Hyper-personalisation Selection

The independent variable, hyper-personalisation selection (*Selection*) was captured through the participants' choices in each wave using a Discrete Choice Experiment (DCE). As detailed in the experiment design (see *Section 4.2.5*), participants selected one of four content clusters, progressively varying in hyper-personalisation level, and hence coded from 1 (**Cluster 1** – *Low hyper-personalisation*) to 4 (**Cluster 4** – *High hyper-personalisation*):

1. Demographics only (*Cluster 1 coded as 1*)
2. Demographics + Telecom (*Cluster 2 coded as 2*)
3. Demographics + Telecom + Entertainment (*Cluster 3 coded as 3*)
4. Demographics + Telecom + Entertainment + Active Goals (*Cluster 4 coded as 4*)

This variable is a *between-individual* time-varying (having different value at each time point) covariate that is added to Level 1 of a linear mixed model to explain the variance at *within-individual* variation. Unlike time-invariant covariates (having fixed values over time), time-varying covariates need to be carefully handled as they can lead to confounded estimates – changing the meaning of individual growth parameters at Level 2 of the linear mixed model (Hoffman, 2025). To avoid confounding *within-individual* and *between-individual* variance in hyper-personalisation selection, the predictor variable (*Selection*) was decomposed into grand-mean centered and person-mean centered variables (Gottfredson, 2019). This follows best practices recommended and adopted in longitudinal studies (Enders; 2022; Hoffman, 2025), preventing biased estimations, reducing multicollinearity, and properly disentangling Level 1 and Level 2 variances. Collinearity is broadly defined as redundancy, interdependency, or shared variance among predictors in a data set (Yaremych et al., 2024).

As highlighted by (Gottfredson, 2019), the *between-person* component (trait-like *Selection* variable) is calculated by taking the average of all repeated measures available for each participant to arrive at the *person-mean*. The *within-person* component (state-like at a specific time point) is calculated by person-mean centering to obtain a time-specific deviation from the person-mean. These two disaggregated components of *Selection* variable are used as two separate predictors in the mixed models to obtain unique estimates of both *within-person* and *between-person* effects.

Two hyper-personalisation variables were, hence, derived from *Selection* and incorporated into the study's linear mixed models:

1. **Grand_SelectionMean (Grand-Mean Centered Hyper-Personalisation - between-individual)**: This variable represents each participant's grand mean selection score across the three waves (*Selection_Mean*), centered around the sample mean (M = 2.4862). It was computed as *Grand_SelectionMean = Selection_Mean – 2.4862*

2. **Centered_Selection (Person-Mean Centered Personalisation - within-individual)**: This variable captures the within-individual momentary deviation at each wave, calculated as the difference between an individual's selection at a given wave and their own grand mean: *Centered_Selection = Selection - GrandMean_Selection*.

The use of grand mean-centered hyper-personalisation (*Grand_SelectionMean*) supports a clear understanding of how individual differences in hyper-personalisation preferences affect consumer goal strength. This method helps isolate the general tendency of an individual to select higher or lower personalisation compared to the average individual, making it easier for the model to interpret fixed effects (Vandelanotte et al., 2023). Grand mean-centering approach is recommended in hierarchical linear modelling as it separates *within-individual* fluctuations (Level 1) from *between-individual* differences (Level 2) (Curran and Bauer, 2011; Yaremych et al., 2024; Hoffman and Walters, 2022; Hoffman, 2025). This centering technique is particularly useful when modelling consumer responses in adaptive digital environments. It becomes especially relevant when modelling time-varying predictors in AI-driven digital environments, where *within-person* variation is more likely to reflect user states rather than stable individual traits (Zhou et al., 2023a).

Moderator: Privacy Framing Group

Participants were randomly assigned to one of two privacy framing conditions:

- **Group A (Neutral Framing):** No privacy framing mentioned to participants (control group)
- **Group B (Negative Framing):** Messaging presented to participants highlighted potential privacy risks in data usage (experimental group).

The ***Group*** variable was coded as 1 (neutral, i.e. positive framing) and 2 (risk-based, i.e., negative framing), with **Group B** set as the reference group in the linear mixed models.

Time

Time variable captured the three-waves in the longitudinal study and was used a 3-level repeated factor:

- **Wave 1** *(Baseline)*
- **Wave 2** *(10 days from the baseline)*
- **Wave 3** *(5 months from the baseline)*

To ensure interpretability, *Time* was re-coded as 2, 1, 0, so that *Wave 1* (Baseline coded as *Time* = 2) became the reference time point. This recoding was to avoid setting the highest value as the reference.

Perceived Hyper-personalisation Importance

The *PersonalisedImportance* variable recorded the participants' rated importance of hyper-personalisation, captured at *Wave 1* of the study on a 7-point Likert scale. This variable captured the participant's subjective perception of how important it is to receive hyper-personalisation content to their experience.

- **PersonalisedImportance:** coded as 1 (*Strongly disagree*) to 7 (*Strongly agree*)

Table 11 lists all the key variables used within the study's linear mixed models to test and verify the two hypotheses: **Hypothesis 1 (H1)** and **Hypothesis 2 (H2)**. The *PersonalisedImportance* variable was not used to test the hypotheses but rather used in the post-hoc exploratory *Model 3* for additional insight, useful for future hypothesis development.

Table 11*: Variable Descriptions and Model Use*

Variable	**Description**	**Model(s) Used**
Goal Strength	The dependent outcome variable as a product of two 7-point Likert scale variables (motivation and commitment), with values ranging between 1 and 49	All models
Time	Wave of data collection Coded inversely as 0 (*Wave 3*), 1 (*Wave 2*), and 2 (*Wave 1*)	All models
Group	Experimental condition Coded as (1 = Neutral, 2 = Negative)	Model 2, 3
Grand_SelectionMean	Grand-mean centered hyper-personalisation per participant - centered *across individuals*	Model 2, 3
Centered_Selection	Person-Mean Hyper-personalisation Momentary deviation from personal average - centered *within individuals*	Model 2, 3
PerceivedImportance	Subjective importance of personalisation (time-invariant 7-point Likert scale)	Model 3

4.3.2 Data Preparation

Data was collected in a three-wave longitudinal study and analysed using Linear Mixed Model (LMM) with restricted maximum likelihood (REML). REML was chosen over the traditional maximum likelihood (ML) due to its known accuracy in estimating variance components, especially in small or unbalanced datasets (Bauer et al., 2020). This approach accounts for individual variability in the initial status (*intercept*) and rate of change (*slope*) over time. To prepare the data for linear mixed modelling (longitudinal analysis), data was re-structured across the three waves of study from a *wide* format to a *long* format. Data in the *wide* format (with one row per participant including all recorded repeated measurements) was converted into a *long* format with one row per participant representing a single measurement. In the *long* format, each participant now has three rows, with each row representing a single wave measurement. This restructuring is required for linear mixed models, as it helps account for *within-individual* and *within-individual* variation over time (Shak and Ma, 2011; Zhou et al., 2023a; Walther et al., 2024).

The Linear Mixed Model was setup using "*Worker*" as the Subjects variable, representing the participant unique identification number. *Goal strength* and hyper-personalised value *Selection* variables were continuous variables with different values (*random*) in each wave, and hence captured with each wave measurement on a row. Time-invariant variables such as *Age*, *Gender*, *PersonalisedImportance*, and *Group* (Group A or Group B) remained fixed across all the three rows as they did not change. INDEX is a variable capturing the order of observation (per wave of study) and *Time (linear time)* was recorded as a categorical variable, created as INDEX-1 to represent 3 levels: *Time*=2 for *Wave 1*, *Time*=1 for *Wave 2* and *Time*=0 for *Wave 3* – hence considering *Wave 1* measurements as the reference with intercept being at *Time = 0* (see *Section 4.3.1).* By centering the *Time* variable using "*INDEX*–1," the interpretation of the parameters becomes clearer as *Wave 1* can be interpreted as the initial level (*intercept*) of *Goal Strength* scores. The variable *qtime* was calculated as *Time* * *Time* to assess if a quadratic time trend is a better fit. Following the findings in *Appendix B*, *Time* was retained in the models used in this study, rather than *qtime*.

4.3.3 Data Collection

As not all participants took part in all three waves of study, the dataset presents an example of an **unbalanced** study design. Data were collected from **1,434** participants at *Wave 1* (*Time* = 2 representing the baseline), **1,235** participants at *Wave 2* (*Time* = 1 with a *10-day interval* from the baseline), and **847** participants at *Wave 3* (*Time* = 0, with a *5-month* interval from the baseline). This represents an **86.1%** retention rate at *Wave 2 (after 10-days)* and **68.5%** at *Wave 3 (after 5 months)*, as shown in **Table 12** below.

Table 12: *Participant Retention Summary across experiment waves*

Wave	Time Point	N Participants	Retention (%) from Previous
Wave 1	*Time* = 2	1,434	—
Wave 2	*Time* = 1	1,235	**86.1%**
Wave 3	*Time* = 0	847	**68.6%**

Handling Missing Data

Missing data were addressed using Restricted Maximum Likelihood (REML) estimation within a linear mixed-effects modelling framework. This approach provides unbiased estimates of variance components, accommodates unbalanced panel designs due to attrition, and retains participants with partially observed data (Hoffman, 2021; 2025).

The gradual increase in missing data over time is common in longitudinal designs and is usually related to time or study fatigue (missing at random). In fact, it is typical to lose between 30-40% of participant involvement in online studies over time due to fatigue or time burden (Straiton et al., 2023). Linear mixed models (LMMs) are inherently capable of handling missing data under the **Missing at Random (MAR)** assumption. No imputation of data is, hence, required when sufficient observations are available for each participant. Participants with at least one wave of data were retained in the analysis. This inherent flexibility makes linear mixed models an appropriate method for longitudinal designs, especially in cases where attrition or study drops are expected over time (Delporte et al., 2025). Linear Mixed Models (LMMs) can accommodate types of unbalanced study designs and datasets, where not all individuals need to have the same number of observations and not all individuals need to be measured at the exact (same) time points. This flexibility is closer to real-world longitudinal datasets as a perfectly balanced structure — having the same number of measurements per individual, with all individuals measured at the exact same timepoints — is seldom the case. The participant demographic characteristics including *Age*, *Gender,* and *Location* as well as *Group* (control versus experimental) and perceived importance of hyper-personalisation (*PerceivedImportance*) are recorded at *Wave 1* (baseline) and presented below. Other experimental variables and modelling predictors are discussed in detail in **Chapter 4**.

Demographic Characteristics

Gender

A total of **1,065** males (**74.3%**) and **351** females (**24.5%**) took part in the study, while **18** respondents (**1.3%)** preferred not to mention their gender (*Prefer not to say*). Out of the **847** participants who took part in all 3 waves of the study, **603** were males **(71.2%)**, **226** were females **(26.7%)** and **18 (2.1%)** preferred not to indicate their gender. The descriptive distribution (frequencies) of *gender* across all three waves are shown in **Table 13** below. As presented in the table and visually summarised in **Figure 17**, *male* as a gender was over-represented in the dataset across all three waves, with retention rates declining over time for both males and females.

Table 13: *Gender distribution across the three waves of study*

Wave	N Participants	Males	Females	Prefer Not to Say	Retention (%)
Wave 1	1,434	1,065 (74.3%)	351 (24.5%)	18 (1.3%)	**100%**
Wave 2	1,236	907 (73.4%)	311 (25.2%)	18 (1.5%)	**86.1%**
Wave 3	847	603 (71.2%)	226 (26.7%)	18 (2.1%)	**68.6%**

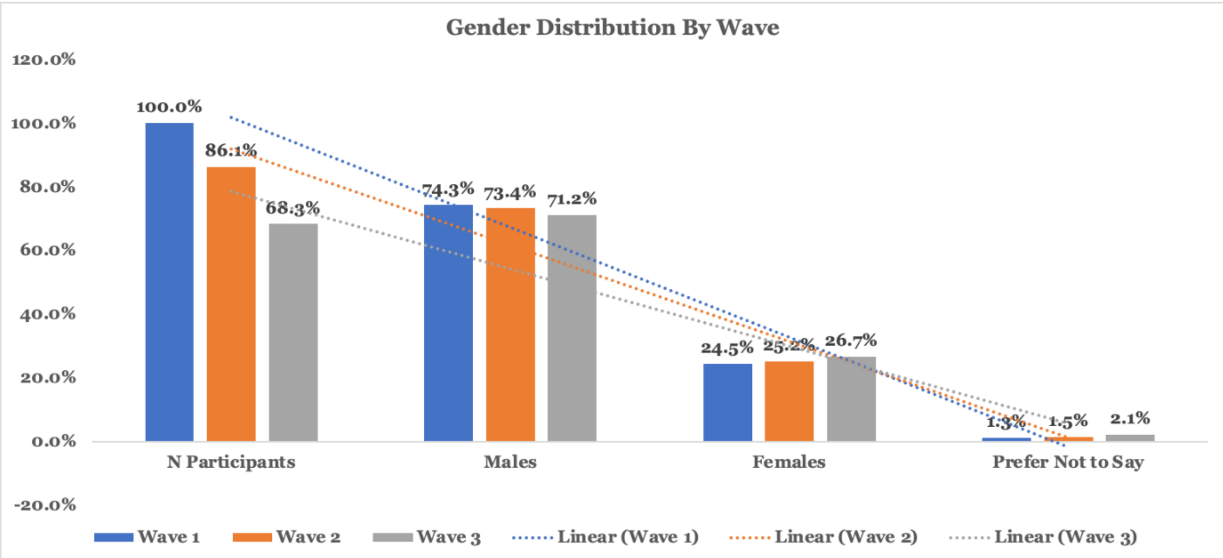


Figure 17*: Visual Representation of Gender Distribution Across the three Waves*

Age

Out of the whole sample collected, **67.4%** of participants were in the **[25 - 34]** age group, **22.9%** were in the **[35 - 44]** age group and the remaining were spread across other age groups. Out of the **847** participants who completed all three waves, **68.8%** were in the **[25 - 34]** age group, **23.4%** were in the **[35 - 44]** age group and the remaining were spread across other age groups. The descriptive distribution (frequencies) of *Age* across all three waves are shown in **Table 14** below. As presented in the table and visually summarised in **Figure 18**, **[25 – 34]** age group was over-represented in the dataset across all three waves, with retention rates declining over time.

Table 14: *Age distribution across the three waves of study*

Age Group *(Years)*	**Participants N (%)** *(Wave 1)*	**Participants N (%)** *(Wave 2)*	**Participants N (%)** *(Wave 3)*
18 - 24	48 (3.3%)	43 (3.5%)	37 (4.4%)
25 - 34	967 (67.4%)	835 (67.6%)	546 (68.8%)
35 - 44	328 (22.9%)	275 (22.2%)	198 (23.4%)
45 - 54	64 (4.5%)	58 (4.7%)	45 (5.3%)
55 - 64	24 (1.7%)	22 (1.8%)	18 (2.1%)
>= 65	3 (0.2%)	3 (0.2%)	3 (0.4%)
Total	**1,434**	**1,236**	**847**

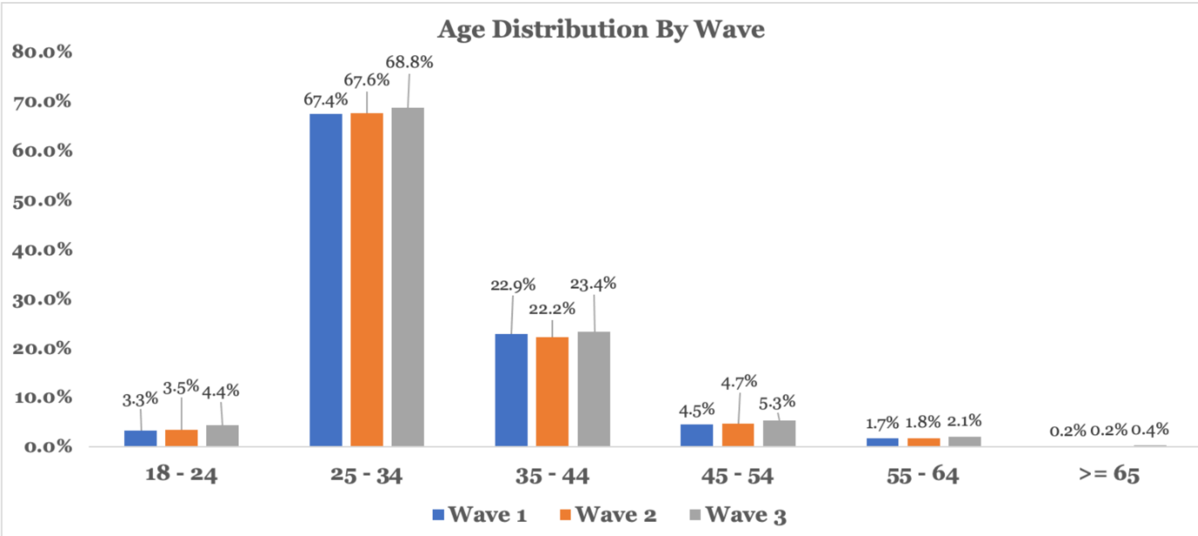


Figure 18*: Visual Representation of Age Distribution Across the three Waves*

Location

During participant demographic profiling in *Wave 1* (baseline), participants' geographical locations were captured to examine the diversity of the sample. As shown in **Figure 19**, the sample included participants from Africa (3.2%), East/West Asia (8.6%), Europe (6.3%), Middle East (10.3%), North America (43.4%), and South America (35.1%). The high distribution of participants in North and South America (over 70%) is most likely attributable to the use of Amazon Mechanical Turk (MTurk) as a data collection platform. This distribution aligns with prior research showing MTurk having a dominant user base in the United States and surrounding regions (Difallah et al., 2018). While the sample is not geographically balanced, it still includes global representations from other regions of the world, reinforcing the validity and reliability of the findings. The diverse cultural and regional heterogenous base reflects generalisability, while the skewed distribution highlights the need for future research to replicate the study targeting a more geographically balanced respondent pool.

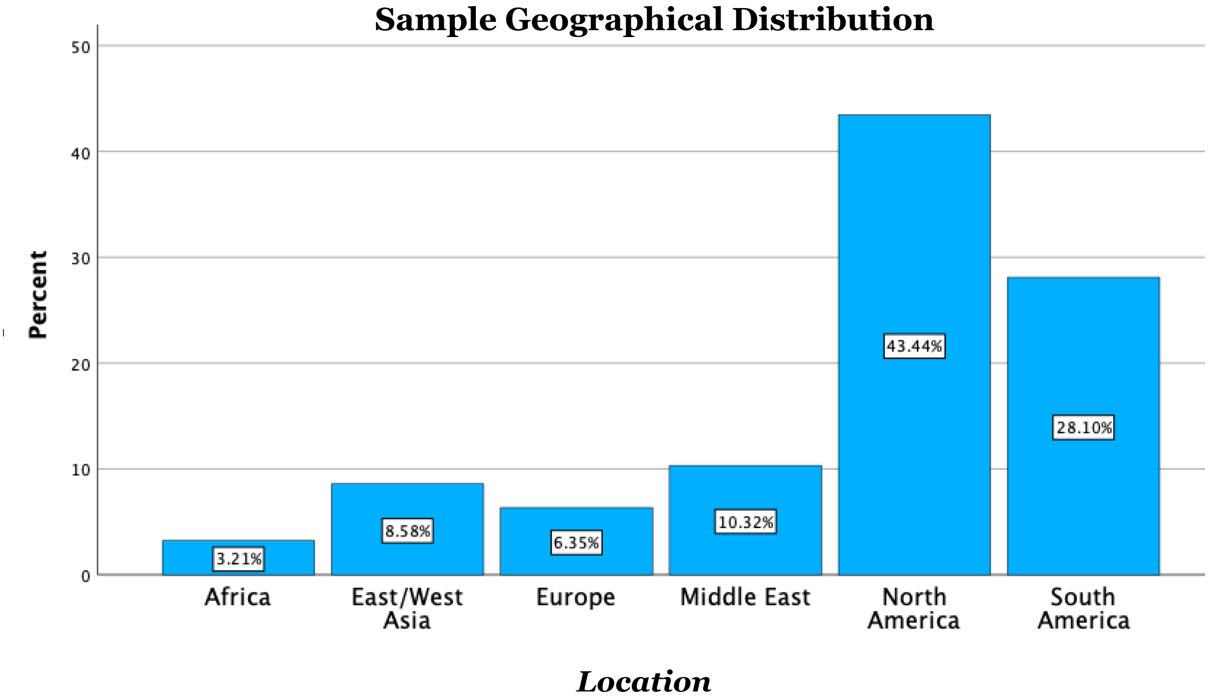


Figure 19: *Sample Geographical Distribution*

Group

Out of the **1,434** participants, **755 (52.6%)** participants were randomly placed in Group A (control group) while **679 (47.4%)** participants were randomly placed in Group B (experimental negative framing group). To avoid biasing participant behaviour in subsequent waves, placement in a group occurs only during *Wave 1* (baseline), without repeating group assignment or framing information in *Wave 2* or *wave 3*. Once a participant is placed in a group, they remain in the same group in subsequent waves. During subsequent waves (*Wave 2* and *Wave 3*), participants are not reminded of which group they are in. This approach aligns with literature on longitudinal behavioural studies, which supports minimal intervention post the baseline wave to observe intervention effects over time without confounding due to repeated exposure (Shen and Li, 2023). This strategy is consistent with the Minimal Intervention Needed for Change (MINC) mode, which emphasises that small, well-targeted inputs at the right time points can enhance contextual validity without overloading participants or distorting behavioural outcomes (Curran et al., 2022). It helps isolate the specific impact of the minimal intervention by minimising the potential for carryover effects from the baseline or subsequent repeated exposure. Out of the **847** participants who completed all 3 waves, **442 (52.2%)** participants were randomly placed in Group A while **405 (47.8%)** participants were in Group B.

The descriptive distribution (frequencies) of *Group* across all three waves are shown in **Table 15** and visually illustrated in **Figure 20** below. Group sizes remained relatively balanced in subsequent waves, despite natural variations in participation. In longitudinal research, it is not uncommon for individuals to differ in the number or timing of repeated measurements due to dropout or availability. While such irregular spacing can be problematic for traditional methods, it is well accommodated by modern linear mixed-effects model approaches. These models are robust to "*imbalance*" and capable of utilising all available data regardless of when it was collected, allowing for unbiased estimation in the presence of missingness and unbalanced designs (Gibbons et al., 2010; Hoffman, 2025).

Table 15: *Group distribution across the three waves of study*

Group	Wave 1 N(%)	Wave 2 N(%)	Wave 3 N(%)
Group A	756 (52.7%)	642 (51.9%)	442 (52.2%)
Group B	678 (47.3%)	594 (48.1%)	405 (47.8%)
Total	**1,434**	**1,236**	**847**

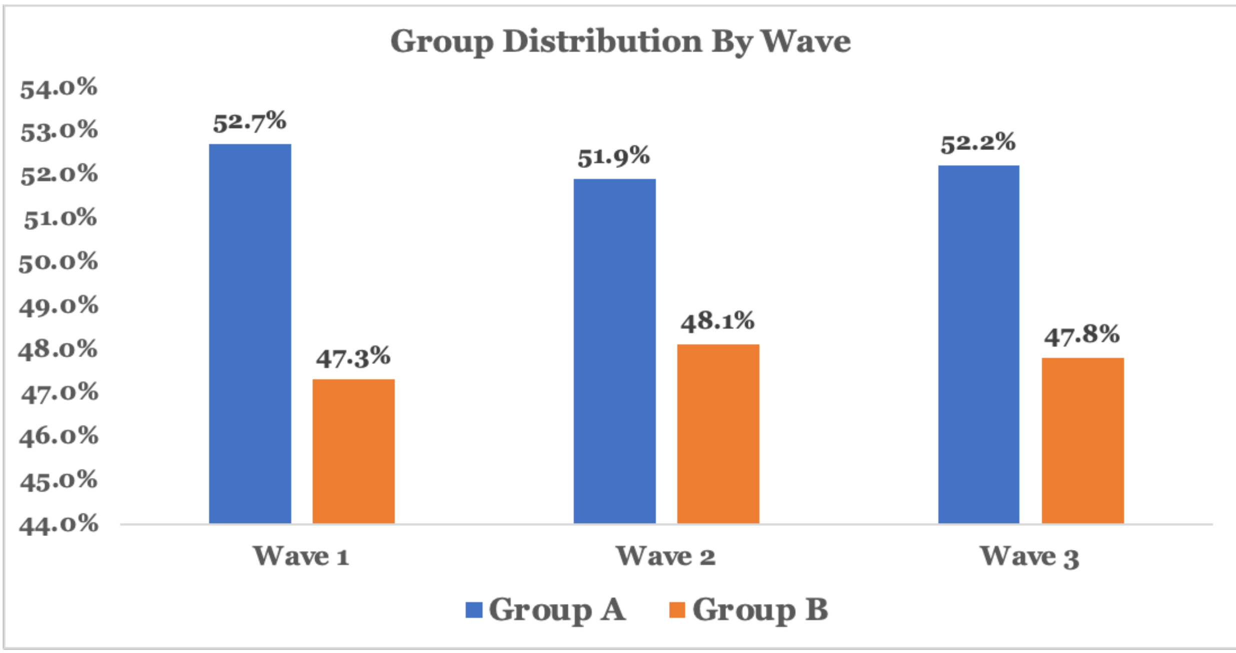


***Figure 20**: Visual Representation of Group Distribution Across the three Waves*

Importance of Hyper-personalisation

To capture the perceived importance of hyper-personalisation, participants were asked to rate it in *Wave 1* of the study (*baseline*), using a 7-point Likert scale. This captured variable was used in the study to complement the behavioural analysis in a post-hoc exploratory linear mixed model (refer to *Section 4.4.3.3*). Descriptive statistics of this variable resulted in a **49.9%** of respondents agreeing to the importance of receiving hyper-personalisation (Agree) and a **16.5%** strongly agreeing (*Strongly agree*). On the other hand, only **2.6%** of respondents strongly disagreed (*Strongly disagree*) and **3.6%** (*Disagree*) disagreed to its importance. This large and positive distribution suggests that most participants perceived hyper-personalisation as meaningful and beneficial to their experience, supporting the inclusion of this post-hoc exploratory predictor in *Model 3* of the study. This reinforces the relevance of investigating consumers' interpretations of hyper-personalisation importance, which could influence their goal-directed behavioural responses. **Figure 21** shows the visual representation of this recorded pattern.

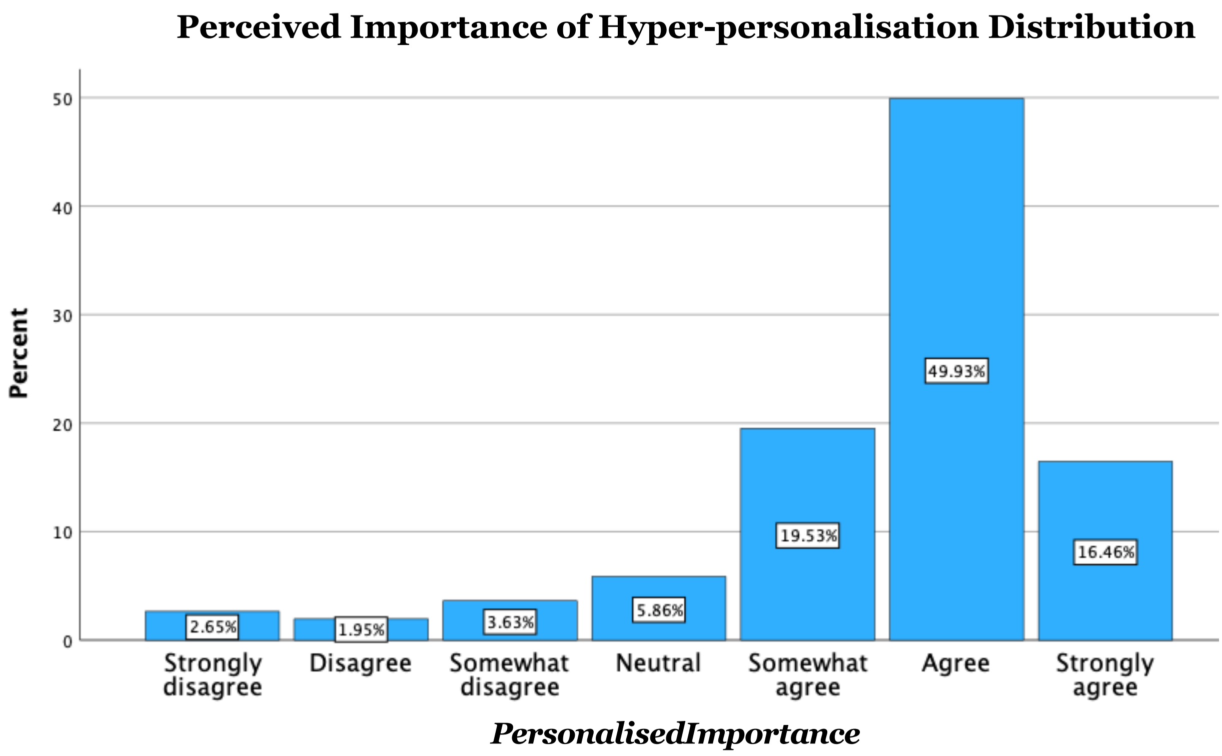


***Figure 21**: Perceived Importance of Hyper-personalisation Distribution*

4.4 Data Analytical Strategy

4.4.1 Analysis of Discrete Choice Experiment

The Discrete Choice Experiment (DCE) involved repeated selections by participants across several rounds, generating multinomial response data. Following Ruíz et al. (2023), a **Generalised Linear Mixed Model (GLMM)** with a **multinomial logit link** was applied to model these repeated choices. This method is well-suited for analysing *within-person* variations over time and estimating both *fixed* effects (hyper-personalisation and privacy framing) and *random* effects (individual differences). The multinomial logit specification approximates a random utility model (McFadden and Train, 2000), ensuring an appropriate fit for repeated-measures DCE data.

a

This analytical approach was employed to:

1. Examine how the likelihood of selecting each personalisation level changed across groups and waves, ensuring the **internal validity** of the DCE.

2. Account for **repeated measures** within participants, capturing both individual and overall effects.
3. Identify **systematic variations** in choice probabilities over time.

The GLMM assessed whether the probability of selecting each hyper-personalisation level (V1 – V4) changed significantly across waves (*Time*) and privacy framing groups (risk-framed versus neutral). Each choice was modelled as a [0 – 3] outcome, representing the intensity of hyper-personalisation selection in each wave. The **dependent variable** (*Selection*) reflected the likelihood of choosing a specific cluster from the available four hyper-personalisation levels. **Fixed effects** included the four hyper-personalisation levels (V1–V4), the two privacy framing conditions (Group A: neutral; Group B: risk-framed), and their interaction with *Time* (*Index x Group*). Participant ID was added as a **random intercept** to control for *within-subject* correlations and individual heterogeneity in baseline preferences.

The estimated parameters from the GLMM represent **part-worth utilities** (*preference weights*) for each experimental condition. Positive coefficients indicate stronger preference or higher likelihood of selection, whereas negative coefficients reflect relative disutility. To assess the experiment's structural validity, the GLMM also tested for **systematic changes in choice probabilities** across the three waves evaluating whether participant preferences remained stable or shifted over time. Results confirmed the robustness and internal validity of the DCE design, supporting its suitability for subsequent longitudinal modelling using the three Linear Mixed Models (LMMs) - refer to next sections.

Summary of Findings

The Generalised Linear Mixed Model (GLMM) analysis (refer to *Appendix B – DCE-GLMM Findings*) confirmed that the DCE design was internally valid and sensitive to systematic variations across experimental conditions. Estimated part-worth utilities (see **Table A.B.2** in *Appendix B*) showed that both hyper-personalisation level (*Selection*) and *Time* (Index) positively influenced selection utility, indicating that consumers increasingly engaged with higher levels of personalisation over time. Privacy framing (*Group*) had a significant moderating effect: participants exposed to risk-based framing were less likely to select higher personalisation levels compared to those in neutral framing condition. The significant *Index x Group* interaction demonstrated that the moderating effect of framing varied over time, explaining approximately **44%** of total variance in choices.

The **importance scores** revealed that the interaction between *time* and privacy framing **(~44%)** had the strongest influence on consumer preferences, demonstrating that personalisation preferences evolve **dynamically** as framing influence shifts across waves. Time (**18.4%**), personalisation level (**19.9%**), and privacy framing (**17.8%**) also had meaningful but smaller effects. Overall, these findings indicate that personalisation preferences are **dynamic** and **context-dependent**, changing with both temporal exposure and framing condition.

Table 16 interprets main findings in terms of the purpose of DCE.

***Table 16**: Findings of GLMM relative to its purpose*

Purpose of GLMM	**Findings**
Internal Validity of DCE	1. A **significant** main effect of *Group* indicated systematic differences in selection behaviour between framing conditions. 2. A **significant** *Index* × *Group* interaction term confirmed that participants' choices varied systematically as a function of experimental manipulations – validating the DCE's internal consistency. 3. The consistent direction of coefficients and an overall classification accuracy of **44.9%** (above random chance) supported the structured, non-random nature of responses.
Repeated measures *(individual and overall effects)*	Negative coefficients for Group A (neutral framing) across waves decreased as *Selection* increased, indicating that participants in the neutral framing showed a greater preference for more personalised clusters (**Clusters 3** and **4**).

Systematic Variations *(Part-worth Utilities)*	Parameter estimates (**Tables A.B.2** and **A.B.3** in *Appendix B*) showed that participants under neutral framing condition (Group A) were significantly **less likely** to select **lower** personalisation clusters (Cluster 1: $\beta = -1.62$, $p < .001$; Cluster 2: $\beta = -0.73$, $p < .001$) compared with those in the risk-framed condition, reflecting *negative coefficients* for lower personalisation levels.

This finding provides **empirical justification** for transitioning to the Linear Mixed Models (LMMs), in Section 4.4.2. Whereas the DCE captured discrete choice behaviour across waves, the LMMs extend this analysis by modelling how consumer goal strength evolves over time in response to hyper-personalisation *between-* and *within-person* variation and contextual framing. This progression from momentary preferences to longitudinal goal adaptation directly addresses the study's core **contribution** – demonstrating how goal-aligned hyper-personalisation operates as a **dynamic**, **time-sensitive process** that shapes motivational outcomes in real-world consumer ecosystems.

4.4.2 Individual Growth Curve Modelling (IGCM)

This study used an **Individual Growth Curve Modelling** (*IGCM hereafter*) to analyse how consumer goal strength changes over time, and whether these changes are influenced by hyper-personalisation as a time-varying covariate. IGCM is particularly suited for repeated-measures longitudinal data, as it allows each person to have their own growth trajectory defined by an **intercept** (*starting level*) and **slope** (*rate of change*). This makes it effective for studying behavioural change when individuals begin at different baseline levels and evolve at varying rates (Raudenbush and Bryk, 2002). In this study, IGCM provided the framework to model *between-person* and *within-person* changes in goal strength across the three experimental waves (Curran and Bauer, 2011; Du et al., 2025; Li and Zhang, 2023; Singer and Willett, 2003).

Unlike traditional methods such as Analysis of Variance (ANOVA), Analysis of Covariance (ANCOVA), or Multivariate Analysis of Variance (MANOVA), which require balanced and dependent data, IGCM accommodates unbalanced or incomplete longitudinal data. They allow for unequal time intervals, varying sample sizes, and missing observations without the need for listwise deletion – offering a flexible, more realistic approach for modelling behavioural change in real-world settings (Bauer et al., 2020; Curran et al., 2014). Furthermore, it supports modelling temporal sensitivity in behavioural change, particularly in response to digital stimuli (Albert et al., 2024; Curran et al., 2014). Growth curve models, including both latent curve and mixed-effects approaches, offer an alternative to traditional ANOVA by modelling individual trajectories of change over time and capturing both *within-* and *between-person* variability (Curran and Bauer, 2011; Hox, 2010; Ledermann and Kenny, 2017).

Traditional approaches such as ANOVA, MANOVA, or ANCOVA remain useful but are often limited in real-world longitudinal research (Bauer et al., 2020; Shak and Ma, 2011).. These models generally:

1. Require complete, balanced data, excluding cases with missing values and reducing statistical power if not missing at random (Baldwin et al., 2005).
2. Assume equal timing and spacing of measurements across participants (Zhou et al., 2023a), which is unrealistic in behavioural studies (Shek and Ma, 2011).
3. Cannot easily handle time-varying covariates or model individual trajectories of change (Bauer et al., 2020).
4. Treat repeated observations as independent, overlooking the nested nature of data within individuals (Raudenbush and Bryk, 2002).
5. Lead to an increase in Type I and Type II errors due to missing data, outliers, or lack of normality of response distribution (Polushkina-Merchanskaya et al, 2025).

In contrast, IGCM can handle unbalanced and incomplete datasets, model both *within-person* and *between-person* variability, and capture individual change trajectories even when data is missing or time points differ. This makes IGCM a robust and flexible framework for analysing behavioural dynamics over time in complex, digital contexts. The limitations of traditional models versus IGCM are highlighted in **Table 17** below.

***Table 17**: Comparison of Traditional Models vs. IGCM*

Limitation of Traditional Models	**How IGCM Addresses It**
Requires complete data *(listwise deletion with missing measurements)*	Handles incomplete/unbalanced data using mixed-effects estimation
Assumes fixed measurement intervals	Allows irregular spacing between time points
Cannot model time-varying covariates	Incorporates covariates that vary across waves
Treats repeated measures as independent	Models nested data within individuals
Inflates Type I error due to independence assumption (Francis et al., 1991)	Accounts for correlated observations and individual variability (Bauer et al., 2020; Shak and Ma, 2011)

With these limitations in traditional techniques, Individual Growth Curve Modelling (IGCM) has gained traction as a more advanced approach for analysing both intra-individual (*within-person*) and inter-individual (*between-person*) change over time (Hoffman, 2025; Sliwinski, 2011; Zhou et al., 2023a). IGCM belongs to the family of multilevel or mixed-effects models (also known as hierarchical linear modelling or HLM) and extends regression analysis to repeated-measures data where observations are nested within individuals (Kozlowski et al., 2013; Snijders and Bosker, 2012).

IGCM's advantage lies in its ability to include participants with incomplete data, allowing greater precision and reduced estimation errors (Bauer et al., 2020; Zhou et al., 2023a). It allows analysis of changes in outcomes (*dependent variables*) at both the *individual* and *group* levels. At the individual level, repeated measures of goal strength are modelled across **time** to capture each participant's **growth trajectory** — defined by an *intercept* (initial level of the dependent variable) and a *slope* (rate of change over time). These trajectories may follow linear, quadratic, or more complex forms, depending on how goal strength evolves across the experimental waves (Han et al., 2023; Zhou et al., 2023a). By modelling variation in intercepts (initial status) and slopes (rates of change), they provide a more comprehensive and precise understanding of how individuals and groups evolve over time (McNeish and Matta, 2018; Zhou et al., 2023).

To distinguish *within-person* and *between-person* effects, IGCM separates stable differences between individuals (**trait-like**) from fluctuating deviations at each time point (**state-like**) (Mund et al., 2024). To illustrate the distinction between *between-person* and *within-person* differences, Mund et al. (2024) explain that for each time-varying variable, every individual has a unique and relatively stable mean score around which their values fluctuate over time. These stable differences represent *trait-like* levels, indicating that some individuals consistently score higher or lower than others on certain variables. However, at each measurement occasion, individuals may temporarily deviate from their own mean—either higher or lower—representing *state-like* levels that capture person-specific fluctuations at a given time point.

This approach quantifies how individuals differ in both their starting points and their rates of change, referred to as **random effects**, while **fixed effects** represent the average trajectory across all participants or experimental groups (e.g., Group A versus Group B). At the group level, dependent variable trajectories and parameters representing sample averages are estimated by averaging individual *intercepts* (initial levels) and *slopes* (rates of change). Differences between individuals in these parameters are captured by estimating the variance of the intercept and slope, where larger variances indicate greater individual variability in change over time. Including covariates—such as hyper-personalisation or privacy framing—helps explain systematic variations in these growth trajectories (Zhou et al., 2023a; Kozlowski et al., 2013). Growth curve models can also flexibly accommodate both **time-varying** (e.g., hyper-personalisation) and **time-invariant** (e.g., framing condition, age) predictors, allowing examination of how these factors shape individual change trajectories over time (Raudenbush and Bryk, 2002; Shek and Ma, 2011).

When covariates are introduced to the unconditional model (baseline model with *time* only as a predictor), a reduction in variance indicates that these predictors explain part of the variability in growth trajectories at either the individual or group level (Zhou et al., 2023a; Kozlowski et al., 2013). For example, in educational studies, if a covariate representing instructional support increases, the rate of change in engagement may decrease, as higher support helps maintain consistent performance over time (Zhou et al., 2023a). Similarly, in this study, including experimental covariates such as framing or personalisation allows the model to capture both individual differences in change and systematic variations in these trajectories across groups (Kozlowski et al., 2013; Shak and Ma, 2011).

Table 18 summarises key concepts in the IGCM model structure and their role in this study.

***Table 18**: Summary of IGCM Model Structure and Role in this Study*

Model Component	Description	Role in This Study
Dependent variable	Repeated measure of goal strength	Outcome variable changing across three waves
Intercept *(Fixed Effect)*	Average initial level of goal strength	Baseline goal strength per group
Slope *(Fixed Effect)*	Average rate of change across time	Trend in goal strength change across waves
Random Effects	Individual deviations from group averages	Captures person-specific intercepts and slopes
Within-person variation	Change in an individual's score over time	Measures intra-individual growth
Between-person variation	Differences between individuals or framing groups	Compares trajectories under different experimental conditions
Covariates	Hyper-personalisation (time-varying), Privacy framing (between-person)	Explains systematic variations in intercept/slope

Lastly, growth curve models offer greater flexibility than traditional ANOVA-based methods by allowing researchers to model the covariance structure of repeated measures directly, thereby better capturing patterns of behavioural change over time (Hoffman, 2025; Shek and Ma, 2011). However, reliable model identification typically requires at least three measurement waves (Du et al., 2025; Hori and Miyazaki, 2023; Parsons and McCormick, 2024). Accordingly, this study adopts a three-wave design and applies a Linear Mixed Model (LMM), a class of growth curve models, to:

1. Model within-person change (slopes) in goal strength across time.
2. Estimate how hyper-personalisation interacts with time to influence change.
3. Account for heterogeneity in baseline levels (intercepts) across individuals.

These aims align directly with the methodological strengths of Linear Mixed Models (LMM), detailed in the following section.

4.4.3 Linear Mixed Models (LMM)

Data was analysed in two main steps. First, a *multilevel growth curve* model was used to assess patterns of change in goal strength (a repeated-measure variable) across the three experimental waves. This approach accounts for the fact that hyper-personalised selections presented in each wave are nested within individuals and time-dependent (Hu et al., 2021).

The **Linear Mixed Model** (LMM) framework extends the Individual Growth Curve (IGC) approach by combining *fixed effects* (effects that are constant across all participants) and *random effects* (effects that vary across individuals). This enables the model to estimate both overall group-level trends and individual-level variations over time (Hoffman, 2021; Luke, 2020; Meteyard and Davies, 2020). The term "*mixed*" refers to the fact that these models include both fixed effects and random effects within the linear regression framework.

In this study, LMMs were used to examine the **temporal dynamics** of consumer goal strength and the influence of hyper-personalisation and privacy framing across the three waves. The LMM structure supports incomplete or unbalanced data, which is common in longitudinal research, while still producing unbiased parameter estimates (Snijders and Bosker, 2012).

Each LMM was structured hierarchically with two levels:

- **Level 1** (*within-person*): captures individual change in goal strength across time (intra-individual variation).
- **Level 2** (*between-person*): captures differences between participants across framing conditions (inter-individual variation).

Each Linear Mixed Model (LMM) was implemented within the Individual Growth Curve (IGC) framework, allowing both *intra-individual* (Level 1) and *inter-individual* (Level 2) variations to be modelled simultaneously. This approach combines fixed and random effects and is well suited for longitudinal designs where participant attrition or unbalanced data may occur (Hoffman, 2021; Luke, 2020; Snijders and Bosker, 2012).

LMMs are particularly suited for repeated-measures data, as they:

- Handle **unbalanced data** (e.g., missing observations across waves)
- Capture **individual differences** in baseline goal strength (intercepts), and
- Model **within-person** changes in goal strength over time (slopes)

Linear Mixed Models (LMMs) offer several methodological advantages over traditional repeated-measures ANOVA (rmANOVA), particularly for analysing longitudinal behavioural data. They can incorporate both *time-varying* and *time-invariant* covariates, handle missing and unbalanced data, and model both *fixed* (group-level) and *random* (individual-level) effects (Bauer et al., 2020; Luke, 2020; Hox et al., 2017; Hoffman, 2021). LMMs also provide flexibility in specifying alternative covariance structures, improving estimation accuracy when data is collected at irregular intervals or vary across participants. These advantages (refer to **Table 19** below) make LMMs especially suitable for modelling changes in goal strength across experimental waves in this study.

Table 19*: Advantages of LMM and Relevance to Current Study*

LMM Advantage	Purpose / Benefit	Relevance to This Study
Time-varying and time-invariant covariates	Captures effects that change or remain constant over time	Models temporal effects of hyper-personalisation and framing
Handling missing or unbalanced data	Accommodates incomplete or uneven longitudinal measures	Preserves participant data across all waves
Random effects modelling	Accounts for within- and between-person variability	Captures individual goal strength trajectories
Flexible covariance structures	Improves model fit across repeated measures	Enhances accuracy in estimating changes across waves

Given this flexibility and the limitations present in using traditional repeated measure ANOVA, this study employs a Linear Mixed Model (LMM) to examine the effects of hyper-personalisation value, time, and information framing (*positive or negative framing*) on goal strength, accounting for variability between and across individuals and its repeated measures over time. A multilevel growth curve model is, hence, appropriate when analysing patterns of change for a time-dependent variable (that is, goal strength as *dependent variable* and time as a *repeated measure*) while also considering that the hyper-personalisation value selection is nested to, and time-dependent for, each individual (Hu et al., 2021). In the context of experimental design (Shak and Ma, 2011), fixed factors refer to factors that can be controlled a priori and throughout the experiment (across all three waves in this study). Random factors, by contrast, represent elements that vary across individuals and cannot be experimentally controlled. In this study, random effects accounted for individual variability in intercepts and slopes across the three experimental waves.

4.4.4 Tested Linear Mixed Models

To examine the core research question – *how* does goal-aligned *hyper-personalisation influence consumer goal strength in AI-enabled, multi-actor consumer ecosystems over time over time* – this study employed a **multilevel modelling approach** using three Linear Mixed Models (LMMs). This statistical framework accommodates nested longitudinal data, captures both within-person and between-person variability, and handles unbalanced data structures across the three experimental waves (*over time*).

Three linear mixed models were developed, each targeting a different analytical unit:

- **Model 1: Unconditional Growth Model (Baseline)**
  This baseline model - known as the null model – assesses overall changes in consumer goal strength across time without including predictors other than *Time*. It establishes whether significant variation exists, thereby confirming the suitability of a multi-level structure for the data before introducing explanatory predictors.

- **Model 2: Theoretical Hypothesis Model**
  This model incorporates both *between-person* (grand-mean centered) and *within-person* (person-mean centered) variations in hyper-personalisation to test their influence on consumer goal strength. This dual-level analysis enables

a deeper understanding of how both stable tendencies and contextual shifts in hyper-personalisation affect consumer goal strength. It also examines the moderating role of privacy framing (*Group*) on hyper-personalisation effects, thereby testing the primary study hypotheses (Hypothesis 1 and Hypothesis 2).

- **Model 3: Post-hoc Exploratory Model (Perceived Importance)**
  Although not part of the main hypothesis testing, this exploratory model investigates participants' subjective perceptions of hyper-personalisation importance (a baseline, a time-invariant variable measured at *Wave 1*) and its relationship with consumer goal strength. This provides contextual insight into how individuals' perceived value of hyper-personalisation aligns with behavioural outcomes, supporting future hypothesis development.

A summary of the three models, their analytical levels, and contributions is presented in **Table 20**.

Table 20*: Overview of Models Used to Test Hypothesis 1 and 2*

Model	**Purpose**	**Level**	**Contribution**
Model 1	unconditional growth trajectory (*reference or baseline model*)	Descriptive	Evidence for variation in goal strength over time with only *Time* as predictor
Model 2	Between-individual effect of average hyper-personalisation (*grand mean centered*) Within-individual deviations from own average (*person-mean centered*)	Between-person Within-person	1. Tests if higher average hyper-personalisation predicts greater goal strength over time 2. Examines momentary deviations from hype-personalisation average and how they link to consumer goal strength. 3. Assess the moderating effect of Group to test Hypothesis 2 (H2)
Model 3	***Exploratory*** *(Post-hoc):* Perceived importance of hyper-personalisation ***This model is not used to test any Hypothesis***	Between-individual (*Exploratory*)	Provides subjective context to investigate the effect of perceived hyper-personalisation importance

Note. *Model 3* was conducted post-hoc to explore consumer perception of hyper-personalisation importance versus behaviour, whereas *Model 2* is used to test and verify Hypothesis 1 (H1) and Hypothesis 2 (H2).

4.4.4.1 Model 1: Unconditional Baseline Model

This section presents the results of the first linear mixed model, *Model 1*, commonly referred to as the unconditional or null model (Singer and Willett, 2003; Zhou et al., 2023). This model includes *Time* **only** as a repeated measure predictor and incorporates random intercepts for each participant to account for individual differences at the baseline (*Wave 1*). The primary aim of this model is to determine whether the dependent variable, *Goal Strength*, varies significantly over time and whether substantial *between-person* differences exist at the initial measurement point (*Wave 1*). In doing so, *Model 1* establishes a temporal baseline against which subsequent models can be compared.

Model Rationale and Specification

In this model, *Time* was treated as a fixed categorical variable, with the baseline set at the initial time point (*Wave 1)*. A random *intercept* was specified to account for *between-person* differences in the initial *Goal Strength (*starting score*)*. The model used an *unstructured covariance structure* for *Time*, enabling the estimation of relationships between repeated measures without imposing restrictive assumptions. This flexible structure allows within-person variations to emerge freely over the three waves. Estimation was conducted using *Restricted Maximum Likelihood (REML),* a method particularly robust with smaller sample sizes and recommended for comparing nested models that differ in their fixed effects (Enders, 2022). This estimation approach reduces bias and provides more stable variance component estimates (Hoffman, 2021), ensuring accurate modelling of within-person variation over time.

This baseline model serves as a reliable foundation for assessing the longitudinal structure of the data before introducing experimental predictors in subsequent models. By evaluating whether consumer goal strength changes systematically over time, *Model 1* establishes the suitability of a Linear Mixed Model (LMM) framework for this study's longitudinal design. **Table 21** summarises *Model 1* specification.

***Table 21**: Model 1 Specification Summary*

Model Component	Specification	Purpose
Fixed Effect	*Time* (3 waves)	Tests for change in consumer goal strength across time points
Random Effect	*Intercept* by participant (ID)	Accounts for baseline individual differences
Repeated Measure	*Time* with an unstructured covariance matrix	Allows flexible estimation of temporal relationships
Estimation Method	Restricted Maximum Likelihood (REML)	Ensures unbiased, stable variance estimates

Covariance Structure Justification

The decision to use an *unstructured covariance type* warrants additional attention given its value in modelling irregular measurement intervals and capturing individual-level variation. A key advantage of **Linear Mixed Models (LMMs)** lies in their ability to accommodate variability across repeated measures. In this study, the unstructured covariance structure was selected to capture potential shifts in the relationships between time points, allowing changes in goal strength to emerge naturally without assuming equal spacing or consistent trends between waves. This specification is particularly relevant in real-world longitudinal research, where measurement intervals and response variability may not be perfectly regular. Prior research supports that unstructured covariance structures yield more reliable estimates when modelling growth trajectories, as they relax restrictive assumptions that rarely hold in practice (Singer, 1998; Shak and Ma, 2011; Zhou et al., 2023a). Accordingly, this approach was considered the most appropriate for capturing the dynamic changes in *Goal Strength* across the study period.

Statistical Findings

The full summary of fixed and random effects estimates for *Model 1* is presented in **Appendix B** (refer to **Tables A.B.5 and A.B.6**).

Results of *Model 1*, as shown in **Table A.B.5** (Appendix B), confirmed:

1. A **statistically significant** fixed effect of *Time,* F (2, 1178.864) = 21.416, $p < .001$, indicating that *Goal Strength* varied significantly across waves.
2. The *intercept* estimate was also **significant**, B = 30.510 (SE = 0.288, p < .001), suggesting a high average baseline score of *Goal Strength* across participants.
3. Compared to the baseline (*Wave 1*), findings showed that *Goal Strength* was significantly higher at:
   - *Wave 2* (after 10 days) with (B = **1.986**, SE = 0.325, p < .001)
   - *Wave 3* (after 5 months) with (B = **1.912**, SE = 0.392, p < .001)

This pattern indicates a consistent increase in consumer goal strength over time, although the rate of growth slightly stabilized by *Wave 3,* suggesting a possible ceiling effect or behavioural equilibrium. As shown in **Table A.B.6** in *Appendix B***,** findings from the random effects revealed:

1. **Baseline variance** in *Goal Strength* (intercept variance = **50.714**) varied considerably across individuals, even before accounting for any predictors other than *Time*.
2. **Residual variance** (within-individual variability across **distinct** time points) was also **significant**, indicating meaningful intra-individual fluctuations in goal strength across waves.
3. **Covariances** between time points were statistically **significant** and **negative**, suggesting that participants with higher goal strength at one wave tended to report slightly lower scores at the next wave, and vice versa. This pattern reflects a modest reversal or oscillation effect, rather than a simple, steady increase or decrease in goal strength.

These findings indicate that consumer goal strength is **dynamic** rather than static, varying across both time and individuals. This variability provides strong justification for employing a Linear Mixed Model (LMM) approach in subsequent analyses. The observed oscillating pattern may reflect adaptive adjustments in goal strength over time, as individuals respond to changing motivational or contextual cues - rather than following a uniform trajectory (Zhou et al., 2023a; 2023b).

Intraclass Correlation (ICC) – Justifying LMM

To further assess whether individual differences justify the use of a multilevel model, the **intraclass correlation coefficient** (ICC) was calculated. The ICC quantifies the proportion of total variance in the dependent variable (*Goal Strength*) that is attributable to *between-person* differences, as opposed to *within-person* fluctuations (Shek and Ma, 2011).

The ICC was computed by dividing the random intercept variance (**50.714**) by the total variance (intercept + residual), yielding a value of approximately **0.474** (ICC ~ 0.47). This substantial ICC (> **0.25**) indicates that nearly half of the variance in goal strength arises from stable, between-person differences rather than purely within-person changes. Such results strongly support the application of a mixed-effects framework over traditional single-level models (Shak and Ma, 2011; Heinrich and Lynn, 2001).

ICC = 50.714 / (50.714 + 56.17) ~ 0.474

- Approximately **47%** (ICC ~ 0.474) of the variance in *Goal Strength* is due to differences between individuals (*between-person*)
- Remaining **53%** is attributable to the same individual (*within-person*) variability over time.

Model 1 Key Interpretation

Taken together, the findings from *Model 1* findings demonstrate that *Goal Strength* is **dynamic** and varies significantly both over time and across individuals. These results confirm that changes in goal strength occur *longitudinally* and justify the application of Linear Mixed Models (LMMs) for capturing individual growth trajectories. Thus, *Model 1* establishes the statistical foundation for subsequent models in this study.

Additionally, the unconditional model supports the evaluation of model improvement, as subsequent models including predictors can be compared using -2 Log Likelihood, Akaike's Information Criterion (AIC), and Schwarz's Bayesian Criterion (BIC) values (refer to **Table A.B.6** in Appendix B). Employing an unconditional growth model as a baseline before adding predictors is a recommended best practice in longitudinal modelling (Shak and Ma, 2011; Shen and Li, 2023; Zhou et al., 2023).

Purpose of Model 1

Model 1, establishes the baseline for multi-level longitudinal analysis:

1. **Temporal Effect**: *Model 1* tests whether *Goal Strength* changes systematically over time, using *Time* as the only predictor across the three waves.
2. **Model Fit**: *Model 1* functions as a reference model to evaluate improvements in model fit when additional predictors - such as hyper-personalisation (*Selection*) and privacy framing (*Group*) - are added in subsequent models.
3. **Justifies Multi-level Modelling**: The significant differences in the intercepts and slopes across individuals confirm the need of a multilevel approach, supporting the use of Linear Mixed Models (LMMs) to account for both *within-person* and *between-person* variability.

Preliminary Data Exploration

To visually examine how *Goal Strength* varies over time and across individuals, a spaghetti plot was generated for a random sample of 100 participants across the three study waves (**Figure 22**). Each line in the plot represents an individual's trajectory, highlighting both the starting point (*intercept*) and the rate of change (*slope*) over time. The plot revealed notable variability between individuals. Some participants showed steady increases in goal strength, while others showed minor declines or maintained relatively stable. This heterogeneity aligns with *Model 1* ICC findings and supports using Linear Mixed Models (LMMs) to capture both individual- and group-level differences more accurately than single-level methods such as ANOVA. Additional spaghetti plots comparing linear and quadratic growth trends and examining differences by Group are presented in *Appendix B*.

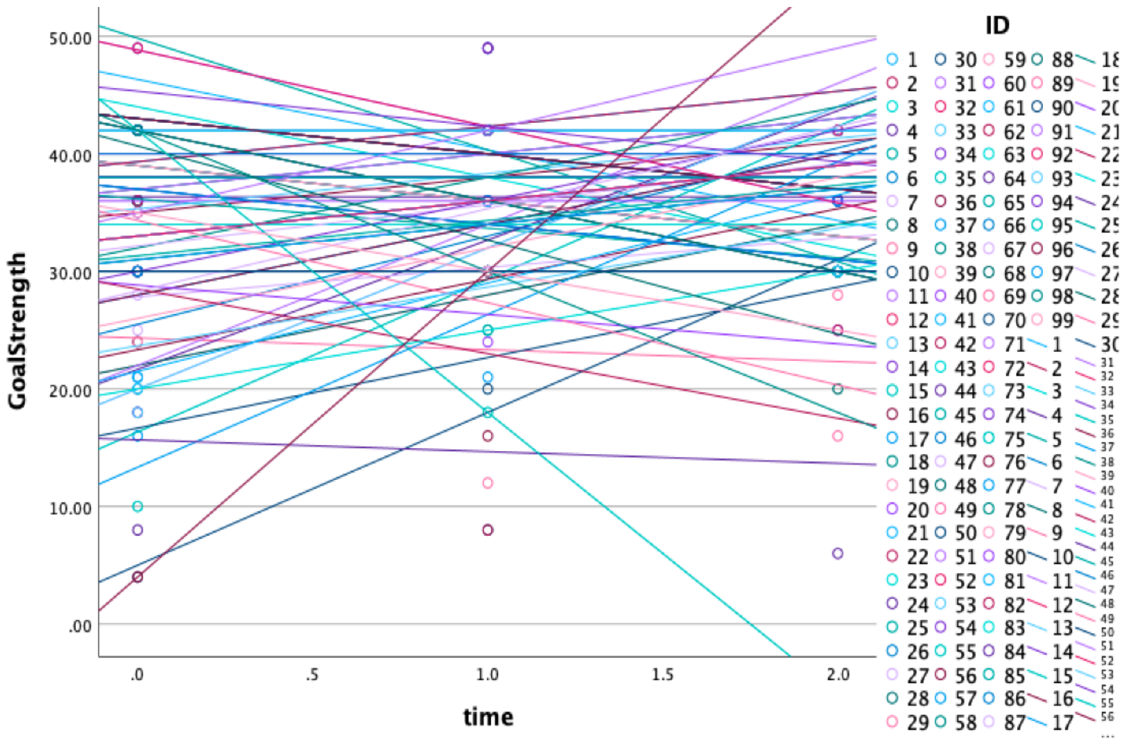


Figure 22*: Spaghetti Plot of Intra-Individual Goal Strength Trajectories Across Time*

Note: This plot represents 100 randomly sampled participants and illustrates variation in goal strength patterns over the three waves - emphasising the need for individual-level modelling

4.4.4.2 Model 2: Theoretical Hypothesis Model

Model 2 builds upon the unconditional baseline model (*Model 1*) to test the main hypotheses of this study. While *Model 1* confirmed Goal Strength varies both between- and within-individuals over time, *Model 2* explores the factors that may explain these changes. Specifically, it examines how hyper-personalisation and privacy framing influence consumers' goal strength trajectories. *Model 2* includes both **fixed** and **random** effects to capture overall trends and individual variation. It was designed to test the following key hypotheses:

Hypothesis 1 (H1): *Higher levels of hyper-personalisation significantly increase consumer goal strength over time*

Hypothesis 2 (H2): *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

Hypothesis Testing

To accurately test **Hypothesis 1 (H1)**, *Model 2* decomposed the initial **time-varying** *Selection* variable (refer to *section 4.3.1*) into two distinct variables:

- **Grand_SelectionMean** (*between-person*): represents each participant's *average* level of hyper-personalisation selection across all three waves. This variable captures ***stable***, ***trait-like*** differences between individuals – reflecting each person's overall tendency to select more or less hyper-personalised options. This variable is centered around the sample mean, and hence is fixed for each participant across the three waves.

- **Centered_Selection** (*within-person*): represents *momentary* deviations in a participant's hyper-personalisation selection from their own average at each time point (wave). This variable captures ***time-specific*** (***state-like***) fluctuations in hyper-personalisation, showing whether an individual selected more or less hyper-personalised options compared with their usual pattern. Hence, it varies across time points.

This decomposition followed best practices in longitudinal modelling, which recommend separating between-person and with-person to avoid *contextual confounding* (Enders, 2022; Hoffman, 2025; Wang and Maxwell, 2015). Without this step, it would be unclear whether changes in goal strength were driven by stable individual differences or by short-term, time-specific fluctuations in hyper-personalisation. By separating the raw *Selection* variable in this way, *Model 2* could precisely identify how much of the variation in *Goal Strength* was explained by between-person traits and how much by with-person, time-varying effects – meeting key methodological standards in longitudinal growth analysis (Curran and Bauer, 2011; Yaremych et al., 2024; Wang and Maxwell, 2015).

Because time-varying covariates like *Selection* combine both trait-like and time-specific components, a proper centering approach was applied to disentangle these effects. Grand-mean and person-mean centering were used to ensure accurate interpretation of fixed and random effects, in line with established longitudinal multilevel modelling procedures (Gottfredson, 2019; Hoffman, 2025; Wang and Maxwell, 2015; Raudenbush and Bryk, 2002) – refer to section 4.3.1.

As shown in **Table 22**, post this decomposition, both hypotheses were re-examined at two analytical levels—*between-person* (stable, trait-like effects) and *within-person* (momentary, state-like effects). This decomposition enabled the model to distinguish general tendencies from time-specific fluctuations in hyper-personalisation and goal strength across privacy framing conditions.

Table 22*: Hypotheses Decomposition into Between- and Within-Person Effects*

Hypothesis	**Analytical Focus**	**Question Tested** *(post decomposition)*
H1: *Higher levels of hyper-personalisation significantly increase consumer goal strength over time.*	**Between-person effects** *(stable, trait-like influence)*	*Do individuals who* ***generally*** *select higher levels of hyper-personalisation experience* ***stronger*** *overall goal strength?*
H2*: Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and goal strength.*	**Between-person moderation** (*stable, cross-group influence*)	*Do individuals who* ***generally*** *select higher levels of hyper-personalisation show different effects on goal strength depending on the* ***framing group*** *(risk-based versus neutral)?*
H1: *Higher levels of hyper-personalisation significantly increase consumer goal strength over time.*	**Within-person effects** (*time-specific, state-like influence*)	*Do individuals experience* ***stronger*** *goal strength at* **moments** *when they select higher-than-usual levels of hyper-personalisation?*
H2*: Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and goal strength.*	**Within-person moderation** (*time-specific, cross-group influence*)	*Do* ***momentary*** *increases or decreases in hyper-personalisation have different effects on goal strength depending on the* ***framing group*** *(risk-based versus neutral)?*

Model Rationale and Specification

By incorporating *Grand_SelectionMean* and *Centered_Selection* instead of the raw *Selection* variable (refer to *Section 4.3.1*), *Model 2* can independently assess both *between-person* (trait-like) and *within-person* (state-like) effects of hyper-personalisation on *Goal Strength*.

This decomposition enhances the precision of **Hypothesis 1 (H1)** by distinguishing stable individual tendencies from dynamic, momentary changes in consumer behaviour (Gottfredson, 2019; Zhou et al., 2023a). In line with **Consumer-Dominant Logic (CDL)**, this model recognises that value is not only cumulative and enduring (trait-level), but also context-dependent and immediate (state-level) (Heinonen and Strandvik, 2022). This dual-level modelling approach aligns with evidence suggesting that both persistent personal tendencies and situational responses jointly influence motivation and engagement outcomes (Raudenbush and Bryk, 2002; Snijders and Bosker, 2012). Separating these two sources of variance strengthens the explanatory power of the model, providing a more realistic view of how hyper-personalisation operates in real-world consumer decision-making.

In addition, *Model 2* tests whether privacy framing (*Group* variable) moderates the relationship between hyper-personalisation and goal strength (**Hypothesis 2** - **H2**). Specifically, it examines how consumers' perceived control (risk-framed versus neutral) interacts with both *Grand_SelectionMean* and *Centered_Selection* to influence goal strength over time.

Model 2 incorporated both **fixed** and **random** effects to examine the main hypotheses. The interaction between the grand-mean centred personalisation (*Grand_SelectionMean*) and the person-mean centred personalisation (*Centered_Selection*), as well as their interaction with *Group* (privacy framing), was used to test the direct and the moderating effects proposed in both hypotheses. **Table 23** summarises *Model 2* specification.

Table 23*: Model 2 Specification Summary*

Model Component	**Specification**	**Purpose**
Fixed Effects (*Main*)	▪ *Time* (3 waves) ▪ *Group* (Neutral *Group A* versus Negative Privacy Framing *Group B*) ▪ *Grand-Mean centered Personalisation (Grand_SelectionMean)* ▪ *Person-mean centered Personalisation (Centered_Selection)*	Tests main effects of Time, Group, and hyper-personalisation (*Grand_SelectionMean, and Centered_Selection) on* consumer goal strength across time points to test Hypotheses H1 and H2.

Fixed Effects (*Interaction*)	▪ *Time x Centered_Selection* ▪ *Time x Group* ▪ *Group x Grand_SelectionMean* ▪ *Group x Centered_Selection* ▪ *Time x Group x Centered_Selection*	Tests interaction effects of Time with hyper-personalisation (*Grand_SelectionMean, and Centered_Selection)* to examine temporal effects over *time* (H1) and with *Group* to evaluate the moderation effects of privacy framing *(*H2).
Random Effect	*Intercept* by participant (ID)	Accounts for baseline differences and individual variation in change trajectories across waves.
Repeated Measure	*Time* treated as a repeated measure with an unstructured covariance matrix	Allows flexible estimation of within-person temporal relationships and irregular measurement intervals.
Estimation Method	Restricted Maximum Likelihood (REML)	Ensures unbiased, stable variance estimates

Note that since *Grand_SelectionMean* is a time-invariant variable reflecting stable *between-person* preferences that *do not vary* across waves (grand-mean centered), interactions terms with it are *unnecessary* unless a cross-level moderation hypothesis is being tested (Snijders and Bosker, 2012). Hence, only *Group x Grand_SelectionMean* interaction term is retained to test **Hypothesis 2 (H2)**.

Model Fit (Model 2 versus Model 1)

To assess whether *Model 2* provided an improved fit, the model's performance was compared to *Model 1* (baseline model) since both are nested models. A **chi-square difference test** was conducted to evaluate the relative goodness of fit (Zhou et al, 2023a). Chi-square difference, Δχ2, is computed by subtracting the deviance of *Model 2* from the deviance of *Model 1* unconditional model (i.e., the -2 Restricted Log Likelihood). The chi-square difference follows approximately a chi-square distribution with degrees of freedom, Δdf, being the difference in degrees of freedom between the two models. In this case, Δχ2 = 26,147.67 – 26,086.97 = 60.70, Δdf = 14 – 1 = 13, p = 3.9383E-08 < .05. This result indicated that *Model 2* demonstrated a **significantly** better fit than *Model 1*, suggesting that including hyper-personalisation and privacy framing variables (and their interactions) accounted for a meaningful increase in the explained variance of *Goal Strength*.

This improvement confirms the theoretical expectation that individual differences (both stable and momentary) and privacy context contribute significantly to predicting changes in consumer goal strength over time.

Model 2 Statistical Findings

Refer to **Tables A.B.7 and A.B.8 in Appendix B** for the statistical findings of *Model 2,* used for testing Hypothesis 1 (H1) and Hypothesis 2 (H2).

Goal Strength and Time

1. The initial *Goal Strength* at *Wave 1 (intercept)* was estimated at ($B = 30.944$), suggesting a high starting value across all participants.
2. *Time* had a **statistically significant** effect on goal strength, $F(2, 1184.877) = 19.137$, $p < .001$.
   - At *Wave 2* (after 10 days), a **positive** ($B = 0.712$, $p = .129$) but **not significant** increase in *Goal Strength* was estimated overall across the whole sample, compared to *Wave 1*.
   - At *Wave 3* (after 5 months), a **positive** and **significant increase** ($B = 2.552$, $p < .001$) was recorded compared to *Wave 1,* suggesting **overall** motivational growth over time.
   - Across the whole sample (including both groups), the effect was weaker or more varied in the *short-term* compared to the *long term*.

While the overall fixed main effects of *Wave 2* were not significant when averaged across the whole sample, pair-wise comparisons revealed a **significant increase** in *Goal Strength* from *Wave 1* to *Wave 2* ($B = 1.875$, $p < 0.01$), but a **negligible** flattened effect from *Wave 2* to *Wave 3* ($B = -0.012$, $p = .975$), suggesting a plateauing effect in the long term (**Figure 23** below).

Over longer periods of time, however, the initial boost in goal strength (after 10 days) seems to decay or fade at *Wave 3* without reinforcement, aligning with theories of motivational decay and temporal self-regulation (Albert et al., 2024; Vandelanotte et al., 2023).

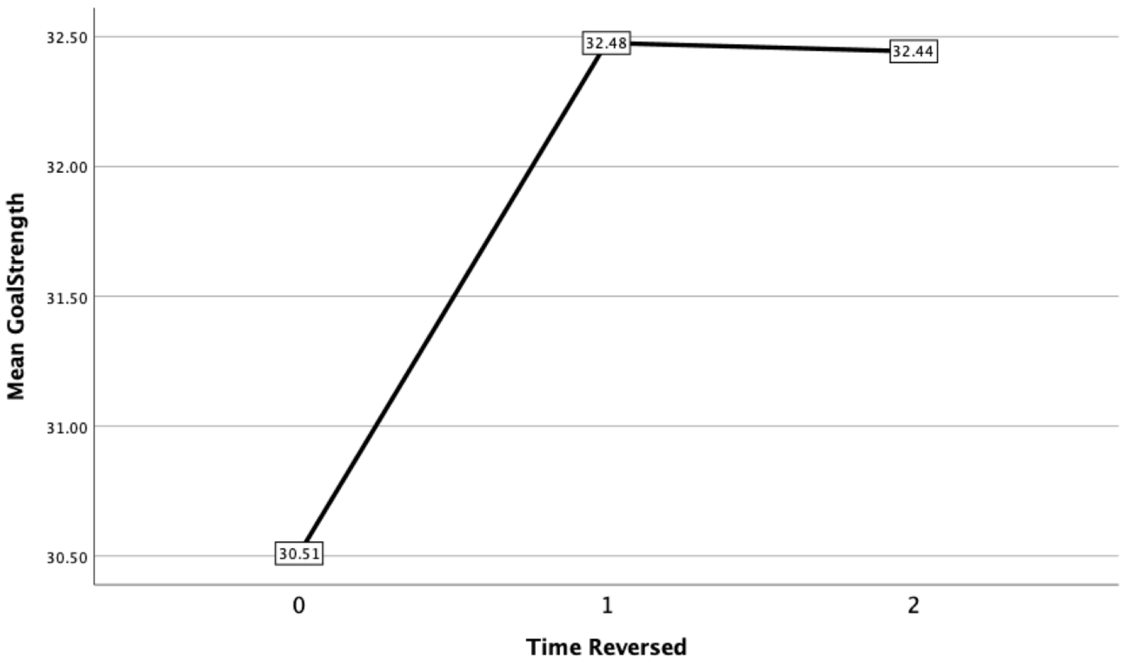


***Figure 23**: Goal Strength Trajectory over Time - Irrespective of the Group*

This **divergence** between fixed main effects and pair-wise comparisons suggests that *Wave 2* gains are more likely driven by *Group*-specific effects that seem to be diluted in the average effect. These results demonstrate the need to examine interaction effects with *Group* over *Time*.

Group and Time Interaction

1. The **two-way interaction** between *Time* and *Group* was **statistically significant** with F (2, 1184.877) = 13.612, p < .001.
2. The interaction of *Time* = 1 (at *Wave 2*) and *Group* = 1 (neutral framing, *Group A*) was **statistically significant** with (B = 2.327, SE = .652, p < .001). In other words, participants in Group A (neutral framing) reported **positively** and **statistically significant** higher goal strength at 10 days from the baseline.
3. At *Wave 3* (after 5 months), however, participants in Group A experienced a drop in their *Goal Strength* with (B = -1.330, SE = 0.798, p = .096), compared to those in Group B.
4. Although not significant (p = .096), these findings demonstrate that participants not exposed to negative framing experienced a significant spike in their goal strength in the short-term (10 days) than participants in the negative

framing group. However, this effect did not sustain on the long-term. Hence, *Group* moderates the temporal effect.

The effect is more pronounced in the short-term when hyper-personalisation exposure is recent - in this case closer to the introduction of the service (baseline) - and when privacy framing is neutral (**positive** and **significant** 2-way interaction at Time = 1, Group = 1). These findings suggest that consumer goal strength evolves differently over time (**temporal**) depending on privacy framing (**contextual**), particularly during early exposure in the short-term.

This finding aligns with the baseline insights from *Model 1 (section 4.4.3.1),* supporting further examination of how hyper-personalisation interacts with these temporal and contextual dynamics. Plotting the trajectory of *Goal Strength* per *Group* (Group A = neutral framing, Group B = negative framing) in **Figure 24** below visually confirms the divergence between the fixed main effects and pair-wise comparisons is attributable to *Group* differences and calls for examining the interaction between *Group* and hyper-personalisation (*between-person* and *within-person*).

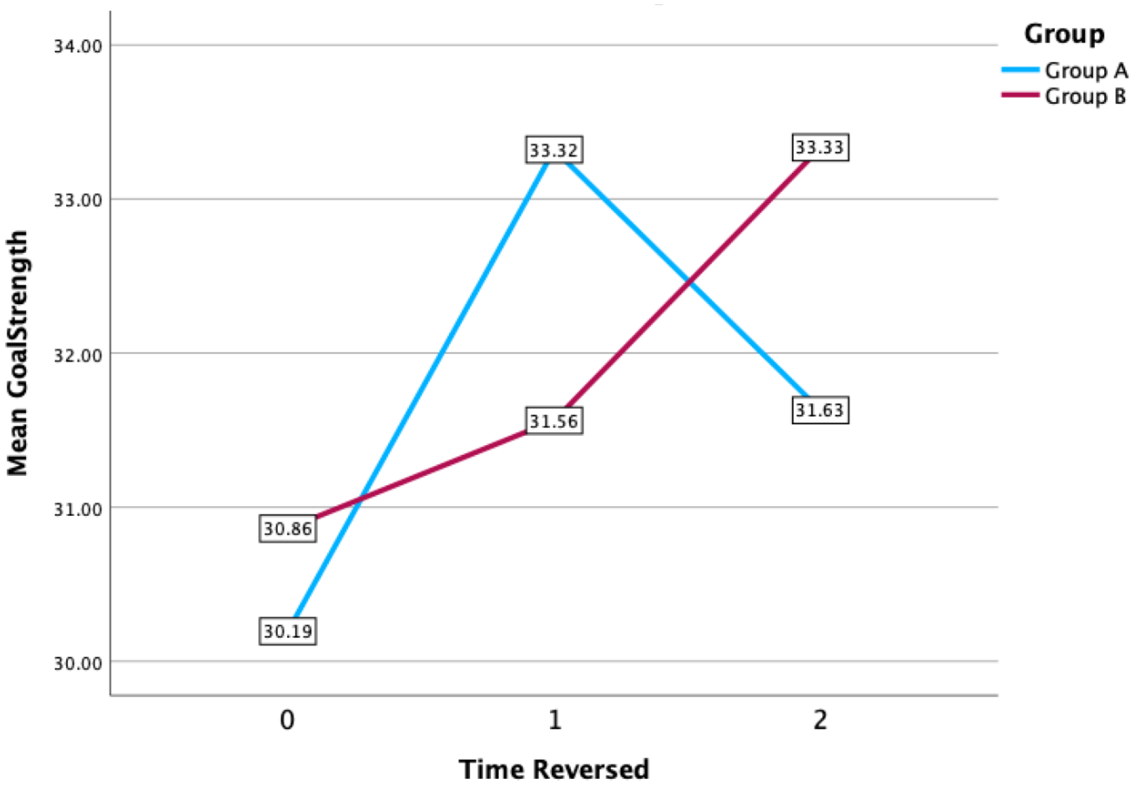


***Figure 24**: Goal Strength Trajectory over Time – Group A versus Group B*

Having established the **temporally** and **contextually** moderated effects of *Time* and *Group* on *Goal Strength*, the role of hyper-personalisation selection on consumer goal strength is examined next, specifically in terms of its stable, trait-like between-person (*Grand_SelectionMean*) effects and momentary, state-like within-person (*Centered_Selection*) effects. These predictors directly relate to **Hypothesis 1 (H1)**, which posits that higher levels of hyper-personalisation significantly increase consumer goal strength over time. The interaction of these predictors with *Group* is also examined to test **Hypothesis 2 (H2)**, positing that privacy framing *(risk-based versus neutral)* has a moderating role on personalisation efficacy.

Grand_SelectionMean and Group

1. Results revealed that *Grand_SelectionMean* was a **strong** and **statistically significant** predictor of consumer goal strength. Specifically, each one unit **increase** in grand-mean centered personalisation (*Grand_SelectionMean)* was associated with a **positive** and **statistically significant increase** of **1.072** points in *Goal Strength* (B = **1.072**, SE = .396, p = .007). This indicates that individuals who **generally** select **higher** levels of hyper-personalised content report **stronger** goal strength across time.

2. In contrast, the main effect of *Group* was not statistically significant (p = .243), with the estimate for Group = 1 (neutral framing) showing a slight but not-significant decrease (B = -.844, p = .148), compared to participants in the negative framing group (Group B).

3. Furthermore, the **two-way interaction** between *Grand_SelectionMean* and *Group* was also **not significant** (F (1, 1518.932) = .135, p = .713), indicating that the positive association between the overall hyper-personalisation selection and goal strength holds **consistently** across both privacy framing conditions. These results provide **strong support** for **Hypothesis 1 (H1),** confirming that consumers who generally engage with **higher** levels of hyper-personalised contend tend to report **greater** consumer goal strength, **regardless of contextual framing**.

Takeaway:

- **Between-person effects** (stable trait-like influence): Do individuals who *generally* select higher levels of hyper-personalisation experience stronger goal strength? ***Answer:*** **supported across both neutral and negatively framed privacy contexts**.

- **Does Group moderate between-person effects** (stable trait-like influence): Do individuals who *generally* select higher levels of hyper-personalisation experience **different effects** on goal strength based on the *Group* (control group versus experimental)? ***Answer:*** **no, stable trait-like effects of hyper-personalisation are not moderated by Group, confirming their stability over time**

Centered_Selection and Group

1. The within-person *Centered_Selection* was **not a significant** predictor of *Goal Strength,* with (B = .089, SE = .491, p = .857), suggesting that within-person deviations from an individual's typical hyper-personalisation level (one's own norm) were not predictive on their own.

2. The **two-way interaction** of *Centered_Selection* with *Time* was also **not significant**, with F (2, 2004.234) = .679, p = .507. This **non-significant** momentary within-person effect compared to the **strong** and **statistically significant** effect of between-person (*Grand_SelectionMean*) on *Goal Strength* is supported in literature. Zhou et al. (2023a) found lower effect sizes and more measurement error from *within-person* variations compared to *between-person* components, especially if individuals have little fluctuations. This aligns with studies reporting that between-person variance has a more predictive power than within-person variations (Enders, 2022; Harris et al., 2023).

3. While *Group* did not moderate stable trait-like between-person hyper-personalisation effects (Grand_SelectionMean), the **two-way interaction** between *Group* and *Centered_Selection* was **statistically significant** with F

(1, 2023.777) = 4.890, p = .027, indicating that momentary state-like within-person effect of hyper-personalisation **differs** across groups. This supports *Group's* moderating role on within-person hyper-personalisation effects, **supporting Hypothesis 2 (H2)**.

4. The **three-way interaction** (*Time* x *Group* x *Centered_Selection)* also reported **positively** and **statistically significant** higher goal strength at 10 days for Group A (neutral Group) with (B = 2.471, SE = 1.072, p < .021), although the main effect of the three-way interaction was not significant overall (p = 0.063).
   - This finding suggests that at 10 days from baseline (*Wave 2*), participants in Group A (neutral framing) who selected **higher-than-usual** hyper-personalisation revealed a **statistically significant** increase in *Goal Strength* with (B = 2.471, SE = 1.072, p = .021), **supporting Hypothesis 1 (H1)**.
   - However, this effect was **not evident** in Group B (negative framing) nor at *Wave 3* (5 months from baseline), suggesting a **temporal** and **context-specific** effect, with between-person hyper-personalisation being more effective when time proximity is short and privacy framing is neutral. This finding also **strengthens** the moderating role of *Group*, with the effect being more pronounced in the short-term exposure.

These findings demonstrate that the effect of *within-person* hyper-personalisation does not significantly predict *Goal Strength* across time points **unless** *Time* and *Group* differences are considered (*Time* and *Group* effect). Specifically, the below findings present a **strong support for Hypothesis 2 (H2)**:

1. A **significant** *Time* x *Group* interaction confirms that consumer goal strength varies by framing (*Group*) across waves, which supports **temporal** moderation by framing.

2. A **significant** *Group x Centered_Selection* interaction suggests that the *within-person* effect of hyper-personalisation on goal strength differs by *Group* (Group B is the reference), supporting a **contextual** moderation by framing.

3. A **three-way interaction** (*Time x Group x Centered_Selection*), demonstrating a notable **statistical significance** in Group A (neutral framing) and *Wave 2* (after 10 days from the baseline), but not in Group B (negative framing) or *Wave 3* (5 months from the baseline), suggests that increases in goal strength are more pronounced in the short-term and neutral framing but weakens over time or under negative privacy framing (Group B). This suggests that *Group* negatively moderates (weakens) the relationship between hyper-personalisation and consumer goal strength over time.

The above three findings all indicate that *Group* indeed plays a moderating role on the relationship between hyper-personalisation and consumer goal strength. Hence, **Hypothesis 2 (H2) is supported**. This aligns with findings that privacy concerns suppress adaptive motivation in digital environments (Acquisti et al., 2020; Hassan et al., 2025).

The lack of statistical significance at *Wave 3* (after 5 months) for either *Group* might reflect one of two possible interpretations:

(1) **No sustained** effect of hyper-personalisation on consumer goal strength on the long term

or

(2) **An attenuated** effect due to the longer time span (after 5 months), weakening the significant effect observed in the short-term (*wave 2*)

To better interpret which of these effects is the case, visual probing of temporal and contextual effects is examined next between Group A and Group B over time.

Visual Probing of Temporal and Contextual Effects

To enhance interpretability and visual clarity, *within-person* deviations in hyper-personalisation were grouped into three actionable categories: **Low**, **Medium**, and **High**, using ±0.75 standard deviations to define the categories' boundaries. This classification allows for a clear visual distinction between individuals with **Low** (<= -0.75), **Medium** (-0.75 to +0.75), and **High** (>= 0.75) hyper-personalisation levels across distinct time points. This method of categorisation is commonly adopted in research to capture within-person patterns and balance between statistical robustness and sensitivity (McCabe et al., 2018; Harris et al., 2023).

Instead of using the sample's actual standard deviation (M = 0.817), **±0.75** value was adopted following best-practice recommendations by McCabe et al. (2018) who demonstrated that using thresholds such as **±0.75** standard deviation (SD) improves the interpretability and accuracy of visual probing in interaction plots. Their research showed that this categorisation enhances clarity in identifying within-person patterns, particularly when visualising moderator effects over time. A new variable (*Centered_Group*) was then computed based on the three categories as follows and used in the visual probing of the interaction effects between *Group* and across the three distinct time points:

- **Low Personalisation**:
    - *Centered_Selection* < −0.75
    - *Centered_Group = 1*
- **Medium Personalisation**:
    - −0.75 ≤ *Centered_Selection* ≤ +0.75
    - *Centered_Group = 2*
- **High Personalisation**:
    - *Centered_Selection* > +0.75
    - *Centered_Group = 3*

Table 24 shows the predicted goal strength values across the three categories of hyper-personalisation (**Low**, **Medium**, **High**) over time, segmented by *Group*. These patterns are based on a person-mean centering approach, where participants are categorised relative to their own average level of hyper-personalisation across the three waves of the study.

For instance, a participant will be in the **High** personalisation category at a **given** wave if they selected **higher-than-usual** hyper-personalisation content at that specific wave. Likewise, the same or another participant will be in the **Low** personalisation category at a **given** wave if they selected **lower-than-usual** hyper-personalisation content at that specific wave. This relative assessment enables detecting state-like deviations in hyper-personalisation and their association with consumer goal strength at specific time points. As shown in **Table 24**, around **68%** of participants belonged to the **Medium** category, suggesting that the majority of participants were above their mean by no more than **±0.75 standard deviation,** while only around **16%** were in the **Low** or **High** category at a given point of time. This skewed distribution explains the insignificance of *Centered_Selection* on goal strength.

Table 24: *Predicted Goal Strength Across Hyper-Personalisation Levels and Time Per Group*

	Group A *Neutral Framing*		
Wave	**Low Personalisation** *(-0.75 SD)*	**Medium Personalisation** *(Mean)*	**High Personalisation** (+0.75 SD)
Wave 1	30.26	30.25	29.76
Wave 2	30.00	33.71	34.32
Wave 3	33.38	31.09	32.39
%	**15.3% in High Category**	**68% in Medium Category**	**16.7% in Low Category**
	Group B *Negative Framing*		
Wave	**Low Personalisation** *(-0.75 SD)*	**Medium Personalisation** *(Mean)*	**High Personalisation** (+0.75 SD)
Wave 1	30.86	31.07	30.14
Wave 2	30.05	32.41	29.21
Wave 3	33.03	33.33	33.89
	16.3% in High Category	**67% in Medium Category**	**16.6% in Low Category**

To further explain the observed dynamics across Low, Medium, and High hyper-personalisation categories, **Figures 25** and **26** below show the visual growth trajectories of each category, for Group A and B respectively. As *Time* was re-coded to start at value 2, a *Reversed_Time* variable with *Wave 1* = 0 is used for better visuals than using *Time (coded as Wave 1 = 2).* Note that Low, Medium and High refer to *within-person* deviations from each participant's average hyper-personalisation level (±0.75 SD), capturing momentary fluctuations in their selections at distinct time points.

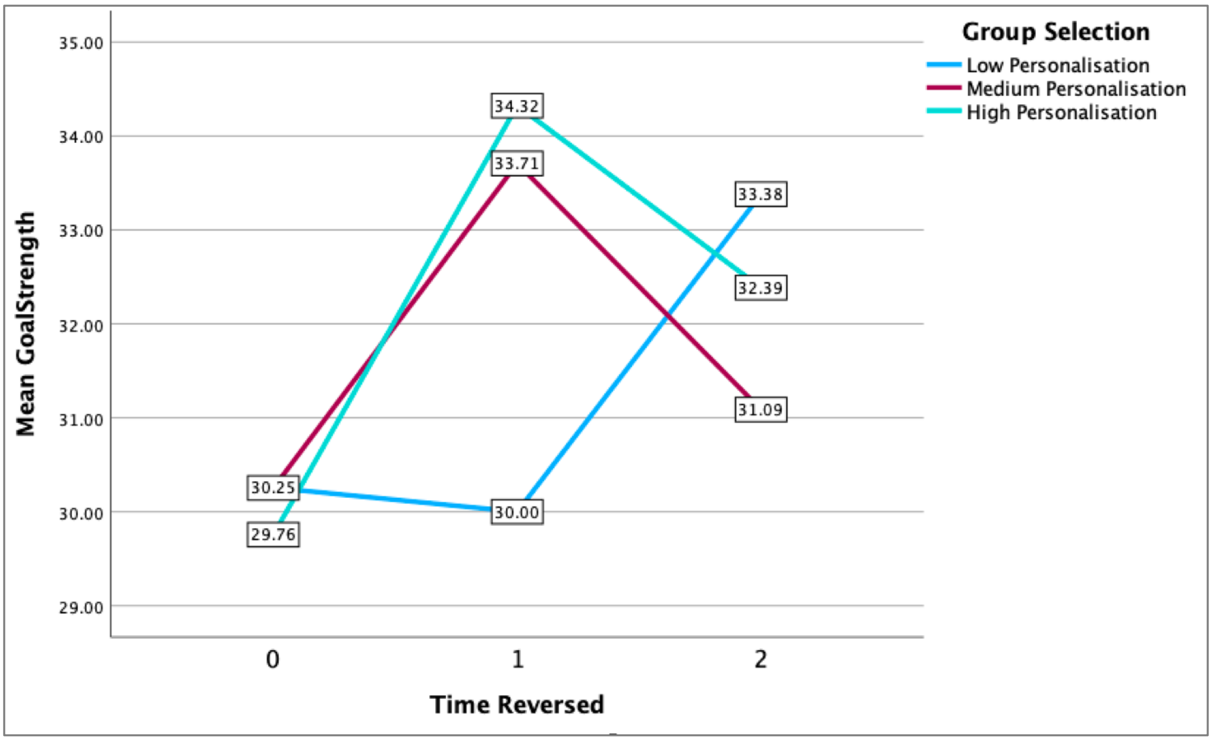


***Figure 25**: Predicted Goal Strength across Hyper-personalisation Categories of Group A*

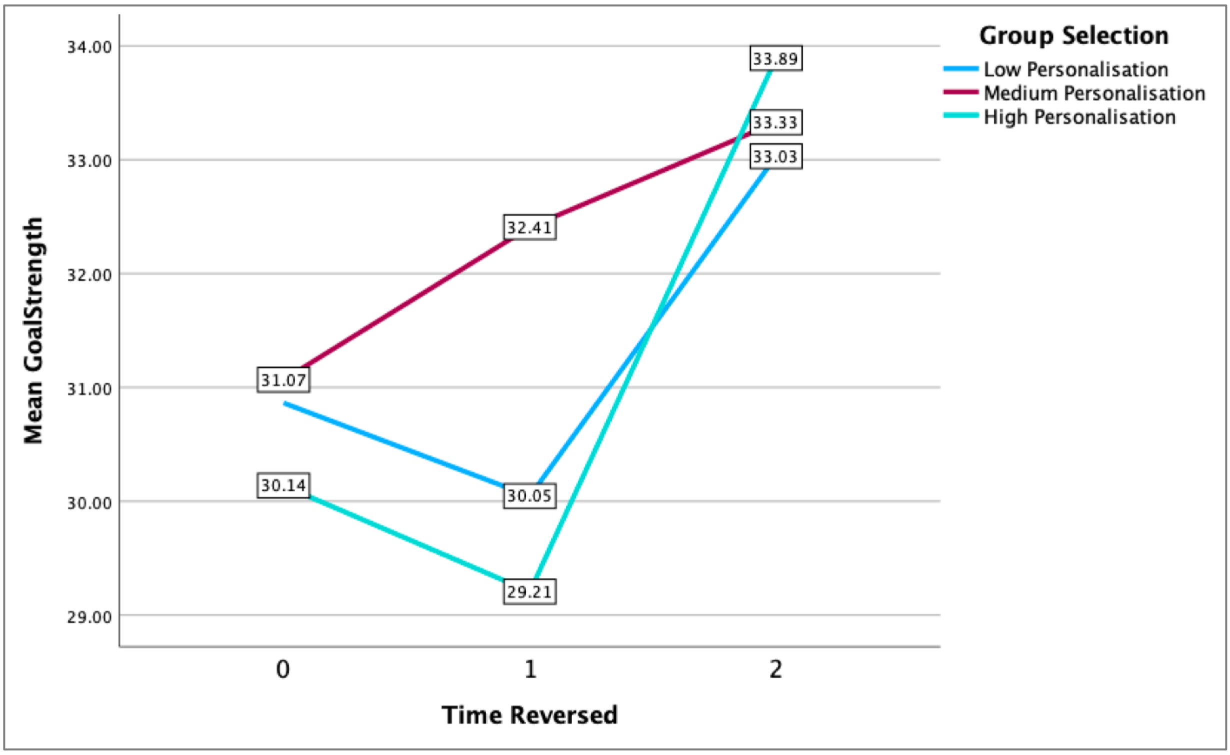


***Figure 26**: Predicted Goal Strength across Hyper-personalisation Categories of Group B*

1. In **Group A (Figure 25)**, at *Wave 2* (10 days after baseline), participants in the Medium and High hyper-personalisation categories demonstrated a **notable spike** in goal strength, confirming that **higher-than-usual** within-person personalisation can enhance short-term consumer goal strength under neutral conditions. This statistically significant increase among participants with higher-than-usual personalisation reinforces **Hypothesis 1 (H1).** This peak effect is consistent with prior research suggesting that initial novelty and relevance of tailored content enhances consumer engagement and conversion rates in digital environments (Albert et al., 2024; Bastani et al., 2021; Polyportis, 2024; Tsay et al., 2020). However, by *Wave 3* (after 5-months), goal strength among these groups declined suggesting a temporal decay in personalised effectiveness over the long-term but remained **above the baseline**. Participants with **higher-than-usual** personalisation (High) still demonstrates **stronger** goal strength than the Medium category, again reinforcing **Hypothesis 1 (H1)**.

   This suggests that the observed insignificance in *Wave 3* (reported earlier) is a **weakened** (**attenuated**) effect, rather than an absence. This decline aligns with *personalisation fatigue* – where consumers become unresponsive to repeated personalisation efforts (Albert et al., 2024; Mustafa et al., 2022; Polyportis, 2024), positing that the initial engagement benefit of personalised content fades without continued novelty or contextual reinforcement. This trend emphasises the value of temporal proximity and framing in sustaining consumer motivation through hyper-personalisation. In other words, without reinforcement, even highly personalised selections do not sustain heightened goal strength over time.

   Interestingly, *Wave 3* reveals an unexpected pattern: participants in the Low hyper-personalisation category showed a localised unexpected increase in goal strength, eventually matching or surpassing those in the High category. This may reflect a recovery effect or delayed engagement, possibly driven by increased habituation or adaptive consumer engagement over time. Such effects align with research suggesting that late adopters of AI-enabled systems – those encountering such systems with lower expectations – may demonstrate delayed engagement or longer-term engagement resilience compared to early adopters who experience engagement saturation faster (Ganuthula et al., 2024; Polyportis, 2024). While participants in the High category experienced a drop in goal strength due to personalisation fatigue – where overly personalised content loses novelty without reinforcement – participants in the Low category may have built up interest over time, resulting in a rebound in their goal strength.

However, Low personalisation category represents only a **small minority (~14%)** of the sample. In contrast, participants in the High and Medium categories – both representing over **80%** of the sample – maintained **higher** goal strength than the baseline and above the Low category across the study. This affirms the robustness of positive association between hyper-personalisation and consumer goal strength, **supporting Hypothesis 1 (H1)**. The spike at *Wave 3* in the Low category may reflect content novelty effects or isolated anomalies that does not undermine the overall pattern.

2. In **Group B (Figure 26)**, participants with **higher-than-usual** personalisation (High category) begins with lower mean goal strength (M = 30.14 at *Wave 1*) but **surges dramatically** by *Wave 3* (M = 33.89), surpassing both Low and Medium hyper-personalisation categories, which despite the initial lag, ultimately **supports Hypothesis 1 (H1)**. This delayed increase suggests that, under negative framing conditions, participants initially reacted cautiously to hyper-personalised content due to heightened privacy concerns, but over time, repeated exposure to relevant and personally meaningful content can help overcome initial scepticism, leading to a delayed boost in engagement and motivational strength. When exposed to highly personalised content under risks of data misuse, consumers may experience discomfort, causing a lower goal strength. This aligns with literature suggesting that negative framing can moderate initial responses to tailored content, but goal-directed motivation may recover or even strengthen when personal relevance persists (Albert et al., 2024). At *Wave 2*, the negative framing may trigger psychological reactance with participants feeling their autonomy compromised (Lukoff et al., 2022; Zhang et al., 2018; 2022), supporting the **moderating** role of *Group* and **Hypothesis 2 (H2)**. Medium category participants, however, experience a more stable pattern striking a balance between relevance and comfort (Aguirre

et al., 2015; Bleier et al., 2020). Negative framing, therefore, does not uniformly suppress goal strength as the effect may be temporally dependent and subject to cumulative relevance effects (Fishbach and Woolley, 2022; Heinonen and Lipkin, 2023).

These observed dynamics in **Low**, **Medium**, and **High** hyper-personalisation categories in both Group A and Group B further illustrates that **Hypothesis 1 (H1)** is **supported** and shows the moderating role of *Group* over time, **supporting Hypothesis 2 (H2)**.

Takeaway:

- **Within-person effects** (time-specific state-like influence): Do individuals experience stronger goal strength at *moments* when they select higher-than-usual levels of hyper-personalisation? ***Answer:*** **Yes, individuals report stronger goal strength when they momentarily select higher-than-usual levels of hyper-personalised content. This effect is temporal (time-dependent) and contextual (Group-dependent), hence supporting Hypothesis 1 (H1).**

➔ **Does Group moderate within-person effects** (time-specific state-like influence): Does the **momentary increases or decreases** in hyper-personalisation have a **stronger or weaker** influence on goal strength depending on the *Group*? ***Answer:*** **Yes, Group (privacy framing condition) significantly moderates the within-person effect of hyper-personalisation on goal strength: hyper-personalisation has stronger effects on goal strength under neutral framing (Group A) and delayed effects under negative framing (Group B), supporting Hypothesis 2 (H2).**

Model 2 Key Interpretation

In summary, both **Hypothesis 1 (H1)** and **Hypothesis 2 (H2)** received strong empirical support under *Model 2* findings:

1. Individuals who **generally** select **higher** levels of hyper-personalisation (between-person effect) consistently reported **stronger** consumer goal strength across time, **confirming Hypothesis 1 (H1)**.

2. Momentary increases in hyper-personalisation (within-person effect) also predicted **stronger** consumer goal strength, particularly in the short-term and under neutral privacy framing conditions (Group A). Although the effect in the long-term or in Group B was not captured in the statistical findings, visual probing illustrated a consistent directional pattern, either attenuated or delayed. This reinforces the contextual and time-specific nature of this pattern, **supporting Hypothesis 1 (H1)** for within-person effects of hyper-personalisation.

3. Although unexpected increases emerged in the momentary Low personalisation category at *Wave 3*, this pattern was limited to a small minority (~14%), hence not contradicting the strong consumer goal strength consistently observed in the High and Medium categories, together representing over 80% of the sample. This demonstrates the robustness of the **positive** effect of within-person hyper-personalisation on consumer goal strength, even with the attenuated or delayed effects demonstrated in the long-term across groups.

4. *Group* (privacy framing condition) significantly moderates the relationship between within-person hyper-personalisation on consumer goal strength, **supporting Hypothesis 2 (H2)**. The moderating effect of *Group* was more pronounced in the short-term and under neutral framing group. The effect, however, was weakened or delayed in the long-term or negative framing group, reinforcing **Hypothesis 2 (H2)**.

5. Importantly, this moderating effect of *Group* did not emerge for stable, trait-like between-person effects of hyper-personalisation, confirming their stability and reinforcing **Hypothesis 1 (H1)**.

The overall findings of *Model 2*, therefore, confirms that both *between-person* (stable trait-like effects) and *within-person* (momentary state-like effects) of hyper-personalisation shape consumer goal strength, *dynamically* moderated by *time* and *contextual framing*.

Table 25: *Summary Table of Model 2 Findings*

Effect	Statistical Result	Interpretation	Hypothesis
Between-Person Effects of Hyper-personalisation			
Grand_SelectionMean (Between-person)	B = 1.072, p = .007	Consumers who *generally* select higher levels of hyper-personalised content report stronger goal strength	**Hypothesis 1 (H1) Supported**
Group × Grand_SelectionMean	F = .135, p = .713 (Not Significant)	Consumers who *generally* select higher levels of hyper-personalisation experience different effects on goal strength based on the *Group* (control group versus experimental)	**Hypothesis 2 (H2) Not Supported in between-person**, Group does not moderate between-person effects, reinforcing trait-like stability of Hypothesis 1 (H1)
Within-Person Effects of Hyper-personalisation			
Centered_Selection (*Within-person*)	B = .089, p = .857 (*Not Significant*)	Do consumers experience stronger goal strength at *moments* when they select higher-than-usual levels of hyper-personalisation? No standalone effect, but meaningful patterns emerged in Group A at wave 2, reinforced with visual probing	Hypothesis 1 (H1) **Supported** *(temporally, contextually, visually)*
Time × Group × Centered_Selection	B = 2.471, p = .021 (wave 2, Group A)	Short-term spike in goal strength under neutral framing	Hypothesis 1 (H1) **Supported** Hypothesis 2 (H2) **Supported** *(temporally, contextually, visually)*
Time × Group	F = 13.612, p < .001	Time effects vary by *Group*, confirming temporal moderation	Hypothesis 2 (H2) **Supported**

Group × *Centered_Selection*	F = 4.890, p = .027	Do consumer experience different effects on goal strength at *moments* when they select higher-than-usual levels of hyper-personalisation based on the *Group* (control group versus experimental)?	Hypothesis 2 (H2) **Supported** **Group moderates within-person effects**

Overall, this summary affirms that:

- **Hypothesis 1** is **supported** across both *between-person* and *within-person* levels of hyper-personalisation. Consumers who ***generally*** (*between-person*) or ***momentarily*** (*within-person*) engage with higher levels of hyper-personalised content report stronger consumer goal strength. This was confirmed by the statistically significant effects at between-person level, and the temporal, contextual, and visual significance at the within-person level. The within-person effects were more pronounced in the short-term under neutral framing and in the long-term under negative framing, with implications aligning with prior theoretical findings.

- **Hypothesis 2** is **supported** for *within-person* effects only, where *Group* (privacy framing) moderates the relationship between momentary increases in goal strength. This effect was statistically significant in the short-term and under neutral framing, and visually confirmed in the long-term under negative framing, demonstrating an attenuated or delayed effect. The absence of moderation effects for *between-person* influences reinforces the stability of trait-level hyper-personalisation on consumer goal strength, while the moderated momentary state-level effects support the dual-level nature of hyper-personalisation dynamics.

4.4.4.3 Model 3: Post-Hoc Exploratory Model

A linear mixed-effects model (*Model 3*) was conducted as a **post-hoc exploratory** analysis to explore the role of perceived hyper-personalised importance in predicting consumer goal strength, and on the relationship between hyper-personalisation and consumer goal strength. Specifically, the model assessed the relationship between perceived importance and both trait-level and state-level hyper-personalisation in shaping consumer goal strength across time and group conditions.

Model 3 included fixed effects for *Time* and *Group* as well as the perceived importance of personalisation (*PersonalisedImportance),* and its interactions with:

- *Grand_MeanSelection* (trait-like hyper-personalisation across time)
- *Centered_Selection (*state-like, momentary deviations from an individual's mean)
- Higher order interactions involving *Time* and *Group*

This model was not part of the original hypothesis testing but was introduced after observing patterns in participant responses during data analysis. Captured as a 7-Likert scale during *Wave 1* part of profile building, the *PersonalisedImportance* variable was included based on its emerging relevance and was used to explore whether the motivational value of hyper-personalisation is enhanced when consumers personally value it - Refer to *section 4.3.1*.

Model Rationale and Specification

As one of the profile questions in the experiment captured the perceived importance of hyper-personalisation, this measure served as a valuable psychological variable. Its inclusion allowed for testing whether subjective beliefs about hyper-personalisation contributed to goal-directed behaviour, beyond system design or exposure to hyper-personalised content alone. *Model 3* specifically explored:

- Whether participants who perceived hyper-personalisation as more important experienced greater consumer goal strength (i.e., main effect of *PersonalisedImportance*)

- Whether trait-like or momentary hyper-personalisation preferences were more effective in motivating consumers when perceived as personally important (i.e., moderation effects)

- Whether these effects changed over time and varied by experimental group

This analysis aligns with emerging literature that emphasises the psychological relevance of personalisation. It complements earlier models by focusing not only on behavioural interactions but also on users' subjective interpretation, consistent with theories of goal motivation and psychological need satisfaction (Albert et al., 2024; Hutmacher and Appel, 2023; Ryan and Deci 2000).

This model primarily investigates between-individual (trait-level) and within-individual (state-level fluctuations) effects using the grand mean centered (*Grand_SelectionMean)* and person-mean centered *(Centered_Selection)* variables, earlier used in *Model 2,* in interaction with *PersonalisedImportance*. The model tested whether these effects are strongly associated with goal strength when perceived as personally important, and whether these effects vary across the three time points. In summary, *Model 3* was introduced to capture the psychological dimension of hyper-personalisation and provide insights into ***when*** and for ***whom*** personalisation strategies are most effective. **Table 26** summarises *Model 3* specification.

Table 26*: Model 3 Specification Summary*

Model Component	**Specification**	**Purpose**
Fixed Effects (*Main*)	▪ *Time* (3 waves) ▪ *Group* (Neutral *Group A* versus Negative Privacy Framing *Group B*) ▪ *PersonalisedImportance* – continuous, time-invariant variable	Tests main effects of Time, Group, and importance of hyper-personalisation *on* consumer goal strength across time points
Fixed Effects (*Interaction*)	▪ *Time x Group* ▪ *Time x PersonalisedImportance* ▪ *Group x PersonalisedImportance* ▪ *Grand_SelectionMean x PersonalisedImportance* ▪ *Centered_Selection x PersonalisedImportance* ▪ *Time x Group x PersonalisedImportance*	Tests interaction effects of Time with importance of hyper-personalisation and between- and within-person to examine its effects.
Random Effect	*Intercept* by participant (ID)	Accounts for baseline differences and individual

		variation in change trajectories across waves.
Repeated Measure	*Time* treated as a repeated measure with an unstructured covariance matrix	Allows flexible estimation of within-person temporal relationships and irregular measurement intervals.
Estimation Method	Restricted Maximum Likelihood (REML)	Ensures unbiased, stable variance estimates

Model 3 Statistical Findings

Refer to **Tables A.B.9** and **A.B.10** in **Appendix B** for full statistical outputs of *Model 3* and its model fit. Key findings are summarised below:

Main Effects:

1. *Time* has a **statistically significant** effect on consumer goal strength, F (2, 1106.72) = 106.4, p < .001. Specifically, *GoalStrength* was **significantly higher** at *Wave 3* (B = 19.881, p < .001) compared to *Wave 2* (B = 15.923, p < .001) compared to the reference time point (*Wave 1*). These results indicate temporal shifts in motivation over time following exposure to hyper-personalised experiences.

2. Perceived Importance was a **strong positive** and **statistically significant** predictor of consumer goal strength, F (1, 1255.303) = 358.69, p < .001. The effect size was substantial with a **statistically significant** coefficient (B = 4.784, p < .001, 95% CI [4.313, 5.254]), indicating that individuals who rated hyper-personalisation as more important also reported **stronger** motivational engagement. This underscores the role of psychological relevance in enhancing the impact of personalisation strategies.

3. *Group* had no significant main effect, on its own, on *GoalStrength*, F (1, 1307.37) = 0.265, p = .607. This is consistent with findings from *Model 2*, suggesting that group assignment (privacy framing condition) did not independently influence goal strength when considered outside the context of interaction effects.

Two-way Interaction Effects:

1. Interaction with *Time* was **positive** and **statistically significant**, F (1, 1107.999) = 89.037, p < .001, with effects being more pronounced at *Wave 2* than *Wave 3* – indicating a temporal variation in how perceived importance influenced consumer goal strength. The influence was strongest at **baseline** (*Time* = 2, reference wave) but became increasingly negative over time.
   - *At Wave 2 (at 10 days),* B = -2.727, SE = .239, p < .001
   - *At Wave 3 (at 5 months),* B = -3.084, SE = .283, p < .001

   These results suggest that the impact of perceived importance on goal strength diminishes over time, pointing to a potential decline in motivational salience without reinforcement.

2. Interaction with *Grand_MeanSelection* (trait-like between-person) was **statistically significant**, F (1, 1536.91) = 17.52, p < .001, with a **positive** and **statistically significant** coefficient (B = .171, SE = .041, p < .001, 95% CI [.091, .251]). This indicates that individuals who perceived hyper-personalisation as personally important showed **stronger** effects of **trait-like** hyper-personalisation on *GoalStrength*. In other words, perceived importance amplified the motivational value of dispositional hyper-personalisation. This finding supports the idea that trait-like influences benefit from alignment with personally meaningful beliefs.

4. Interaction with *Centered_Selection* (state-like within-person) was **not significant**, F (1, 2152.64) = 1.287, p = .257, with a **not significant** coefficient (B = .034, SE = .030, p = .257, 95% CI [-.025, .092]). This suggests that the effect of perceived hyper-personalisation importance did not significantly moderate the relationship between the momentary fluctuations of hyper-personalisation on *GoalStrength*. The influence of perceived importance appears to operate primarily at the **trait** rather than **state** level.

5. Interaction with *Group* was **not significant**, F (1, 1317.885) = 0.663, p = .416, indicating that the effect of perceived importance on goal strength was not moderated by *Group* as a condition. This implies that the motivational

influence of perceived importance remained consistent across both framing groups, at least when not considered in interaction with *Time*.

Three-way Interaction Effects:
The three-way interaction *Time, Group, and Perceived Importance* was **statistically significant** with $F(2, 1172.70) = 15.76$, $p < .001$. Follow-up analysis of the interaction effects at each time point revealed two key patterns:

- At *Time* = 1 (*wave 2 at 10 days)* and for Group A *(neutral framing)*, the three-way interaction was **statistically significant** and **positive** with ($B = .329$, $SE = .111$, $p < .001$), suggesting that participants in the neutral framing condition who rated perceived importance of hyper-personalisation as more personally important exhibited **greater** consumer goal strength at *Wave 2* (10 days). This finding underscores the motivational value of endorsing hyper-personalisation as personally important on consumer goal pursuit.

- At *Time* = 0 (*Wave 3 at 5 months)* and Group A *(neutral framing)*, the three-way interaction was **statistically significant** but **negative** with ($B = -.323$, $SE = .134$, $p < .016$), suggesting that participants with higher perceived importance of hyper-personalisation reported **lower** consumer goal strength at *Wave 3* (*5 months later*) when placed in the neutral framing group. This pattern indicates that the motivational influence of personal importance of hyper-personalisation weakens without reinforcement, even among individuals who initially viewed hyper-personalisation as relevant to their active life goals.

These post hoc exploratory findings provide valuable insights into how consumers perceive the importance of hyper-personalisation. Implications of these findings are discussed in **Chapter 5** section 5.1.3.

4.5 Summary of Findings

This chapter examined how hyper-personalisation influences consumer goal strength over time, accounting for contextual framing, perceived importance, and psychological dynamics through three Linear Mixed Models (LMMs). The analysis addressed two main hypotheses, integrating both *between-person* (trait-like) and *within-person* (state-like) variations, with attention to moderators such as privacy framing and subjective importance to capture motivational complexity.

Hypothesis 1 (H1): *Higher levels of hyper-personalisation significantly increase consumer goal strength over time*

Three models explored this relationship:

1. **Model 1: Temporal Growth in Goal Strength**
   Results confirmed significant temporal variation, showing that consumer goal strength evolves *non-linearly* over time. This validated the use of longitudinal models to capture both individual and contextual changes in motivation.

2. **Model 2: Trait- and State-Level Effects**
   - At the trait level (*Grand_SelectionMean*), consumers who consistently engaged with higher hyper-personalisation reported stronger and more sustained goal strength, supporting Hypothesis 1 (H1). This aligns with Goal Systems Theory (GST), where habitual, goal-aligned behaviour fosters persistence (Kruglanski et al., 2002; 2015; Kruglanski and Szumowska, 2020).

   - At the state-level (*Centered_Selection*), short-term behavioural shifts alone did not predict goal strength, but became significant when interacting with *temporal* and *contextual* factors. Neutral framing exhibited a brief motivational boost that diminished over time - calling for reinforcement over time. Conversely, risk-based framing led to slower but more durable recovery and engagement when privacy concerns subsided. These findings confirm that context and timing shape motivation.

Hypothesis 2 (H2): *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

Significant *Time* × *Group* interactions showed that under neutral framing, goal strength peaked early (*Wave 2*) and then plateaued, whereas under risk-based framing, motivation increased gradually, indicating trust recovery following initial scepticism. A *Group* × *trait-level hyper-personalisation* interaction revealed that privacy framing moderated the relationship between personalisation and goal strength, reinforcing the temporal and contextual sensitivity of personalisation effects (Fishbach and Woolley, 2022; Lukoff et al., 2022; Ryan and Deci, 2023).

3. **Model 3: Perceived Importance as Psychological Relevance**
   A post hoc analysis explored how perceived importance influenced motivation. Perceived importance was a strong and consistent predictor of goal strength across all time points. A significant three-way interaction (*Time* × *Group* × *Importance*) showed that under neutral framing, importance spiked early but declined without reinforcement—demonstrating the fragile, time-sensitive nature of motivation. When consumers viewed personalisation as personally meaningful and aligned with their active goals, motivation was amplified and sustained, especially when aligned with trait-level behaviour.

Overall Findings

Across all three models, the results demonstrate that:

- Consumer goal strength is dynamic and time-sensitive.
- Trait-level hyper-personalisation predicts stronger, more stable motivation (H1).
- State-level effects depend on contextual and belief-based moderators (H1).
- Privacy framing shapes both timing and intensity of motivation (H2).
- Subjective importance enhances trait-like effects when personalisation is meaningful.

These findings affirm that goal-congruent personalisation is most effective when it is *consistent*, *meaningful*, and *contextually reinforced* — advancing both personalisation theory and practical applications in digital engagement strategies. Sustained engagement depends on continuous novelty, relevance, and adaptability

(Albert et al., 2024; Ganuthula et al., 2024; Polyportis, 2024), supporting Consumer-Dominant Logic (CDL) that value is co-created, shaped, and reframed by consumers over time through evolving goals and experiences (Heinonen and Strandvik, 2015; 2022). This reinforces the need for service providers to design personalisation strategies that align with consumers' own life goals, accounting for temporal and contextual effects over time.

4.6 Chapter Summary

This chapter outlined the theoretical and methodological frameworks underpinning the study, including the integration of discrete choice model (DCM) informed by a learning automata algorithm with Generalised Linear Mixed Model (GLMM) using a multinomial logit specification. It detailed the experimental design, from the pilot study to the main experiment, describing how key variables were operationalised and data was collected and pre-processed for analysis.

The chapter also introduced the data analytical strategy, which employed an individual growth curve modelling (IGCM) approach using Linear Mixed Models (LMMs). Three models were developed sequentially:

1. **Model 1**: An unconditional growth model establishing baseline variation in consumer goal strength over time.

2. **Model 2**: A theory-driven hypothesis model testing the two main hypotheses using trait- and state-level hyper-personalisation and privacy framing.

3. **Model 3**: A post-hoc exploratory model assessing the psychological role of perceived hyper-personalisation importance.

Together, these models provide a comprehensive foundation for examining how hyper-personalisation, context, and belief shape consumer goal strength over time in digital environments — particularly when aligned with consumers' evolving life goals.

Chapter 5 – Findings and Discussion

5. Findings and Discussion

This chapter interprets the empirical results presented in **Chapter 4**, situating them within the broader theoretical and empirical literature to address the study's central research question: *"How does goal-aligned hyper-personalisation influence consumer goal strength within AI-enabled, multi-actor ecosystems over time?"*

The analysis is based on the longitudinal data collected across three experimental waves, employing Linear Mixed Models (LMMs) to capture both *between-person* and *within-person* variations in consumer goal strength over time. The primary aim of this chapter is to reflect on the findings of these models to verify the two main hypotheses and to explore how AI-enabled hyper-personalisation influences consumer goal strength over time.

Insights from the Linear Mixed Model (LMM) analyses are integrated with existing research on consumer motivation, personalisation, and privacy to explain the theoretical and contextual significance of the observed patterns. In doing so, the discussion extends understanding of the temporal and situational dynamics that underpin consumer goal engagement.

The chapter is organised around two main objectives. The first is to interpret the results in relation to the two central hypotheses, discussing their implications for hyper-personalisation, motivation, and goal pursuit. The second is to synthesise these interpretations in relation to the overarching research framework, linking empirical insights to the study's conceptual model and theoretical foundations. The chapter provides a mapping of the empirical findings to the central research question and its five sub-questions (RQ1–RQ5 presented in **Chapter 1**), highlighting key insights and contributions derived from the analyses and forming the foundation for the interpretive discussion that follows.

5.1 Key Implications

To interpret the findings in light of the study's hypotheses and conceptual framework, this section discusses the theoretical and practical implications of the three Linear Mixed Models (LMMs) introduced in **Chapter 4**. These models collectively illustrate how hyper-personalisation influences consumer goal strength across *temporal*, *contextual*, and *behavioural* dimensions.

Hypothesis 1 (H1): *higher levels of hyper-personalisation would significantly increase consumer goal strength over time*

Hypothesis 2 (H2): *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

The discussion that follows is organised around the three interrelated Linear Mixed Models (LMMs), each addressing a distinct analytical objective. Together, these models provide complementary insights into the motivational, personalisation-privacy, and subjective dimensions of consumer goal strength.

- **Model 1**: Unconditional growth model — establishes the baseline trajectory of consumer goal strength over time.

- **Model 2**: theoretical hypothesis model — tests the *between-person* and *within-person* effects of hyper-personalisation on consumer goal strength and the moderating role of privacy framing.

- **Model 3**: Post-hoc exploratory model — examines emergent subjective perceptions of personalisation and their influence on goal strength.

Each model offers increasingly refined insights into the dynamics of hyper-personalisation and motivational engagement. The following sub-sections interpret the findings from these models in relation to the study's hypotheses, highlighting their theoretical relevance and implications for the broader conceptual framework.

5.1.1 Motivational Trajectory of Goal Strength

Model 1 served as a foundational growth model by establishing a baseline trajectory of consumer goal strength over time. This model examined how consumer goal strength evolves *independent* of any hyper-personalisation effects. Findings confirmed that, on average, consumer goal strength increased significantly following exposure to AI-enabled hyper-personalised services at each of the three time points. Specifically, significant growth in consumer goal strength was observed in both the short-term (after 10 days) and long-term (after 5 months), indicating that goal strength is **dynamic** rather than static — shaped continuously through repeated consumer-service interactions.

This finding reflects a broader understanding of consumer engagement as **accumulative**, aligning with a core principle of the **Consumer-Dominant Logic (CDL)** framework, underlying this study. CDL posits that value is co-created and framed through ongoing experiences embedded in consumers' lives and ecosystems, rather than single service interactions (Heinonen and Strandvik, 2022; Lipkin and Heinonen, 2022; Heinonen, 2023). As consumers repeatedly engage with AI-enabled services, their motivational alignment appears to intensify — suggesting that longitudinal reinforcement may be more effective than isolated exposures. The observed uplift in consumer goal strength over subsequent time waves aligns with the concept of *accumulative value realisation* — whereby consumers continuously evaluate content relevance in relation to their evolving life goals.

From a practical standpoint, these findings indicate that service providers can foster stronger and more sustained behavioural outcomes with continued reinforcement strategies over time.

Importantly, *Model 1* also revealed significant **intra-** and **inter-individual** variability across time, highlighting that motivational trajectories are not uniform across and within individuals. While some participants exhibited early and steady gains, others displayed fluctuating or delayed trajectories. This variability underscores compelling justification for applying Linear Mixed Models (LMMs) to capture nuanced, individual-level dynamics that might account for such differences – specifically hyper-personalisation levels, privacy framing, and subjective perceptions.

This heterogeneity suggests that what influences one consumer may not necessarily influence another. Accordingly, these insights advocate for an *individual-centric* approach to designing hyper-personalisation strategies that adapt to both immediate and sustained motivational states. In other words, a *one-size-fits-all* model of personalisation is insufficient for fostering long-term engagement. Instead, service providers must design AI-enabled systems that are sensitive to both initial and sustained motivational patterns, *dynamically* adapting over time to maintain evolving consumer contexts and motivational momentum.

In summary, this baseline model contributes by providing the benchmark for understanding motivational growth in consumer goal strength, forming the reference point against which the additional effects of hyper-personalisation privacy framing, and subjective importance (explored in subsequent models) can be evaluated. The findings provide *foundational* support for **Hypothesis 1 (H1)**, confirming that consumer goal strength increases significantly over time, illustrating a dynamic and accumulative motivational trajectory rather than a static pattern. This establishes the empirical foundation enabling service providers to understand how motivation and engagement evolve *longitudinally* within AI-enabled consumer ecosystems – a key theoretical contribution to CDL's longitudinal perspective on value formation.

5.1.2 Personalisation and Privacy Dynamics

Model 2 revealed critical insights into how hyper-personalisation and privacy framing jointly influence consumer goal strength over time. Interpreted through the lens of Consumer-Dominant Logic (CDL), these results highlight that consumers do not passively receive personalised content; rather, they *actively* construct meaning from their interactions with AI-enabled systems, endorsing or rejecting personalised information based on its alignment with their values, evolving life goals, and perceived privacy boundaries.

A central implication of these findings is the distinction between *stable*, *trait-like* preferences and *momentary, context-dependent* responses to hyper-personalised content. Consistent with **Hypothesis 1 (H1)**, consumers exhibiting strong, goal-aligned personalisation preferences demonstrated more consistent and sustained engagement across time, suggesting that hyper-personalisation becomes meaningful when it reflects internal motivational alignment rather than transient novelty. In contrast, temporary reactions are driven more by contextual triggers and perceived risks. This finding aligns closely with **Goal Systems Theory (GST)**, which posits that long-term consumer engagement is sustained when hyper-personalised experiences reinforce intrinsic life goals rather than eliciting reactive responses to contextual cues (Kruglanski et al., 2002; Kruglanski and Szumowska, 2020). In this sense, hyper-personalisation becomes most meaningful when it reflects *internal alignment* – when content resonates with consumers' enduring values and sense of purpose.

These implications align with recent literature demonstrating that stable personalisation preferences predict sustained engagement and satisfaction across digital service contexts (Behera et al., 2024; Nwanna et al., 2025). AI-enabled systems that deliver *dynamically* tailored content ensure alignment with users' enduring values, thereby optimising engagement and perceived utility (Hardcastle et al., 2025; Fishbach and Woolley, 2022). This process aligns with the CDL principle of *value alignment*, where content congruent with consumers' self-endorsed goals enhances emotional value, satisfaction, and perceived control (Albert et al., 2024; Ryan and Deci, 2017).

Conversely, *momentary fluctuations* in engagement revealed that short-term spikes in motivation often decayed without consistent informational reinforcement. These transient effects indicate that hyper-personalisation can lose salience when driven by novelty rather than sustained relevance (Hornray et al., 2019; Mustafa et al., 2022; Schmidt-Kraepelin et al., 2019; Tsay et al., 2020). This finding reinforces emerging perspectives of *state-dependent* personalisation, where temporary engagement occurs when hyper-personalised content matches immediate emotional or contextual relevance (Ford et al., 2023; Tzavar et al., 2023). Such findings call for adaptive strategies that synchronise **long-term** motivational reinforcement with **short-term** contextual sensitivity.

Importantly, this sustained engagement is not easily disrupted by privacy concerns. While early stages of the study showed reduced motivation among participants exposed to risk-based framing, long-term findings revealed that those with stronger hyper-personalisation preferences continued to exhibit high goal strength. This suggests that when personalised content is perceived as *ethically aligned* and *personally relevant*, it can override external barriers and reinforce motivational continuity over time. These insights highlight the **ethical** dimension of hyper-personalisation — underscoring that *transparent* and *trust-based* design can maintain engagement even when privacy sensitivity is heightened.

Consistent with **Hypothesis 2 (H2)**, *Model 2* revealed the moderating role of privacy framing, underscoring the dual *ethical* and *psychological* influence of privacy in shaping engagement outcomes. Under neutral framing, consumers demonstrated faster and deeper engagement — particularly at early stages — whereas under risk-based framing, engagement weakened or delayed, especially among consumers with moderate personalisation preferences. This pattern reveals that consumers' trust, perceived safety, and autonomy significantly mediate how hyper-personalisation is interpreted and acted upon (Lukoff et al., 2022; Darmody and Zwick, 2020; Lumbreras, 2018). Where privacy concerns are heightened, engagement may decline unless transparent communication and ethical reassurance are embedded within the design of the AI-enabled experience (Ryan et al., 2022; Fernandez et al., 2022). This suggests that both environmental stimuli and contextual factors can either support or undermine an individual's ability to pursue a behaviour willingly and proactively in the long-term.

Collectively, these insights reinforce the CDL perspective that value is not delivered to consumers but rather co-created and framed through ongoing interactions between personalised content, contextual cues, and individual interpretation (Heinonen and Strandvik, 2022). From a practical standpoint, this implies that service providers must move beyond static user profiling to design *adaptive*, *goal-aligned*, and *ethically framed* personalisation systems that respect consumer agency, accommodate privacy sensitivities, and align with users' evolving life goals (Amoo et al., 2024). This reinforces the idea that delivering personally relevant and meaningful hyper-personalisation is insufficient. The way it is ***framed*** and ***communicated*** is just as important — a principle central to the Consumer-Dominant Logic (CDL) perspective.

In summary, the implications of *Model 2* extend the theoretical reach of CDL by integrating *behavioural*, *contextual*, and *ethical* dimensions of hyper-personalisation. The findings reinforce **Hypothesis 1 (H1)** by confirming that higher levels of hyper-personalisation enhance consumer goal strength, while also providing strong empirical support for **Hypothesis 2 (H2)**, which establishes that this effect is moderated by privacy framing.

Together, these insights demonstrate that sustained consumer engagement depends not merely on the intensity of personalisation but on its value congruence, goal alignment, and ethical framing. Practically, this model underscores the importance of designing *transparent*, *trust-driven*, and *goal-aligned* AI personalisation systems that can maintain motivational relevance and behavioural persistence across time — reinforcing the principle that how personalisation is *framed* and *communicated* is as critical as personalisation itself.

5.1.3 Subjective Importance and Goal Strength

The findings from *Model 3*, the post-hoc exploratory model, provide deeper insight into the subjective and psychological mechanisms underpinning consumers' engagement with hyper-personalisation, highlighting how the **perceived importance** of personalised content strengthens motivational commitment and consumer goal pursuit over time. Unlike the preceding two models that focused primarily on behavioural and contextual predictors, this model explores the psychological interpretation of hyper-personalisation — how it is not only acted upon but also perceived as personally meaningful, valuable, and worth pursuing.

Findings indicate that hyper-personalisation is most effective when consumers **endorse** and **believe** in its personal value. Consumers who rated AI-enabled personalised content as highly important consistently demonstrated stronger goal strength, reinforcing that psychological endorsement amplifies perceived value and deepens motivational engagement. This insight advances existing literature by emphasising that personalisation's influence is sustained not merely by behavioural relevance, but by consumers' *emotional* and *cognitive* recognition of meaning. This aligns with recent research suggesting that perceived importance of technology-enabled services enhances engagement by fostering a sense of personal significance and emotional connection (Xia and Shannon, 2025). Consumers are more likely to stay committed when they believe the technology delivers personal and meaningful value that is important to them.

However, *Model 3* also reveals that the motivational influence of perceived importance is **time-sensitive**. Its impact was strongest in the short term (at 10 days post-exposure) but diminished over extended periods, underscoring the need for reinforcement mechanisms to sustain relevance. This pattern reflects a process of motivational decay, in which engagement wanes unless personalisation continues to be *contextually renewed* and *emotionally validated*. Practically, this insight signals the need for service providers to design adaptive reinforcement cycles that preserve consumers' sense of meaning and value beyond initial engagement — rather than focus only on static delivery of AI-enabled personalisation features.

These findings collectively demonstrate that behavioural personalisation alone is insufficient — it becomes motivationally powerful only when consumers perceive it as *personally important* and *meaningful*. Over time, this emotional connection can fade unless dynamically realigned with evolving preferences and life goals (Gantubula et al., 2024; Polyvortis, 2024). Importantly, the results reveal an interaction effect between subjective importance and *stable, trait-level* personalisation preferences. When both are aligned, consumer goal strength remains significantly elevated; when misaligned, motivational engagement declines sharply. This finding reaffirms that the effectiveness of hyper-personalisation strategies depends on personal endorsement as much as system precision.

From a Consumer-Dominant Logic (CDL) perspective, these results reinforce the theoretical proposition that value is co-created and framed through consumers' lived interpretation rather than passively received through system outputs (Heinonen and Strandvik, 2024). The **meaning** consumers attribute to hyper-personalised experiences becomes the true driver of engagement and sustained motivation. Behavioural targeting alone cannot generate enduring goal pursuit; rather, the **perceived personal relevance** of these experiences determines their motivational strength (Li et al., 2024), regardless of the actual level of personalisation used. This contributes to CDL perspective by illustrating how psychological significance functions as an *internal mechanism* through which value is co-constructed in AI-enabled ecosystems (Heinonen and Strandvik, 2021). When consumers assign importance to hyper-personalisation, their motivational engagement and behavioural outcomes deepen, indicating that service relevance is both constructed and contextualised.

The Self-Determination Theory (SDT) provides a complementary lens for interpreting these findings. Consumers sustain engagement when interactions with technology fulfill intrinsic needs for autonomy, competence, and relatedness (Ryan et al., 2022; Spiel et al., 2018). Under these conditions, hyper-personalisation becomes a source of self-endorsed motivation—perceived as enriching, goal-aligned, and self-relevant rather than imposed or manipulative. As Albert et al. (2024) argue, perceived value and personal meaning drive sustained engagement more powerfully than objective accuracy in content delivery. Thus, *Model 3* enriches **Hypothesis 1 (H1)** by emphasising that hyper-personalisation achieves its greatest motivational effect when both *behavioural alignment* and *psychological endorsement* converge.

Practically, these insights suggest that service providers should prioritise the *internalisation* of personal meaning within hyper-personalised experiences. Rather than relying on technical precision or static content tailoring, successful AI-driven strategies must evoke *subjective significance* — ensuring that consumers perceive interactions as personally enriching and self-consistent. Grounded in the Technology Acceptance Model (TAM), this implies that perceived usefulness, importance, and personal relevance jointly underpin behavioural intentions and sustained engagement (Li et al., 2024; Guo and An, 2025). Mehmood et al. (2023) argue that the adoption of technology-enabled services is positively and significantly driven by how important users perceive them to be, *independently* from the actual use of the service. Perceived importance thus functions as an affective driver, bridging technological engagement and intrinsic motivation, particularly in long-term digital contexts (Blau et al., 2020).

Overall, although exploratory in nature and not validating hypotheses, *Model 3* offers a crucial contribution by shifting attention from behavioural targeting to subjective meaning-making. It establishes a strong psychological link between perceived importance and consumer goal strength, emphasising that motivational engagement is both behavioural and psychologically endorsed. **Theoretically**, it validates the CDL principle that value is *co-constructed* through *dynamic interpretation*. **Empirically**, it demonstrates that motivational outcomes depend on the *internal validation* of personalisation by the consumer. **Practically**, these findings encourage service providers to design hyper-personalisation strategies that transcend functional accuracy and behavioural predictions, integrating *emotional*, *ethical*, and *psychological* resonance to foster enduring consumer–service relationships.

5.1.4 Mapping to Central Research Question

To clearly link the empirical findings presented in *Sections 5.1.1 – 5.1.3* to the study's overarching research framework, **Table 27** maps how the results from the three Linear Mixed Models (LMMs) collectively address the **central research question (RQ)** and its five sub-questions (**RQ1 – RQ5**, in *Section 1.2*). Together, the models demonstrate how hyper-personalisation influences consumer goal strength both *temporally* and *contextually*, offering a comprehensive perspective on the dynamic, motivational processes underpinning consumer engagement over time.

Model 1 established the baseline motivational trajectory, validating the longitudinal framework and confirming that consumer goal strength evolves significantly through repeated interactions. *Model 2* tested the study's theoretical hypotheses, reinforcing **Hypothesis 1 (H1)** by verifying the direct positive influence of hyper-personalisation on goal strength, while also supporting **Hypothesis 2 (H2)** by demonstrating that this effect is moderated by privacy framing and highlighting the *ethical* and *contextual* contingencies of personalised engagement. *Model 3*, the post-hoc exploratory model, extended these insights by revealing the *psychological significance of subjective importance*, illustrating that perceived personal relevance amplifies or diminishes motivational outcomes, thereby enriching the interpretation of **Hypothesis 1 (H1)** through a deeper understanding of consumer *meaning-making*.

Collectively, these findings provide an integrated answer to the study's central research question: *How does goal-aligned hyper-personalisation influence consumer goal strength within AI-enabled, multi-actor ecosystems over time?*

The longitudinal findings further confirmed the theoretical proposition that *temporal proximity* — the interval between measurement points — plays a decisive role in shaping goal trajectories. Consistent with theoretical expectations outlined in **Chapter 3** (Ajzen and Kruglanski, 2019; Fishbein and Ajzen, 2010), shorter temporal distances (*Wave 2* at 10 days) generated immediate motivational boosts, while longer proximities (*Wave 3* at 5 months) reflected goals-means reconfiguration due to intervening experiences and contextual reassessment. This demonstrates that hyper-personalisation's impact is not static but *temporally contingent*, with sustained engagement depending on reinforcement and evolving interpretations of privacy and personal relevance over time.

The results demonstrate that sustained engagement arises not merely from the intensity of personalisation, but from its alignment with consumers' values, privacy perceptions, and perceived importance. This validates the study's longitudinal design and contributes to the conceptual understanding of *goal-aligned* hyper-personalisation as both a *motivational* and *ethical process* within *AI-enabled, multi-actor ecosystems over time*.

Together, the findings mapped to the central research question and its sub-questions in **Table 27** below form the empirical foundation for the broader discussion that follows in *Section 5.2*, integrating these insights with theoretical and practical implications.

Table 27: *Mapping of Empirical Findings to Research Question (and Sub-Questions)*

Research Question	Key Findings	Main Contribution
Central RQ: *How does goal-aligned hyper-personalisation influence consumer goal strength in AI-enabled, multi-actor consumer ecosystems over time?*	Goal-aligned hyper-personalisation **positively** and **dynamically** influences consumer goal strength **over time**. Longitudinal findings revealed *trait-like stability* and *state-like adaptability*, moderated by privacy framing and perceived importance.	1. Demonstrated that hyper-personalisation is a *dynamic, evolving* process rather than static one-size-fits-all. 2. Integrates *temporal*, *contextual*, and *psychological* dimensions of engagement. 3. Extends CDL by showing how these dynamics unfold *within AI-enabled, multi-actor* ecosystems.

<table>
<tr><td>RQ1: To what extent does goal-aligned hyper-personalisation predict consumer goal strength across different points in time?</td><td>Goal strength increases significantly over time, confirming both short-term (10 days) and long-term (5 months) effects of hyper-personalisation. Longitudinal analysis revealed sustained engagement over waves.</td><td>1. Validates the temporal progression of goal alignment across varying time proximities (short versus long).
2. Reinforces longitudinal LMMs for modelling adaptive behavioural change over time.</td></tr>
<tr><td>RQ2: What is the role of privacy framing and the perceived importance of hyper-personalisation in moderating or mediating this relationship?</td><td>1. Neutral framing amplifies the positive effect on goal strength, risk-based framing weakens it.
2. Perceived importance enhances sustained engagement, even under privacy concerns.
3. Both findings reveal the need for reinforcement.</td><td>1. Reveals contextual and ethical sensitivity of hyper-personalisation.
2. Demonstrates privacy framing as a dynamic (rather than static) evolving inhibitor whose influence weakens over time.
3. Highlights perceived importance as a key psychological mechanism.</td></tr>
<tr><td>RQ3: How do individual differences (trait-level) and momentary fluctuations (state-level) shape consumer responsiveness to hyper-personalisation?</td><td>1. Both stable (between-person) and momentary (within-person) effects shape goal strength.
2. Trait-effects are stronger overall, while state-like effects vary by context and timing.</td><td>1. Demonstrates that hyper-personalisation operates on dual psychological levels – stable and dynamic.
2. Highlights behavioural variability and individual adaptability across contexts.
3. Highlights state-like responsiveness over time, reinforcing adaptive designs.</td></tr>
<tr><td>RQ4: How do brand-oriented, individual-oriented, and social-oriented actors in a Consumer-Dominant Logic (CDL) ecosystem jointly contribute to consumer engagement and value formation?</td><td>Brand-oriented contextual factors (privacy framing, hyper-personalisation) and individual orientation (goal alignment) jointly shape engagement and value formation through relational and social interactions (self-selected procurement/approval goals).</td><td>1. Extends CDL by showing value is socially and dynamically co-created through adaptive personalisation across multi-actors.
2. Verifies the interplay between brand, individual, and social agency in shaping engagement.
3. Demonstrates the temporal central element of CDL operating between actors.</td></tr>
</table>

***RQ5**: What methodological insights can be drawn from applying a longitudinal experimental design with varying temporal proximities to study hyper-personalisation?*	1. The three-wave LMM approach effectively captured **inter-** and **intra-individual** variation and contextual fluctuations over time. 2. Verified that privacy framing is **dynamic**, not static and the multi-dimensional nature of hyper-personalisation	1. Validates DCE-LMM integration for studying *dynamic, real-world* personalisation. 2. Reveals behavioural differences with varying *temporal proximities*. 3. Offers a robust longitudinal framework for examining *adaptive* and *temporal* dynamics in engagement.

5.2 Discussion

This section integrates the core findings from the three linear mixed models (LMMs), based on data collected across three experimental waves, by situating them within the broader theoretical and empirical constructs to address the study's overarching research question:

How does goal-aligned hyper-personalisation influence consumer goal strength in AI-enabled, multi-actor consumer ecosystems over time?

Collectively, these models illustrate the multi-dimensional influence of hyper-personalisation on consumer goal strength — encompassing *behavioural*, *temporal*, *contextual*, and *psychological* dimensions. These findings reveal how consumers actively interpret and assign value to personalised content when it aligns with their active life goals, contextual relevance, and motivational needs rather than passively responding to externally delivered content. Grounded in the Consumer-Dominant Logic (CDL), the discussion interprets these findings as evidence that value is co-created and framed through dynamic interactions among individuals, brand, and contextual actors within AI-enabled ecosystems. This reinforces the view that consumer engagement and motivation are sustained through ongoing, goal-aligned exchanges rather than one-off personalisation efforts.

Empirically, the study tested and verified two main hypotheses:

1. **Hypothesis 1 (H1)**: *Higher levels of hyper-personalisation significantly increase consumer goal strength over time*

2. **Hypothesis 2 (H2)**: *Privacy framing (risk-based versus neutral) moderates the relationship between hyper-personalisation and consumer goal strength*

Overall, the following discussion situates the study's findings within the Consumer-Dominant Logic (CDL) perspective, illustrating how AI-enabled hyper-personalisation unfolds across *adaptive*, *behavioural*, *ethical*, *temporal*, and *contextual* dimensions. Together, these dimensions capture the dynamic and evolving nature of hyper-personalisation, collectively shaping and influencing consumer engagement over time. This integrated perspective connects the empirical findings with the study's broader theoretical aim: to explain how goal-aligned AI-enabled hyper-personalisation evolves within multi-actor consumer ecosystems through ongoing value co-creation and evolving engagement.

5.2.1 Key Takeaways

This study set out to investigate how goal-aligned hyper-personalisation influence consumer goal strength over time, taken from a Consumer-Dominant Logic (CDL) perspective. Data was collected longitudinally across three waves and under varying privacy framing conditions (risk-framed versus neutral). Findings from the three linear mixed models (LMMs) confirm both hypotheses and offer novel insights into consumer motivational engagement, hyper-personalised content design, and privacy perceptions. Four key insights emerged:

(1) Hyper-personalisation that aligns with consumer active life goals significantly boosts goal strength

Model 2 revealed that consumers who selected higher and more goal-aligned hyper-personalised content consistently reported stronger consumer goal strength across time, regardless of the privacy framing conditions. The stable, trait-like (*between-person*) effects affirm that this pattern does not come at random, but is reflective of stable preferences or habitual behaviours that are inherently **goal-driven**, aligning with **Goal Systems Theory (GST)** (Kruglanski et al, 2002; 2015; Kruglanski and Szumowska, 2020). Findings from *within-person* analyses further suggest *dynamic* and *contextual* responsiveness to hyper-personalisation. Under both neutral and negative privacy framing conditions, these momentary deviations confirmed that *higher-than-usual* levels of hyper-personalisation fostered stronger consumer goal strength, offering temporal and contextual insights. These results advance the CDL-based understanding of value formation by showing that goal alignment, rather than simple exposure or transactional tailoring, underpins enduring engagement. This highlights the importance of designing AI-enabled systems that embed consumers' lived experiences and personal aspirations within hyper-personalised encounters, moving beyond static content delivery (Heinonen and Strandvik, 2023).

(2) The effect of hyper-personalisation on consumer goal strength is not static but varies across time and context

Temporal effects that emerged in *Model 1* and *Model 2* revealed significant *between-person* and *within-person* variability in consumer goal strength. This indicates that consumers respond differently to hyper-personalised content across time, reflecting the *adaptive* and *context-sensitive* nature of engagement. Under neutral framing conditions, participants exhibited a short-term boost in motivational engagement (after 10 days from baseline), which plateaued in the long-term (after 5 months). This pattern aligns with literature suggesting that initial engagement may decay over time if not reinforced or meaningfully adapted (Fishbach and Woolley, 2022). Conversely, participants exposed to negative privacy framing initially demonstrated lower goal strength — likely due to scepticism triggered by heightened risk concerns — followed by a delayed recovery in the long-term. These findings highlight that perceived privacy risk does not entirely suppress motivation but reflects a *temporal sensitivity*, where trust and relevance require time to recover post-exposure to risk cues. This reinforces the need for hyper-personalisation to be dynamically adaptive and contextually responsive to sustain consumer engagement across motivational states (Ford et al., 2023; Tazarv et al., 2023).

(3) Privacy framing moderates the contextual relevance of hyper-personalisation

Group as neutral or negative privacy framing revealed no significant differences in the stable *between-person* effects of hyper-personalisation, indicating the stability of overall hyper-personalisation influence on consumer goal strength across time. However, privacy framing significantly moderated momentary (*within-person*) shifts of hyper-personalisation effects at distinct time points. This pattern suggests that consumer engagement fluctuates depending on how personalisation is communicated — whether framed positively (risk-free) or negatively (risk-based). Specifically, exposure to risk-based framing *temporarily* weakened goal strength, reflecting heightened privacy sensitivity, whereas neutral framing helped sustain motivational consistency. These findings highlight the *contextual* and *ethical* sensitivity of hyper-personalisation. Privacy cues shape not only consumers' short-term engagement but also their perceptions of control and trust over time. This underscores that hyper-personalisation should be *transparently* framed and *ethically* communicated to maintain consumer confidence and long-term value alignment (Zhang et al., 2018).

(4) Consumers' subjective interpretations of hyper-personalisation influences its motivational impact

Model 3, the post-hoc exploratory model, revealed the influential role of consumers' subjective interpretations — particularly the perceived importance of hyper-personalisation — in shaping goal strength. Findings show that even when consumers behaviourally respond to higher levels of hyper-personalisation, its motivational impact on goal strength depends on how personally meaningful and important consumers perceive such experiences to be. This aligns with the Technology Acceptance Model (TAM) and *value alignment* emphasising that perceived value and psychological utility influence motivational outcomes (Xia and Shannon, 2025). This model reinforces that hyper-personalisation is only effective when it is psychologically endorsed by consumers as personally relevant and valuable. The moderating role of perceived importance reveals that hyper-personalisation operates not only through behavioural and contextual mechanisms but also through psychological meaning-making. This adds a deeper interpretive layer to the CDL perspective, where value and motivation are co-constructed through consumers' internal evaluation of relevance and significance.

Together, these key findings reveal a **multi-dimensional** relationship between hyper-personalisation, consumer goal strength, and consumer agency — reflecting concepts related to goal congruence and temporal dynamics presented next with reference to tenets from Consumer-Dominant Logic (CDL).

5.2.2 Goal-Aligned Personalisation and Goal Strength

A key finding of this study lies in empirically validating that goal-aligned hyper-personalisation — representing content aligned with consumers' active life goals — leads to significantly stronger and more sustained motivational outcomes. This finding supports **Hypothesis 1 (H1)** and reflects a core tenet of the Consumer-Dominant Logic (CDL) framework, which posits that value emerges through consumers' lived contexts, goals, and sense-making (Heinonen and Strandvik, 2022). The study extends existing evidence by offering a longitudinal validation of how goal alignment fosters enduring engagement across time, advancing beyond prior cross-sectional insights.

Recent research across diverse domains has shown that aligning personalised content with user goals enhances engagement and learning outcomes. In educational contexts, Jayasinghe and Kashurirathna (2022) and Faraji et al. (2022) demonstrated that goal-driven recommendation systems improve learner motivation and efficiency, whilst supporting learners in achieving their goals (Li et al., 2021a). Adaptive interventions such as *Foodbot* (Prasetyo et al., 2020), humanoid social robots (Robinson and Kavanagh, 2021) and *GenMentor* (Wang et al., 2025b) dynamically aligned educational content to evolving learner needs using goal-aligned personalised and adaptive frameworks. Similarly, in health and wellness settings, Sathya et al. (2024) found that tailoring AI-enabled feedback around self-defined goals, such as diet or exercise, significantly improved goal attainment and sustained behavioural adherence. Fang et al. (2025) introduced *Mirai*, a proactive AI-enabled wearable that delivers goal-aligned nudges using voice cloning and environmental sensing. Taken together, this existing research underscores the utility of goal-aligned personalisation in enhancing user engagement and improving the effectiveness of AI-enabled interventions.

While these studies collectively establish the benefits of goal-aligned personalisation, most remain **limited** to *short-term*, *domain-specific*, or *static* evaluations of engagement. They do not fully capture how consumers' goal strength **evolves dynamically** or how *contextual* and *psychological* factors, such as privacy framing, influence this process over time. Addressing this gap, the present study provides longitudinal empirical validation of goal-aligned hyper-personalisation within AI-enabled consumer ecosystems, revealing that sustained motivational engagement arises when personalisation adapts to both *individual differences* and *contextual variations*. This extends prior work by demonstrating that the impact of goal alignment is temporal, dynamic, and behaviourally grounded, rather than situational or one-off.

As such, this study contributes a novel perspective by anchoring goal-aligned hyper-personalisation within the Consumer-Dominant Logic (CDL) framework, emphasising the lived, evolving nature of consumer contexts and experiences. By empirically examining this dynamic through the lens of CDL, the study reframes consumers as *active* and *empowered agents*. As Heinonen and Strandvik (2020) argue, consumer value arises from evolving interpretations shaped by varying cognitive and behavioural patterns – best captured through longitudinal and in-depth research methods. By employing a three-wave longitudinal design, this study demonstrates how value is co-created and reinforced both across individuals and within individuals over time. It also answers recent calls for **longitudinal validation** of personalised interventions (Fang et al., 2025), offering empirical evidence of how motivational engagement (*goal strength*) evolves and sustains over extended periods of time in response to higher goal-aligned hyper-personalisation.

The introduction of consumer goal strength as a **measurable**, **time-sensitive** construct in hyper-personalised service contexts marks a significant advancement in tracking motivational alignment. This directly responds to CDL's call for longitudinally informed consumer behavioural research. By incorporating privacy framing (risk-based versus neutral) into the design, the study enriches the understanding of the dynamic interplay between personal relevance, trust, and goal strength whilst maintaining a focus on consumer agency. These contributions offer a **holistic** and **contextualised** model of hyper-personalisation, grounded in the real-time evolution of consumer behaviours over time and across varied contexts.

The results underscore that goal-aligned hyper-personalisation must also be viewed through **ethical** and **societal** lenses. As AI systems increasingly shape consumer experiences, ensuring transparency, fairness, and respect for consumer autonomy becomes essential. This study highlights that ethical design — where personalisation remains accountable, explainable, and aligned with consumer agency — forms a crucial condition for sustaining trust and engagement in evolving multi-actor ecosystems. Taken together, these insights reaffirm that goal-aligned hyper-personalisation operates as a *dynamic*, *evolving*, and *ethically* grounded mechanism for sustaining consumer motivation and value co-creation over time.

5.2.3 Temporal Dynamics and Motivational Trajectories

A central finding of this study lies in revealing the **temporal evolution** of motivational engagement in response to higher and goal-aligned hyper-personalisation. Empirical results from *Model 2* uncovered complex motivational trajectories that challenge static assumptions in personalisation research. While initial exposure to hyper-personalised content produced a short-term motivational boost, *Wave 2* and *Wave 3* revealed **non-linear** shifts, highlighting that engagement fluctuates *dynamically* rather than declining uniformly over time.

Under neutral privacy framing (Group A), participants initially exhibited a strong short-term increase in goal strength (after 10 days), which later plateaued or declined slightly after five months. Nonetheless, engagement levels **remained higher** than baseline, underscoring the need for novelty or reinforcement to sustain motivation (Mustafa et al., 2022; Tsay et al., 2020). In contrast, risk-framed conditions (Group B) produced lower initial motivation — consistent with **Prospect Theory** (Kahneman and Tversky, 1979; 2013), positing that consumers are more sensitive to potential losses than to equivalent gains. The heightened privacy concerns led consumers to approach personalised content more cautiously, overshadowing its benefits (Le et al., 2024). However, these participants displayed a delayed motivational **recovery** by *Wave 3*, particularly among participants in the High personalisation category, demonstrating that trust and relevance can re-emerge over time once scepticism subsides. The delayed motivational trajectory emphasises the *context-specific* nature of personalised influence and the role of perceived risk in shaping engagement over time.

These **non-linear** motivational shifts echo findings by Sun et al. (2025), who observed an inverted U-shaped relationship between personalisation and engagement. However, while Sun et al. (2025) advocated moderate levels of personalisation as optimal, the current study unpacks a **counter-perspective** by introducing *contextual* differentiation through privacy framing. While the neutral privacy conditions demonstrated a similar inverted U-shaped relationship among High and Medium personalisation categories, consumer goal strength remained significantly higher at *Wave 3* compared to the baseline. This reveals that value does not dissipate entirely at higher personalisation levels but rather stabilises over time. Similarly, under negative framing, recovery patterns suggest that personalisation acts as a dynamic rather than static influence, adapting to varying degrees of trust and risk sensitivity.

Moreover, the current study illustrates complexities embedded within the *temporal* and *contextual* dynamics of hyper-personalisation that seem to be overlooked by Sun et al. (2025):

- Under neutral conditions (Group A), participants in the Low personalisation category, although comprising only ~14% of the sample, still reported a rise in goal strength at *Wave 3* contradicting the assumption by Sun et al. (2025) that low personalisation is uniformly ineffective when compared to the moderate levels.

- Under negative privacy framing (Group B), the High personalisation category demonstrated a delayed recovery at *Wave 3* — suggesting that risk salience influences motivational trajectories beyond mere personalisation intensity based on temporal proximity (**recency** versus **longer** exposure).

- Unlike Sun et al. (2025)'s uniform inverted U-shaped effect, Group B followed a more gradual and sustained curve, without a clear decline and with a motivational increase at *Wave 3* for High personalisation category.

These complexities reflect broader observations in digital technology adoption, particularly those linked to hedonic adaptation and user heterogeneity. While the hyper-personalisation benefits are widely acknowledged, emerging evidence suggests that these advantages may fluctuate over time. Polyportis (2024) identifies a "**satisfaction gap**" whereby users' appreciation of AI-enabled systems declines as capabilities become familiar, aligning with *hedonic adaptation* theory. Studies show that as AI capabilities scale, user expectations quickly recalibrate with increased familiarity and comfort, reducing the novelty and satisfaction associated with these innovations (Ganuthula et al., 2024; Polyportis, 2024). Early adopters experienced sharper declines following initial enthusiasm, while later adopters showed slower but more sustained motivation, indicating that adaptive personalisation may buffer against long-term disengagement. Late-stage engagement patterns observed in this study mirrored hedonic adaptation processes, with a decline at *Wave 3* (after 5 months) following the initial boost at *Wave 2* (after 10 days) among High and Medium personalisation categories. Notably, the delayed rise in engagement among the Low personalisation category participants at *Wave 3* further confirms that late adopters may indeed derive cumulative or delayed benefit. However, the sustained higher ratings of the High group compared to the Medium in *Wave 3* suggest that deeper personalisation may serve as a buffer against complete satisfaction erosion – particularly when aligned with more meaningful or long-term user goals. These observed divergences challenge the generalised and over-simplified inverted U-shaped model proposed by Sun et al. (2025), reinforcing the value of the Consumer-Dominant Logic (CDL) perspective.

Furthermore, while recent studies have advanced understanding of AI-enabled personalisation, much of this work remains *system-centric*—focusing on algorithmic optimisation, behavioural prediction, and short-term engagement effects (Wang et al., 2025a; Zhu et al., 2023). Even studies with goal-oriented perspectives often treat personalisation as a static or one-off stimulus rather than a process embedded in consumers' evolving life contexts (Jayasinghe and Kasthurirathna, 2022). In contrast, this study adopts a *consumer-centric* and *temporally* grounded approach, viewing hyper-personalisation as a co-evolving experience that unfolds alongside consumers' psychological framings and life goals. The dynamic *within-person* fluctuations observed in this study affirm that hyper-personalisation's impact cannot be captured through static "*one-size-fits-all*" measures but must be understood as a continuous dynamic interplay between individual, context, and time.

Building on limitations observed in studies such as Teepapal (2025), which found no enduring effects when personalisation was treated as a discrete stimulus, this study demonstrates that engagement outcomes strengthen when personalisation is *longitudinally* adaptive — continuously re-aligned with consumers' motivational states and contextual experiences. This temporal and context-sensitive perspective extends beyond static stimulus–response models, offering deeper insight into how hyper-personalisation supports sustained goal alignment over time.

Unlike provider-driven views under the traditional Service-Dominant Logic (SDL), CDL positions consumers as active agents whose motivation evolves through *contextual* and *temporal* interpretation in pursuit of their life goals (Fan et al., 2020; 2023; Heinonen and Strandvik, 2022; Rihova et al., 2018). Within this framework, the CDL paradigm better captures the complex dynamics of hyper-personalisation, highlighting how motivational trajectories fluctuate across distinct time points, different framing conditions, and reinforcement intervals. These findings illustrate that value co-creation and framing unfolds through ongoing recalibration rather than fixed pathways.

Consequently, service providers should move beyond generic personalisation strategies and instead adopt *context-aware*, *time-sensitive*, and *ethically grounded* designs that dynamically align with consumers' evolving goals, trust perceptions, and lived experiences (Kim et al., 2019). Recent advancements in AI-enabled adaptive personalisation further reinforce this study's findings (Tazarv et al., 2023; Zhu et al., 2023; Wang et al., 2025a). These systems employ context-aware adaptive learning agents and real-time feedback loops to recalibrate recommendations dynamically, thereby sustaining user motivation and goal alignment across changing contexts. For instance, Tazarv et al. (2023) demonstrated that adaptive agents reduced required user interactions by up to 88% and 32% compared to random and non-contextual systems, respectively, while Zhu et al. (2023) introduced *ADAGA*, a deep learning model that forecasts goal-oriented behaviour by learning temporal dependencies. Similarly, Wang et al. (2025a) developed *JumpStarter*, an AI-enabled adaptive system that refines recommendations in real time based on evolving contextual cues. Together, these advancements validate the importance of adaptive reinforcement — adjusting content timing and relevance rather than intensity — to sustain long-term engagement and prevent motivational decline.

Taken together, these findings confirm that hyper-personalisation operates as a *temporally dynamic* and *contextually* adaptive process, shaped by privacy perceptions, novelty cycles, and reinforcement mechanisms. By illustrating how consumer motivation evolves rather than erodes over time, this study advances a more holistic understanding of hyper-personalisation as an evolving motivational ecosystem — one that integrates behavioural, contextual, and ethical sensitivity within multi-actor AI-enabled environments.

5.2.4 Privacy Framing and Ethical Engagement

Another key insight of this study lies in the moderating role of privacy framing (risk-based versus neutral) in shaping distinct consumer goal trajectories within hyper-personalised services. Participants exposed to neutral or attenuated-risk framing (Group A) initially reported a strong motivational boost, which gradually plateaued over time. This pattern aligns with Sun et al. (2025)'s inverted U-shaped effect, suggesting that early engagement peaks may reflect novelty before stabilising as personalisation becomes familiar. In contrast, risk-framed contexts (Group B) showed lower initial engagement due to heightened privacy concerns but demonstrated gradual and sustained recovery in later waves, particularly among those in the High personalisation category.

This divergence highlights a key contextual factor: while negative privacy framing can initially suppress engagement, it may foster delayed trust recovery as risk concerns naturally dissipate and consumers reevaluate personalised content over time. This gradual rebound occurred without repeated exposure to framed messages to avoid risk of confounding longitudinal engagement patterns with artificial priming effects. This approach enables capturing the persistence of framing influence and the natural evolution of motivational recovery trajectories, as recommended by recent literature (Horiuchi et al., 2022; Klar et al. 2020; Sheagley and Clifford, 2023).

Research shows that framing effects shape individuals' behaviour and intentions (Amatulli et al., 2019; Burböck et al., 2019; Li et al., 2021b). As Martin (2020) notes, consumers often regain trust and re-engage once perceived privacy threats subside. Similarly, Zhang et al. (2018, 2022) highlight that when message framing aligns with an individual's regulatory focus — whether promotion-focused (seeking gains) or prevention-focused (avoiding losses) — they perceive personalisation as more consistent with their internal goals, leading to higher engagement and positive attitudes. Self-regulation, which guides individuals in pursuing their goals (Higgins, 2020), explains the delayed recovery observed in Group B, where participants, especially among High personalisation category, gradually re-evaluated the value of hyper-personalised content as privacy concerns faded.

Wright and Xie (2019) argue that although visible privacy misalignments may initially trigger negative consumer reactions, trust can be progressively restored when service providers implement transparent and ethically aligned practices that recalibrate consumers' perceptions of risk. This literature suggests that message framing is not straightforward but deeply interlinked with individual differences (Burböck et al., 2019; Zhang et al., 2018; 2022). The moderating effects, supporting **Hypothesis 2 (H2)**, are consistent with framing effects theory, which posits that individuals respond differently to identical content depending on its framing (Liu and Mattila, 2021; Wang et al., 2022; Zhang et al, 2018). Risk-amplifying messages typically heighten perceived threat and suppress motivation, whereas risk-attenuating or neutral framings reduce perceived risk and promote sustained interaction (Kapuściński and Richards, 2016). Supporting this, Adjerid et al. (2019) showed that reframing data disclosure from "Privacy Settings" to "Survey Settings" increased willingness to share information. Similarly, Korneeva et al. (2024) found that framing privacy positively can recalibrate trust, aligning with this study's observed motivational recovery trajectory under risk conditions.

Importantly, these findings extend beyond behavioural insights to reveal both the ***ethical*** and ***societal*** implications of hyper-personalisation. By examining how privacy framing shapes consumers' perceptions of trust, fairness, and autonomy, this study provides empirical evidence of the moral responsibility of service providers to design AI-enabled systems that are *transparent* and *responsible*. Guan et al. (2025) highlight that a key limitation in existing personalised implementations lies in failing to adjust meaningfully to consumer contexts, advocating for systems that incorporate consumer preferences and feedback-based re-alignment. While Guan et al. (2025) conceptually argue that effective personalisation should preserve user trust and autonomy, this study demonstrates ***how*** such ethical alignment operates in practice — showing that trust can recover and sustain engagement over time when personalisation is framed transparently rather than intrusively. Greene et al. (2023) warn against the overuse of reinforcement learning-based personalisation, arguing that while these systems can offer granular adaptability, they risk reducing consumer autonomy and raising surveillance concerns when not carefully governed. The current study extends Greene et al. (2023) by illustrating that ethical AI design, when embedded in the **Consumer-Dominant Logic (CDL)** framework, can enhance rather than diminish autonomy through co-creative, consumer-driven participation.

Beyond individual ethics, the study also reveals **societal implications** by illustrating how consumers' relational and trust-based responses to hyper-personalisation extend beyond personal outcomes to collective forms of engagement. The observed longitudinal recovery in trust under risk-based framing (Group B) suggests that ethically aligned AI communication can rebuild public confidence in digital personalisation systems, addressing wider societal concerns about data misuse and manipulation. By showing how ethical framing and goal alignment foster relational motivation — such as social recognition and shared family enjoyment — the findings suggest that ethically designed hyper-personalisation contributes not only to individual empowerment but also to ***socially sustainable*** engagement within multi-actor ecosystems — where consumers, service providers, and algorithms co-create value over time.

In the context of Telecommunications and Entertainment service, this implies that **multi-actor** providers must move beyond isolated data management to establish a *shared data governance* model that integrates both *individual-level* ethics (ensuring transparency, autonomy, and personal relevance) with *collective* or *societal-level* ethics (promoting collective trust, accountability, and inclusivity). Such governance should nurture relational accountability between providers and consumers, while also strengthening community-level confidence in how personal data and personalised interactions are managed. Hence, ethically designed hyper-personalisation not only empowers individuals but also contributes to social trust, accountability, and responsible innovation within AI-enabled service environments.

These **ethical** and **societal** insights are underpinned by the dynamic behavioural patterns revealed in this study. According to Expectation Disconfirmation Theory, these patterns suggest that consumers continuously evaluate service experiences relative to their expectations, producing shifts in *emotional valence* – from negative reactions during perceived privacy threats to positive reappraisal when trust is restored (Abid et al, 2025; Elkhani and Bakri, 2012; Mazhar et al., 2022). This process illustrates then even negative encounters can lead to renewed engagement once consumers reassess the alignment between the service and their personal life goals.

Grounded in the Consumer-Dominant Logic (CDL), this study advances understanding of privacy framing as a **contextual cue** that *dynamically* shapes value formation trajectories. By demonstrating that engagement fluctuates through changing perceptions of privacy and trust, it empirically supports Heinonen's (2018) argument that consumer engagement is *reconfigurable* over time. These results address a key gap in CDL research by evidencing how privacy cues function as **temporal** and **emotional** mechanisms, driving disengagement and re-engagement cycles across evolving consumer lifeworlds rather than being examined as a static inhibitor (Abid et al., 2025; Heinonen, 2018; Siddique et al., 2021; Wang and Kim, 2021). Ultimately, this study contributes a more nuanced view of privacy framing — one that integrates behavioural, temporal, and ethical dimensions — and repositions consumer trust as an adaptive, co-created construct within AI-enabled personalisation ecosystems.

This study also addresses a key research gap by empirically capturing value formation dynamics as a **temporal** and **contextual** process within digital hyper-personalised services – an area underexplored within CDL. While prior CDL literature (Nguyen and Menezes, 2024; Heinonen and Strandvik, 2022) emphasises value formation enablement through consumer life contexts, this study uniquely contributes by demonstrating how **privacy cues** and **emotional dissonance** evolve over time within consumers' lifeworlds and their sense making, shaping not only engagement and trust but also consumers' perceptions of fairness and autonomy.

Furthermore, by identifying the moderating role of privacy framing in AI-enabled service settings, this study responds to calls by Abid et al. (2025) and Quach et al., 2022) to investigate relationships between data privacy, value co-creation, and consumer experiences across digital ecosystems. It also responds to calls for examining value formation dynamics within self-service, zero-touch technologies with the potential to enhance value co-creation experiences (Gao et al., 2023). Overall, the findings highlight that consumers' perceptions of trust and risk are **fluid** and **evolving**, forming part of an ongoing process of value formation and re-evaluation rather than fixed determinants of engagement. This finding is made possible given the current study's *empirical*, *quantitative*, and *longitudinal* design.

For service providers, this underscores the importance of *adaptive*, *goal-aligned*, and *context-aware* hyper-personalised designs that sustain engagement through ethical congruence, strategic timing, and regulatory expectations. The findings highlight three key ethical design imperatives essential for sustaining trust and long-term engagement in AI-enabled environments. First, **Explainable AI (XAI)** practices can provide users with understandable justifications for how their data is used and how algorithmic decisions are made (Gunning and Aha, 2019; Sokol and Flach, 2020). Second, **transparent personalisation** can offer visibility into personalisation logic while enabling users to adjust settings or opt out entirely (Shin and Biocca, 2022). Third, **autonomy-preserving design** principles enables service providers to create interfaces that promote user control and prevent manipulative or coercive nudging (Susser, 2025). Collectively, these practices ensure hyper-personalisation evolves ethically — enhancing consumer agency, trust, and engagement rather than undermining them. Embedding such CDL-informed practices can help service providers foster meaningful and lasting consumer relationships.

5.2.5 Perceived Importance of Hyper-Personalisation

Model 3 offered novel insight into how the perceived importance of hyper-personalisation influences consumer goal strength on one hand, and the relationship between hyper-personalisation and consumer goal strength on the other. Results revealed that consumers who rated hyper-personalisation as personally important reported stronger goal strength. This aligns with recent research positioning perceived importance of technology as a key antecedent of technology acceptance and intrinsic motivation (Guo and An, 2025; Xia and Shannon, 2025). When consumers perceive technology-enabled services as meaningful to their personal needs, it fosters deeper engagement and commitment. Although this model is not part of testing the hypotheses, it enriches the findings of the study.

According to the Technology Acceptance Model (TAM), both cognitive and affective factors — including perceived usefulness, ease of use, and intention to use — shape individuals' acceptance of technology (Davis, 1989; Symasek et al., 2025). Building on this, Yu et al. (2021) expanded the model to include **perceived importance**, which reflects a person's identification with technology and the emotional value they attach to it (Guo and An, 2025; Shen and Li, 2023). When individuals perceive technology as *important* and *aligned* with their personal values, they experience positive emotions and a stronger motivation to engage. Empirical studies (e.g., Guo and An, 2025; Sing et al., 2022) confirm that higher perceived importance promotes deeper involvement and commitment.

In this study, these insights extend to hyper-personalisation, showing that when consumers view personalised technologies as personally meaningful, their engagement and goal strength increase. Thus, perceived importance acts as an affective driver of sustained motivation, reinforcing the psychological connection between users and technology.

However, the effect of perceived importance was found to decline over time — strongest at baseline (*Wave 1*) but decreasing in later waves. This pattern reflects short-term motivational effects and aligns with motivational decay theory (Fishbach and Woolley, 2022). The findings suggest that even high perceived importance may not endure unless it is continuously reinforced or dynamically adapted to maintain emotional connection and value congruence (Abid et al., 2025; Li et al., 2018; Ma and Wang, 2021). By enhancing perceived usefulness and behavioural control, the perceived importance of technology can be renewed (Guo and An, 2025; Martin et al., 2020). Overall, these results highlight that perceived importance is *temporally sensitive* and evolves with consumers' personal values and goals. Service providers must therefore design adaptive engagement strategies that sustain personal relevance and reinforce affective alignment over time.

The interaction between *within-person* and *between-person* perceptions of importance further revealed that when consumers generally favour hyper-personalisation but do not perceive it as personally important, goal strength weakens. In contrast, when personal importance aligns with contextual meaning, engagement intensifies. In other words, consumer's own perceptions of hyper-personalisation can amplify or dilute its effect. This findings underscores that personalisation behaviour alone is insufficient; it must be *psychologically endorsed* and *emotionally relevant* — echoing the Theory of Planned Behaviour (Ajzen and Fishbein, 1980) and CDL's principle that value is *subjectively constructed*. From a CDL perspective, personalisation derives its value when consumers perceive it as aligned with their evolving goals and life contexts (Heinonen et al., 2018). Hence, the perceived importance of hyper-personalisation acts as a **psychological bridge** between design and meaning-making, shaping both motivation and long-term consumer value.

5.3 Chapter Summary

This chapter provided a theoretical and interpretive lens to understand the empirical findings through the Consumer-Dominant Logic (CDL) framework. Building upon the three statistical models (LMMs), it moved beyond technical results to interpret how hyper-personalisation, contextual framing, and consumer meaning-making interact in shaping value formation. The discussion further connected these behavioural insights to broader ethical and societal dimensions of AI-enabled hyper-personalisation, particularly concerning transparent and responsible practices.

Four core themes emerged from the discussion:

1. **Goal-Aligned Personalisation**: findings confirmed that personalisation is most effective when it aligns with consumers' personal life goals and values. Rather than passively responding to technology, consumers actively interpret and co-create meaning through goal-directed engagement, reinforcing CDL's view of consumers as active agents in value formation.

2. **Temporal Dynamics and Motivation**: Goal strength fluctuated over time, showing both immediate and delayed motivational effects influenced by contextual cues and temporal proximity. This highlighted the temporal sensitivity of consumer engagement and the need for adaptive reinforcement mechanisms that sustain motivation ethically and transparently over time.

3. **Privacy Framing as a Contextual Moderator**: Privacy cues — especially risk-based framings — shaped how consumers engaged with personalisation. These findings revealed contextual risk sensitivity, where negative framing initially suppressed engagement but later recovered as concerns dissipated. This underscores the importance of adopting hyper-personalisation strategies that balances value alignment with *ethical*, *responsible*, and *autonomy-preserving* designs.
4. **Perceived Importance of Personalisation**: The post-hoc analysis identified perceived importance as a psychological filter. Personalisation only enhanced goal strength when consumers perceived it as personally meaningful and valuable - reinforcing the role of subjective interpretation in value formation.

Together, these insights reinforce the foundational tenets of CDL: that value is not delivered in fixed units, but continuously shaped by consumers' evolving experiences, life goals, and contexts. This chapter demonstrated how hyper-personalisation operates not as a *one-size-fits-all* solution, but as a dynamic, psychologically mediated process. As such, understanding how consumers interpret, evaluate, and assign meaning to personalised content is just as important as the content itself in fostering sustainable and socially responsible digital relationships.

Chapter 6 – Conclusions & Implications

6. Conclusion and Implications

This chapter presents the study's theoretical, empirical, and practical outcomes by articulating the concluding remarks of the underlying research. It highlights the theoretical and practical contributions, acknowledging limitations and proposing future research avenues. It builds upon the conceptual framework grounded in the Consumer-Dominant Logic (CDL) to examine the implications of consumer interactions with hyper-personalisation and the multi-actor value formation in goal pursuit across time.

6.1 Main Findings

This study investigated the impact of goal-aligned hyper-personalisation on consumer goal strength within an AI-enabled, multi-actor consumer ecosystem, employing a three-wave longitudinal experimental design. It addressed the central research question:

How does goal-aligned hyper-personalisation influence consumer goal strength in AI-enabled, multi-actor consumer ecosystems over time?

By integrating temporal dynamics, psychological privacy framing, and perceived importance within a Consumer-Dominant Logic (CDL) ecosystem model, the study examined both inter- and intra-individual variability in behavioural outcomes. Results from the unconditional model (*Model 1*) confirmed a statistically significant natural variability in consumer goal strength over time, attributable to temporal fluctuations and individual-specific variations, with *Time* as the only predictor. This model established the baseline of temporal influence, revealing that goal strength is not fixed between and within individuals but evolves dynamically – validating the use of Linear Mixed Models (LMMs) over traditional methods such as ANOVA.

This was further verified using hyper-personalisation and psychological privacy framing as predictors in *Model 2,* targeted towards testing the two main hypotheses of the study. The model demonstrated the *multi-dimensional* nature of hyper-personalisation, showing its strongest effects when aligned with consumer active life goals (Cluster 4). Specifically, higher levels of hyper-personalisation, on average, revealed a positive, consistent, and significant predictive association with goal strength across time - regardless of the privacy framing condition - thus supporting its stability as a trait-level factor. In parallel, intra-individual (within-person) analysis unveiled a temporal and contextual sensitivity, with momentary fluctuations (higher-than-usual levels) particularly evident between the varying trajectories of Group A and Group B. These findings provided empirical support for **Hypothesis 1 (H1)** and **Hypothesis 2 (H2)**.

Model 3 extended the analysis through post-hoc exploratory lens, examining the role of perceived importance of hyper-personalisation and its interaction with between-person hyper-personalisation levels in shaping consumer goal strength. This model revealed that even high levels of hyper-personalisation were insufficient to sustain consumer goal strength unless consumers psychologically endorsed it as meaningful and personally important. This aligns with literature emphasising the role of perceived personal value and perceived importance in sustaining engagement.

Overall, the study demonstrates that hyper-personalisation exerts both stable and dynamic influences on consumer goal strength:

- **Stable trait-like** (*between-person*): a consistent predictor of consumer goal strength across individuals and time, independent of framing.

- **Dynamic state-like** (*within-person*): a fluctuating influence demonstrating motivational decay over time unless reinforced by value meaning-making and personally perceived importance.

Grounded in Consumer-Dominant Logic (CDL) framework, the study affirms that consumers' behavioural engagement and psychological perceptions are crucial in shaping value formation within AI-enabled multi-actor ecosystems over time. Its three-wave longitudinal approach provides novel insights into short-term versus sustained consumer influences, revealing that hyper-personalised service content holds the most enduring impact when aligned with consumers' active life goals.

6.2 Practical Implications

The findings of this study have significant implications for practitioners within AI-enabled, multi-actor consumer ecosystems that can inform and guide them in the design of effective and sustained hyper-personalisation strategies. Results demonstrate that it is crucial for service providers to not only focus on system-level and user-level preferences, but also dynamically align hyper-personalised services with evolving consumer goals, particularly under varied temporal and contextual conditions. Although prior literature increasingly advocates goal-oriented personalisation and ethical practices, this study is one of the first to empirically demonstrate the evolving and momentary changes in consumer responses to AI-enabled personalisation over time. By leveraging a three-wave longitudinal design with privacy framing, the study provides rare evidence that ethical practices of personalisation cannot be embedded as *one-size-fits-all*, but rather requires a *moment-to-moment* calibration at the individual level. Based on the study's findings, the following practical guidelines are recommended:

First and foremost, service providers should adopt goal-aligned hyper-personalisation strategies that continuously adapt to momentary shifts in engagement over time. To this end, service providers should design and tailor their hyper-personalised services toward consumers' active goal (or set of goals), allowing consumers to specify these aspects when engaging with the offered service. Ramachandran et al. (2025) emphasise that the effectiveness of Artificial Intelligence (AI) is dependent on its alignment with consumer-centric goals, quality of data, and ethical governance frameworks adopted by service providers. As illustrated by the fluctuating trajectories captured by *within-person* hyper-personalisation, effective strategies require real-time feedback and adaptive interfaces that track consumer preferences and respond to changes in their goals, to ensure service sustainability in consumer lives on a long-term basis. This involves conducting ongoing comprehensive and in-depth research, to capture consumer evolving feedback, behavioural shifts, expectations, and emerging challenges. By doing so, service providers can deliver personally relevant and fine-grained contextual recommendations at the individual-level (Basu et al., 2024; Campbell et al., 2020; Gao et al., 2023; Li et al., 2019; Sun et al., 2021). AI-enabled tools such as chatbots and virtual assistants can act as data gathering interfaces by including richer and more flexible workflows that capture user evolving contexts and feed insights back into refining personalised campaigns (Ramachandran et al., 2025; Wang et al., 2025a). Zhu et al. (2023) recommends that service providers incorporate notifications in their goal-aligned interventions to remind users who are forecasted not to meet their goals. This can include how far away from the goal the user is and recommend activities that can sustain it, hence increase motivation, and reduce dropouts.

Second, integrating adaptive learning systems within hyper-personalisation implementations is crucial to monitor consumer evolving preferences and goals. Rather than relying on static consumer profiling, designing adaptive consumer journeys that can adjust its content, timing, and intensity of hyper-personalised offerings can improve subscription retention, consumer satisfaction and perceived relevance. This aligns with recommendations for continuously evolving recommendation systems (Sun et al., 2025) through responsive strategies such as real-time feedback loops and context-sensitive reinforcement. Furthermore, the temporal dynamics revealed in this study suggest that timing of interventions is essential. Service providers can benefit from implementing temporal nudges that can reinforce engagement, especially at times of motivational dips (Bargh, 2022; Gao et al., 2022; Lu et al., 2022; Mehr et al., 2020). Implementing gamification strategies aligned with consumer goals can mitigate momentary disengagement, elevate emotional dissonance, and deepen brand engagements (Behera et al., 2024; Hsu, 2023; Zhu et al., 2023). The rise of AI-enabled Metaverse-based experiences are introducing multidimensional innovative landscapes that can re-engage brands with their consumers. By leveraging immersive technologies like augmented reality (AR), virtual reality (VR), virtual storefronts, Internet of Things (IOT), and 3D experiences, service providers can create innovative and interactive environments that can deepen brand connections (Li, 2023; Kumar, 2024; Patil, 2024; Mogaji et al., 2024).

Third, with the study's findings of the moderating role of privacy framing, particularly evident in Group B, service providers must incorporate *ethically-aware* personalisation practices. As consumers differ in their willingness to disclose data, this study revealed that they also differ in the way they interpret risk cues. Service providers need to balance hyper-personalisation with transparency and consumer perceived control, ensuring that AI-enabled technologies are implemented and used responsibly (Greene et al., 2023; Paschen et al., 2020). Ethical personalisation requires that system designs anticipate and respond to evolving consumer perceptions — especially those shaped by initial framing — through clarity, control, and communication over time. Wright and Xie (2019) highlight the importance of continuously monitoring and maintaining consumer privacy expectations to mitigate any misalignments between privacy expectations and provider actions. Service providers should implement *privacy-sensitive designs* that treat risk perceptions as *dynamic* and ethically relevant. **Explainable AI (XAI)** has emerged to address the long-standing *personalisation-privacy* paradox through transparency, accountability, interpretability, and trust in AI-assisted marketing (Chang and Bau; 2024; Kumar et al., 2020; Wang et al., 2025c). Service providers can leverage XAI capability of offering interpretable insights into how decisions, such as customer targeting or product recommendations, are made (Hu et al., 2023; Ramachandran et al., 2025), hence supporting regulatory compliance and mitigating consumer trust and privacy concerns. This transparency ensures ethical alignment while enhancing consumer confidence in AI-enabled personalised recommendations. By integrating **responsible** and **ethical** practices into the strategic planning and implementation, service providers can ensure hyper-personalisation remains ethical, adaptive, and sensitive to consumer perceived autonomy and control.

Additionally, consumer ecosystems, particularly those enabled by multi-actor networks, require careful orchestration of goal alignment and trust across all partnering service providers. This can be maintained through *shared data governance* and cross-organisational standard practices and protocols that respect consumers' evolving preferences across interconnected services (Paul et al., 2024; Wieringa et al., 2019; Wirtz et al., 2023). In multi-actor service ecosystems, it is essential that the provider exerting the power within an ecosystem be responsible for upholding shared data governance with aligned values and norms, assessing any risks surrounding data exploitation, privacy or unintended use and analytics (Wirtz et al., 2023).

Fourth, the post-hoc exploratory finding of *Model 3* highlights that hyper-personalisation alone is not sufficient to sustain consumer engagement over time. The perceived importance dimension reveals that service providers should also ensure consumers endorse personalised offerings as personally meaningful and important. This finding aligns with the Technology Acceptance Theory (TAM), highlighting how perceived usefulness, importance, and ease of use can enhance user acceptance of AI-personalised systems (Davis, 1989). Natural Language Processing (NLP) and machine learning techniques can analyse **personal life narratives** from large datasets, from the ground up, to identify data related to values, struggles, relationships, and meaning and without losing the idiographic richness (Kuper et al., 2024; Mishra et al., 2025). They can extract emotional and attitudinal insights from generated content across consumer reviews and multi-actor social platforms. These evolving insights can help service providers refine their consumer personas and profiles, enabling better targeting of hyper-personalised recommendations. Furthermore, recent research demonstrates that consumers' acceptance of AI technologies is influenced by individual differences, such as gender, age, and personal traits (Symasek et al., 2025), indicating that adaptive targeting based on individual differences is crucial for consumer endorsement of these technologies.

Overall, these practical implications reinforce the need for hyper-personalisation strategies that go beyond *one-size-fits-all*. Our findings propose a shift in managerial thinking, from a Service-Dominant Logic (SDL) focusing on service exchange and encounters to a Consumer-Dominant Logic (CDL) focusing on becoming involved in consumers' lives (Heinonen and Strandvik, 2022). The use of CDL enables service providers to enhance their adaptability, responsiveness, and consumer-centricity more suited for environments characterised by digital consumer empowerment and the increasing importance of personalised experiences (Dahl et al., 2023). Mechanisms such as reinforcement learning and *just-in-time* message calibration should be ethically constrained and human-centric, offering both adaptability and transparency. Translating this into service design, personalisation strategies that consider both **privacy salience** and **motivational orientation** are likely to yield greater effectiveness.

Key practical takeaways:

- Continuously calibrate hyper-personalisation implementations to consumers' **dynamic goals** and **temporal engagement shifts**.

- Integrate **adaptive learning systems** to track and respond to consumer evolving behaviour in real-time.
- Embed **ethical**, **privacy-sensitive design** using Explainable AI (XAI) principles.
- Address **heterogeneity in adoption patterns** (for example, early adopters versus late adopters) through tailored engagement strategies.
- Embrace a **Consumer-Dominant Logic (CDL)** lens to guide service personalisation around **value formation**.

6.3 Research Limitations

Despite its novel contributions, this study acknowledges several limitations from the scope and interpretation of its findings.

First, the study focused empirically on the *brand-oriented* and *individual-oriented* consumer ecosystems within the underlying the 3-actor constellations of the Consumer-Dominant Logic (CDL) conceptual model, adapted from Heinonen and Lipkin (2022). Although the *social-oriented* consumer ecosystem was not modelled as a distinct empirical construct, it is conceptually represented through approval-oriented goals (e.g., social recognition, family enjoyment) embedded in participants' self-selected active life goals. Moreover, the hyper-personalised content dynamically reflected these goal orientations, reflecting both individual- and social-oriented pursuits when present in participants' selections. The measurement of goal strength therefore captures both individual- and social-oriented motivations without explicitly distinguishing between them. This focus allowed for a clearer examination of how hyper-personalisation influences goal strength dynamics over time, while acknowledging that future research could explicitly compare individual and social goal pursuits within more interaction-driven service contexts.

Second, the study employed a Discrete Choice Experiment (DCE) with an underlying adaptive learning automaton to simulate hyper-personalisation algorithms. Although this design enabled controlled testing of behavioural responses, the approach inevitably simplifies the complexity of real-life consumer decision-making in AI-enabled environments. The dynamic and spontaneous nature of consumer responses in actual service ecosystems may not be fully captured by simulated choice models.

Third, the longitudinal design of the study empirically investigated a simulated AI-enabled service through a single partnership between two distinct yet converging vertical industries — namely, Telecommunications and Entertainment. Since the Telecommunications service provider is an enabler of connectivity and consumer data visibility, this multi-actor, cross-industry collaboration reflects a common service model in digital ecosystems. This narrows the study's applicability and focus in examining more fragmented sectors or complex, decentralised ecosystems with multiple, dynamic partnerships. The nature of Entertainment services may limit motivational salience compared to more goal-intensive sectors such as Internet of Things (IOT) or smart home automation services.

Fourth, although meaningful findings emerged, the study focused on goal strength as a psychological outcome, without tracking how these motivational effects translate into actual consumer behaviours — such as purchase intentions, service renewals, or usage patterns. This limits the practical implications of the study, particularly in understanding long-term behavioural engagement beyond attitudinal shifts.

Fifth, the psychological framing element in the study was restricted to risk-based messaging (neutral vs. risk-averse) and perceived importance of hyper-personalisation. Other potentially relevant psychological dimensions — such as perceived usefulness, trust, or regulatory focus — were not incorporated. This narrows the scope of psychological cues explored and may limit a fuller understanding of consumers' internal decision drivers.

Overall, although this study is contextually grounded and methodologically valid, these limitations highlight important and promising avenues for future expansion and broader application. The findings and CDL-based framework remain theoretically generalisable and practically relevant across a broad array of AI-enabled service ecosystems.

6.4 Future Research Direction

Building on the limitations listed in section 6.3, several opportunities emerge for future studies to expand the understanding of hyper-personalisation within multi-actor service ecosystems.

First, future studies can empirically differentiate the social-oriented consumer ecosystem. While this study conceptually embedded social-oriented dynamics within participants' approval-oriented goals — such as social recognition and family enjoyment, these influences were not modelled as distinct social-actor constructs. Future research could explicitly capture these social interactional dynamics to examine how peer-based motivations, community-driven privacy negotiations, and collective value alignment shape consumer engagement in AI-enabled contexts. Such extensions would refine the 3-actor constellation of the Consumer-Dominant Logic (CDL) framework and provide a richer understanding of adaptive value formation across brand-, individual-, and social-oriented ecosystems, particularly in socially interactive domains such as tourism and social media platforms.

Second, researchers are encouraged to attempt longitudinal field studies using real-life and fully functional AI-enabled service or multi-actor platform, for example one that facilitates real consumer subscription services. While the use of Discrete Choice Experiments (DCE) with an embedded adaptive learning automaton offers a close simulation of hyper-personalisation algorithms, real-life scenarios capture richer and more authentic behavioural data under dynamic value-enabling experiences.

Third, future research should extend this study to more fragmented sectors or complex multi-actor partnerships beyond the examined Telecommunications and Entertainment context. The constructs examined – hyper-personalisation, goal alignment, consumer goal strength, privacy framing, and perceived importance – are applicable to broader consumer engagement principles. Testing the underlying Consumer-Dominant Logic (CDL) framework in ecosystems involving public-private sector collaborations or other verticals such as financial services, mHealth, smart retail, or e-learning can reveal its adaptability. It can potentially unravel trajectory variations across different consumer groups over time. These sectors may present distinct regulatory, motivational, or technological contingencies influencing consumer goal formation and offering valuable future research pathways.

Fourth, future work can expand the model by incorporating additional privacy conditions and psychological constructs, such as trust, regulatory focus, or perceived usefulness. While this study randomly placed participants across neutral versus risk-framed groups, future studies can benefit more by carefully selecting real risk-averse consumer groups or highly regulated communities, that can help unpack the nuanced role of data sensitivity in AI-based engagements. This can deepen the understanding of consumer engagement dynamics under varied privacy conditions and psychological factors.

Fifth, investigating the less-explored link between consumer goal strength and actual behavioural outcomes, such as purchase intentions, service renewals, or subscription longevity would be valuable. Additionally, comparative studies involving the effect of consumer goal strength versus behavioural intention can further strength the validity of this study.

Finally, this study revealed that hyper-personalisation effects may diminish over time unless they are continuously maintained and reinforced. Future research can explore how behavioural nudges, feedback loops, or gamification techniques may be used to help sustain consumer goal strength over time. Moreover, it is important to examine ethical considerations of AI-enabled hyper-personalisation, especially in high-surveillance service contexts or among vulnerable population, ensuring transparency and fairness. Overall, these avenues can enrich the theoretical foundations and enhance the practical impact of AI-driven hyper-personalisation in complex, multi-actor consumer ecosystems for digitally empowered consumers.

6.5 Theoretical Contributions

This study offers a significant theoretical contribution to contemporary and marketing literature by advancing the Consumer-Dominant Logic (CDL) paradigm to the emerging field of goal-aligned AI-enabled hyper-personalisation. While existing literature has primarily focused on conceptual frameworks or system-centric algorithmic models of personalised engagement (Fang et al., 2025; Wang et al., 2025a; Zhu et al., 2023), this study offers a novel empirical implementation grounded in the CDL perspective. By embedding AI-enabled hyper-personalisation within consumers' lifeworld and contextualised experiences, the study shifts the focus from the provider-driven Service-Dominant Logic (SDL) to consumer-centric motivational trajectories over time — illustrating ***how***, ***when***, and ***why*** hyper-personalisation affects behavioural outcomes, namely consumer goal strength.

By reframing consumers as active, empowered primary actors whose engagement is shaped by their internal values, momentary states, and evolving dynamic contexts within their own lived experiences and ecosystems, this study responds to recent calls in literature for a more temporal and contextual understanding of personalisation effects (Heinonen and Strandvik, 2020; Fan et al., 2023). The study integrates and operationalises key theoretical constructs, namely hyper-personalisation, goal alignment, privacy framing, and consumer perceived importance within a dynamic, multi-actor value ecosystem.

The study also challenges the prevailing assumption that AI-enabled personalisation yields uniform or immediate effects (Sun et al., 2025). Instead, the study demonstrates non-linear engagement trajectories, including delayed momentary fluctuations and delayed recoveries, particularly under different privacy framing conditions. Contrary to the uniform and generalised inverted U-shaped effect proposed by Sun et al. (2025), this study positions hyper-personalisation as a dynamic and evolving interplay between goal alignment, personal relevance, perceived importance, and risk varying across individuals and over time — rather than a *one-size-fits-all* solution.

Furthermore, the study contributes new insight into how goal-aligned personalisation operates across time and context as a multi-dimensional construct. By employing a three-wave experimental longitudinal design — a rare approach in hyper-personalisation literature — this study captures both immediate and delayed effects of hyper-personalisation on consumer goal strength, offering a robust framework for future investigations into behavioural and psychological drivers of value formation. This design is uniquely suited to studying *temporal causality*, which many cross-sectional studies overlook. For instance, it identifies sustained consumer motivational value even after peak exposure (Group A) and delayed recovery under High personalisation conditions despite initial scepticism due to privacy concerns (Group B).

These nuanced patterns, including momentary decline, delayed recovery, and contextual variances between privacy framed groups reveal that hyper-personalisation effectiveness is temporally and contextually dynamic, not static. This contrasts with Teepapal (2025)'s Stimulus-Organism-Response (SOR) framework, which conceptualised personalisation as an external stimulus eliciting uniform behavioural responses but failed to reveal a significant effect on consumer engagement in social media contexts. In contrast, this study captures how hyper-personalisation effects are *dynamic* and *temporally fluid*, unfolding longitudinally across consumer trajectories. This addresses a key theoretical gap and highlights the advantage of adopting a Consumer-Dominant Logic (CDL) lens, to better reflect the co-created consumer value formation in multi-actor service settings. Furthermore, the integration of privacy framing and perceived importance introduces new contingencies into the Consumer-Dominant Logic (CDL) framework, validating that consumer value formation is not solely constructed from service attributes and brand-consumer interactions but is co-created and reframed through consumers' internal beliefs, contextual cues, and life goals.

Importantly, the study contributes to the Consumer-Dominant Logic (CDL) theoretical lens through a first-time empirical application of the three-actor constellation model proposed *conceptually* and *qualitatively* by Heinonen and Lipkin (2022), namely *brand-oriented*, *social-oriented*, and *individual-oriented* consumer ecosystems (detailed in **Chapter 3**). While the study's empirical focus centered on the brand- and individual-oriented consumer ecosystems, the social-oriented consumer ecosystem was conceptually represented through participants' approval-oriented goals (e.g., social recognition, family enjoyment) included in their self-selected active life goals. This inclusion reflects the socially embedded nature of goal pursuit within the CDL framework, even though social-oriented interactions were not modelled as a distinct construct. The findings, therefore, reinforce the relevance of the brand-, social-, and individual-oriented consumer ecosystems in shaping value formation within AI-enabled hyper-personalised contexts.

Specifically, the study empirically advances the theoretical understanding of multi-actor constellations (Heinonen and Lipkin, 2019; Mahadevan and Shainesh, 2024) by showing how brand-oriented AI-enabled hyper-personalisation and privacy contextual cues interact with consumers' evolving life goals and perceived importance of hyper-personalisation – reflecting both individual- and social-oriented goal pursuits – to shape motivational outcomes over time. Furthermore, the study extends Consumer-Dominant Logic (CDL) by illustrating the *temporal*, *contextual*, *behavioural*, and *psychological* factors of value formation within multi-actor service ecosystems. Importantly, the study reinforces the value of goal alignment and perceived importance in sustaining hyper-personalisation influence on consumer goal strength. These insights offer a theoretically grounded, contextually adaptive utilisation of CDL tenets in dynamic, technology-enabled service settings.

Taken together, these findings reinforce the CDL emphasis on subjective value formation: consumers co-create value not merely by engaging with hyper-personalisation but by interpreting it within their own psychological, motivational, and temporal contexts (Heinonen and Strandvik, 2022). Thus, the perceived importance of hyper-personalisation functions as a contextual cue, influencing the extent to which personalisation efforts translate into meaningful engagement. This behavioural interpretation aligns with CDL's application by recognising not only what content consumers choose but how they interpret the meaning of personalisation in their own individual contexts.

Methodologically, the study introduces an innovative integration of Discrete Choice Experiments (DCEs) and Linear Mixed Models (LMMs) to simulate and analyse AI-enabled hyper-personalisation. Departing from conventional DCE validation techniques, this approach embeds learning automata algorithms within the choice design to model adaptive, behaviourally grounded personalisation dynamics. This embedded simulation enables a more realistic representation of how hyper-personalisation operates in adaptive, AI-enabled environments. By combining the DCE's simulation of AI-driven decision environments with the LMM's ability to capture *within-individual* temporal variations, the study provides a novel analytical framework for examining dynamic shifts in consumer goal strength across time.

This integrated method departs from the typical multinomial logit or hierarchical Bayesian techniques commonly used in DCEs, offering a more granular, longitudinal understanding of how consumers' personalised choices evolve. Through this hybrid design, the study captures not only between-person preference structures but also momentary intra-individual fluctuations, reflecting the adaptive, co-evolving nature of AI-personalised consumer interactions — often overlooked in static modelling approaches.

Methodologically as well, this study contributes a longitudinal design across three waves, offering rare empirical validation of how perceived importance unfolds over time in a hyper-personalised service context. While existing studies have primarily explored consumer attitudes at a single point in time, this research in contrast captures temporal fluctuations, demonstrating that consumers' interpretation of value is a *dynamic* process — influenced not only by exposure but by ongoing personal meaning-making. Methods that employ dynamic intra-individual modelling N-of-1 designs - less-employed to date - offer valuable insights into how variables fluctuate and interact within an individual over time, rather than generic over-simplified models comparing people to one another (van Zyl and Dick, 2025; Piccirillo and Rodebaugh, 2019; Vieira et al., 2017). Today, advances in science and technological tools are opening new means of research towards studying one person at a time. For example, personal life narratives provide rich insights of idiographic data about what matters in an individual's life such as internal values, goals, struggles, relationships, and meaning (Kuper et al., 2024). These narratives can now be explored and analysed using modern natural language processing (NLP) and machine learning techniques, that can digest large-scale narrative datasets and identify patterns without losing the idiographic richness (Mishtra et al., 2025). These capabilities make service providers much closer to unlocking the true potential of AI-enabled hyper-personalisation strategies.

Together, these contributions offer a revised *temporally-grounded*, *psychologically-aligned*, and *contextually-embedded* understanding of how hyper-personalisation influences value formation. They reinforce the need to move beyond static, one-size-fits-all models toward a model of personalisation that recognises consumers as *active meaning-makers*, navigating evolving personal and technological constructs. By embracing the Consumer-Dominant Logic (CDL) lens, which positions value as emergent, contextual, and experience-dependent, the study demonstrates that *goal-congruent* hyper-personalisation can foster deeper consumer engagement when it dynamically aligns with consumers' evolving lifeworlds, and when it is psychologically endorsed as meaningful and personally important. The study also opens new theoretical avenues for understanding how AI-enabled personalisation sustains engagement beyond system-level attributes and provider-centric service encounters.

6.6 Chapter Summary

This chapter concluded the study by synthesising its key findings, theoretical contributions, practical implications, and directions for future research — directly addressing the central research question:

How does AI-enabled, goal-aligned hyper-personalisation shape consumer goal strength and engagement within dynamic, multi-actor ecosystems?

By adopting a **Consumer-Dominant Logic (CDL)** perspective, the study demonstrated that hyper-personalisation shapes consumer goal strength not through provider-driven mechanisms, but through **value formation processes** unfolding within consumers' own multi-actor ecosystems — where motivation, trust, and meaning are co-created through lived experiences and contextual interactions. This finding directly answers the central research question, revealing that consumer engagement and goal strength emerge when personalisation aligns with consumers' evolving life goals and values, rather than being externally imposed by AI systems.

Unlike the provider-driven focus of Service-Dominant Logic (SDL), CDL emphasises *value-in-context*, positioning consumers as active co-creators of meaning and engagement. The integration of **Goal Systems Theory (GST)** further explained *how* this relationship occurs. AI-enabled hyper-personalisation functions as the **mechanism** that activates and sustains goal pursuit over time. When hyper-personalisation aligns with consumers' personal life goals, it reinforces commitment and long-term motivation. When misaligned, it risks undermining autonomy and amplifying privacy concerns. Importantly, privacy emerged not as a *static inhibitor* but a *dynamic*, *evolving* construct — suggesting that transparent and ethically framed communication can rebuild consumer trust and agency and strength engagement over time.

Methodologically, the study answered the research question by advancing a *multi-level*, *temporal* approach that integrates **Discrete Choice Experiments (DCEs)** with **Linear Mixed Models (LMMs)** to simulate adaptive AI-personalisation processes and track both *between-* and *within-individual* variations over time. This innovative integration provided empirical evidence that consumer goal strength evolves *dynamically* and *contextually*, mirroring real-world adaptation in AI-driven engagement. By adopting the **three-actor constellation** of CDL, the study operationalised value formation across *brand-*, *individual-*, and *social-oriented* consumer ecosystems. Combined with the DCE-LMM analytical approach, this design empirically captured ***how***, ***when***, and ***why*** value evolves over time, bridging behavioural simulation with longitudinal psychological modelling.

Overall, the study shows that AI-enabled hyper-personalisation influences consumer goal strength by fostering *goal-congruent*, *time-sensitive*, *ethically aligned*, and *contextually adaptive* engagement. It advances both theoretical and practical understanding by positioning hyper-personalisation as a co-evolving process of value formation — one that enhances rather than undermines — consumer autonomy, trust, and long-term value co-creation in AI-driven environments. It further underscores that sustaining engagement depends on maintaining psychological relevance, ethical transparency, and dynamic responsiveness to consumers' evolving contexts and goals.

By advocating this multi-dimensional design, the study contributes to the development of AI-enabled hyper-personalisation strategies that are not only adaptive and goal-congruent but also *ethical*, *transparent*, and *responsible* — enabling service providers to engage ***with*** and ***into*** the lives of their consumers.

Appendix A

This appendix provides additional supplementary visual materials used during the experimental setup. The included screenshots illustrate selected user interface elements and question prompts presented to participants during their engagement with the AI-enabled service simulation. These materials are referenced in **Chapter 4** (*section 4.2.2 Experiment Setup*) and serve to demonstrate the structure, visual framing, and content presentation of the experimental activities. They are included here for documentation purposes and to assist future replication or comparative research. Note that some of the experiment screenshots are placed in *section 4.2.2*.

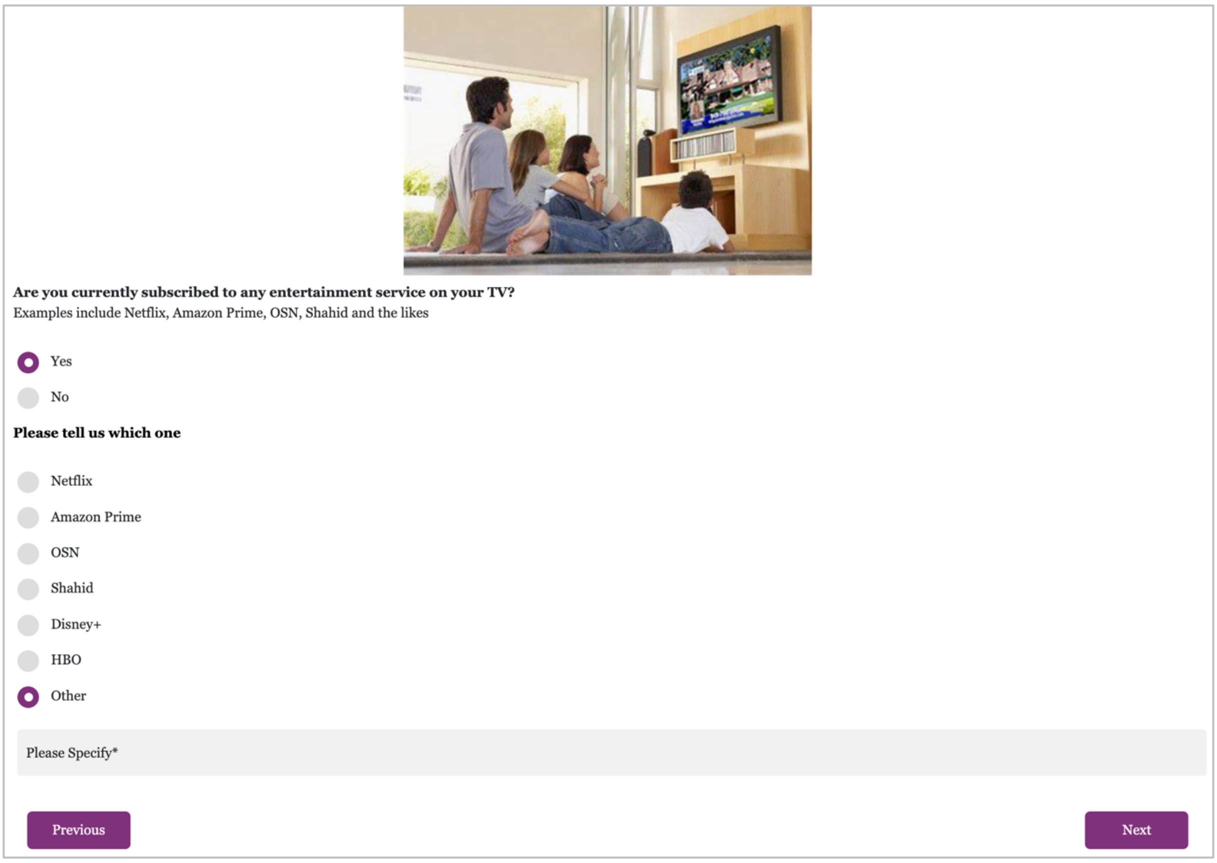
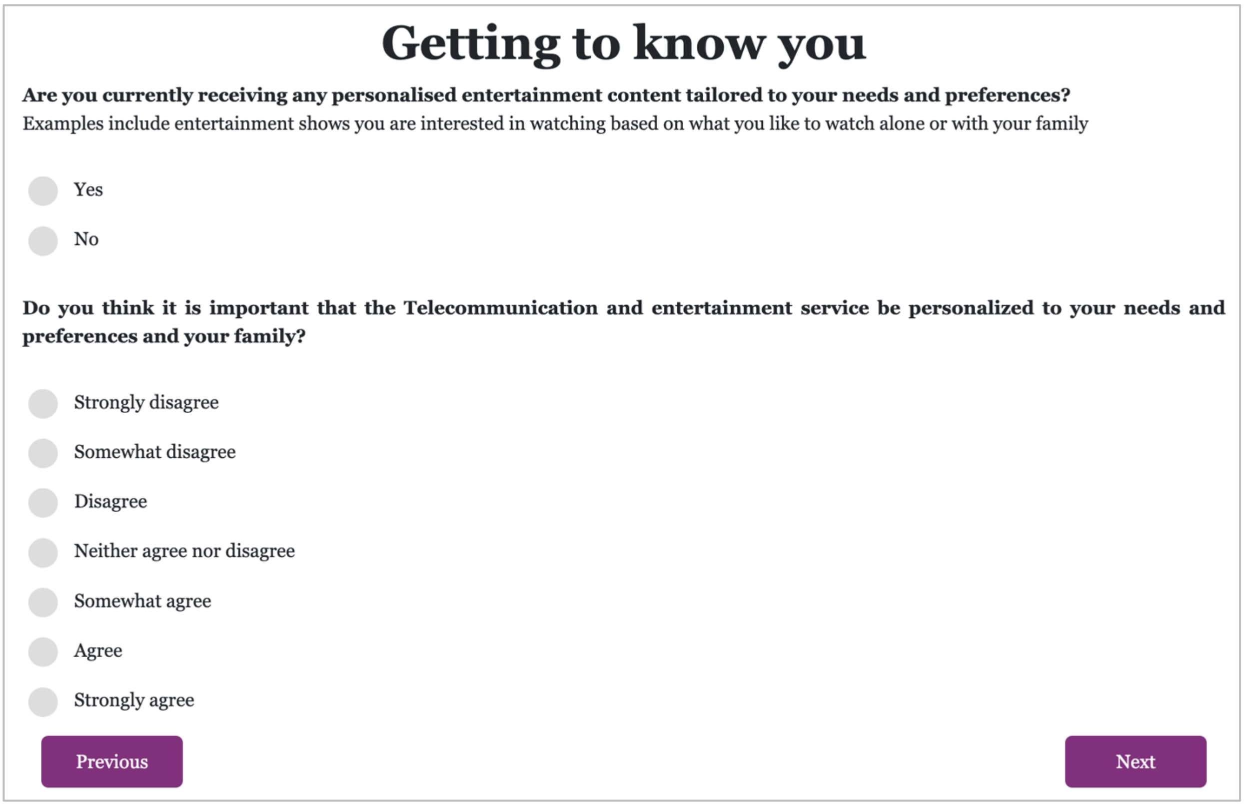


Figure A.A 1: *"Are your currently subscribed to any entertainment service" Question and Options*



Getting to know you

Are you currently receiving any personalised entertainment content tailored to your needs and preferences?
Examples include entertainment shows you are interested in watching based on what you like to watch alone or with your family

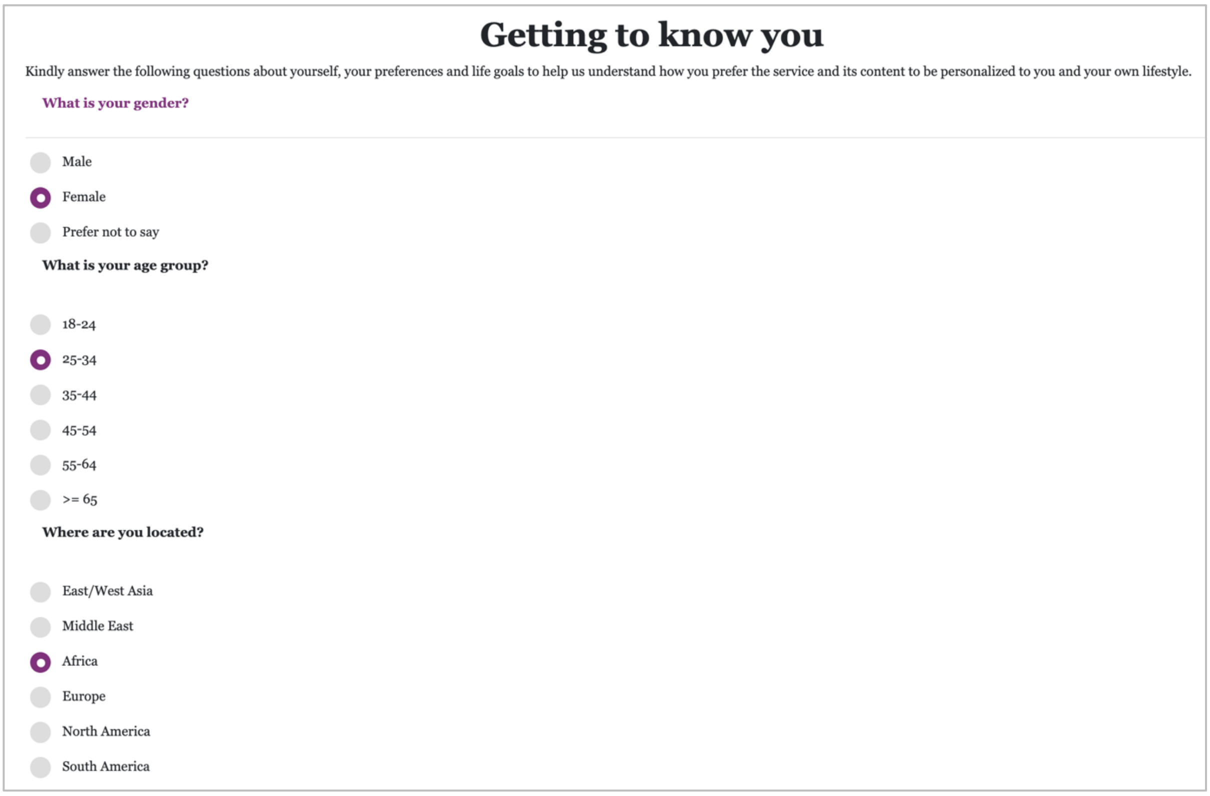
- Yes
- No

Do you think it is important that the Telecommunication and entertainment service be personalized to your needs and preferences and your family?

- Strongly disagree
- Somewhat disagree
- Disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Previous Next

Figure A.A 2: *Receiving Personalisation and Personalisation Perceived Importance Questions*



Getting to know you

Kindly answer the following questions about yourself, your preferences and life goals to help us understand how you prefer the service and its content to be personalized to you and your own lifestyle.

What is your gender?

- Male
- Female
- Prefer not to say

What is your age group?

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- >= 65

Where are you located?

- East/West Asia
- Middle East
- Africa
- Europe
- North America
- South America

Figure A.A 3*: Participant's demographic data including gender, age, and Location*

What are the three top content categories you frequently use your internet to browse?

Please choose 3 categories only from the below. You can add free text if you do not find your selection from the options below

- Books and magazines
- Food and cooking
- Cars and Motorbikes
- News and Podcasts
- Video Streaming (like YouTube and Live TV)
- Home Décor and Furniture
- Fashion and retail
- Music Streaming (like Spotify and YouTube)
- Training and Personal development
- Lifestyle and celebrities
- Online gaming and gaming Apps
- Trading and banking
- Please provide your own selection here
- Please provide your own selection here
- Please provide your own selection here

What are three destinations you frequently travelled to in the past 24 months? Please choose up to 3 from the below

Destination

Figure A.A 4: *Telecommunication data including frequently browsed content and travel destinations*

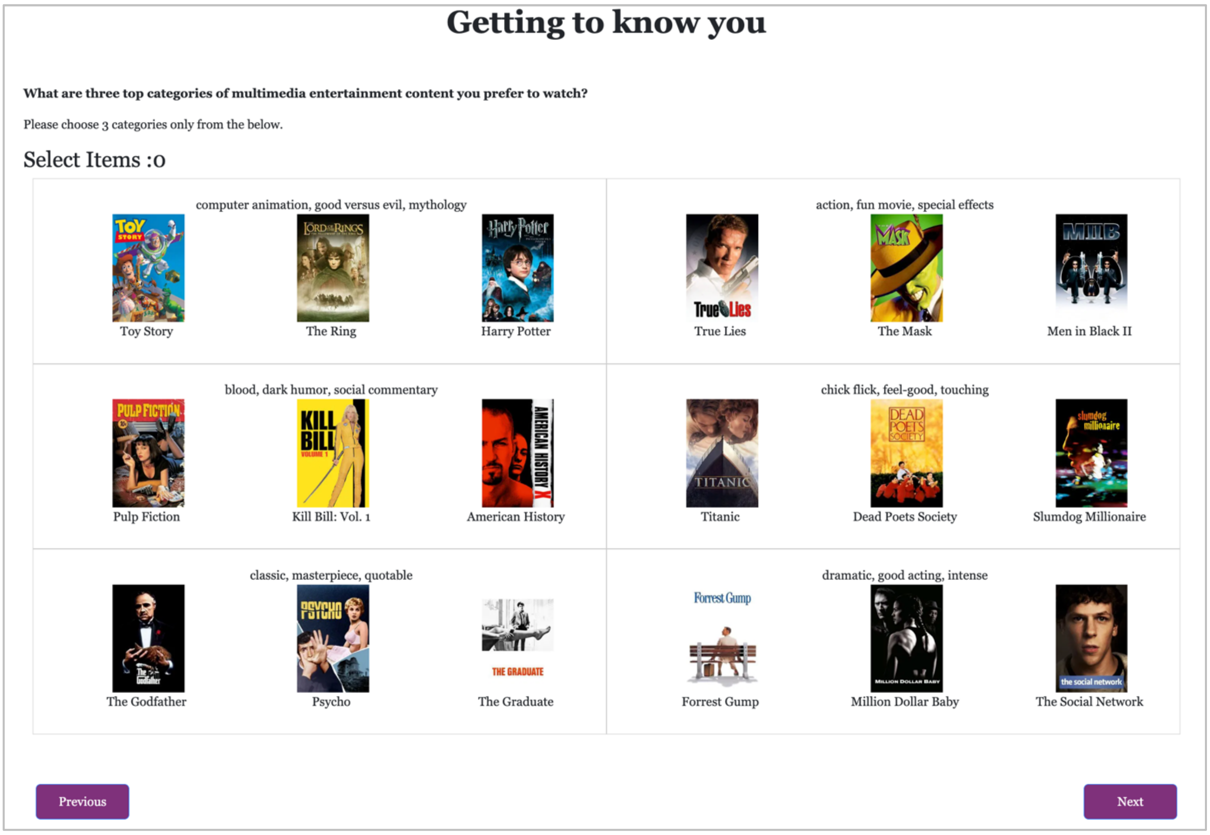


***Figure A.A 5**: Non-Telecommunications Entertainment Preferences Adapted from MovieLens Interface*

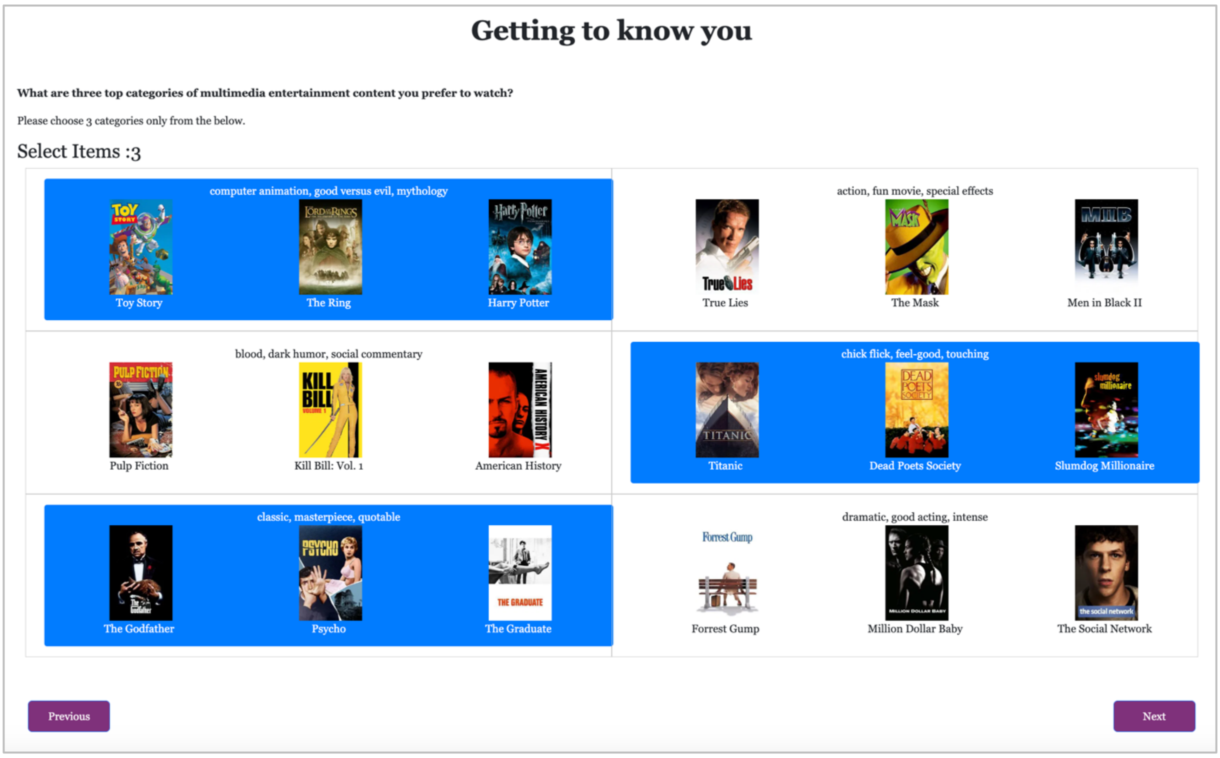
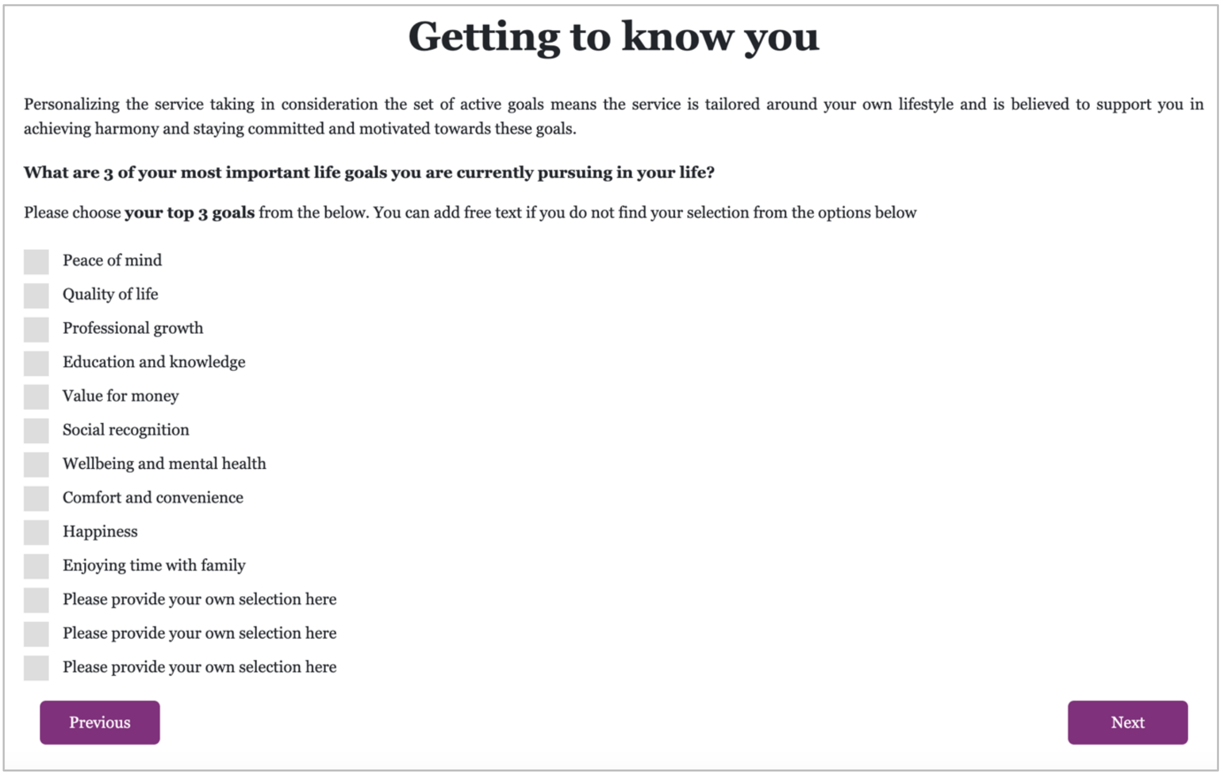


***Figure A.A 6**: Selection of Non-Telecommunications Entertainment Preferences - Adapted MovieLens Interface*



Getting to know you

Personalizing the service taking in consideration the set of active goals means the service is tailored around your own lifestyle and is believed to support you in achieving harmony and staying committed and motivated towards these goals.

What are 3 of your most important life goals you are currently pursuing in your life?

Please choose **your top 3 goals** from the below. You can add free text if you do not find your selection from the options below

- [ ] Peace of mind
- [ ] Quality of life
- [ ] Professional growth
- [ ] Education and knowledge
- [ ] Value for money
- [ ] Social recognition
- [ ] Wellbeing and mental health
- [ ] Comfort and convenience
- [ ] Happiness
- [ ] Enjoying time with family
- [ ] Please provide your own selection here
- [ ] Please provide your own selection here
- [ ] Please provide your own selection here

Previous

Next

Figure A.A 7*: Participant Selection of Top Three Consumer Active Life Goals*

Appendix B

DCE-GLMM: Findings

This section presents the results of the **DCE–GLMM** model test, conducted to assess the internal validity of the experimental design and confirm that the manipulated framing conditions produced systematic variation in participants' choice behaviour.

***Table A.B 1**: Model Test Summary – Internal Validity of Experimental Design*

Source	**F**	**df1**	**df2**	**p**	**Interpretation**
Corrected Model	8.768	15	3499	< .001	The overall model **significantly** explains variance in choice behaviour
Index *(Wave)*	1.453	6	3499	.190	No main effect across waves (**choices stable across time**)
Group *(Privacy Framing)*	19.798	3	3499	< .001	**Significant** differences between framing conditions
Index × Group	12.070	6	3499	< .001	**Strong** interaction supports systematic variation (valid experimental manipulation)

<u>*Note*</u>. Probability distribution = multinomial; link = generalised logit.
Target: Selection (*dependent variable*)

→ **Interpretation:** The significant interaction term (Index × Group) provides empirical evidence of ***internal validity***, confirming that participants' choices systematically varied as a function of experimental manipulations (personalisation × privacy framing).

***Table A.B 2**: Model Impact Estimate and Relative Importance of Levels (Part-Worth Utilities)*

Attribute / Level	**Utility Estimate**	**Importance Score (Range)**
Personalisation Level (Selection)		**0.996 (19.9%)**
Level 1 (V1)	0.602	
Level 2 (V2)	0.175	
Level 3 (V3)	-0.394	
Level 4 (V4 - *reference*)	0	
Time (Index)		**0.919 (18.4%)**
Wave 1 (*baseline*)	-0.647	
Wave 2 *(after 10 days)*	-0.469	
Wave 3 *(after 5 months)*	0.272	

Privacy Framing (Group)		**0.893 (17.8%)**
Neutral at Level 1	-1.622	
Neutral at Level 2	-0.729	
Neutral at Level 3	-0.16	
Risk-framed *(reference)*	0	
Interaction (Index × Group)		**2.197 (43.9%)**
Wave 1 × Group	1.738	
Wave 2 × Group	0.889	
Wave 3 × Group	-0.459	

→ **Interpretation:** The interaction term (Index × Group) has the greatest influence on participants' selection, suggesting that preferences are dynamic and context-dependent.

Table A.B 3*: Systematic Variations in Choice Probabilities – Part-Worth Utilities*

Predictor	**Coefficient (B)**	**SE**	**Exp (B)**	**95 % CI (ExpB)**	**p**	**Interpretation**
Selection 1 vs 4 (Baseline)						
Intercept	0.602	0.136	1.826	[1.399, 2.383]	< .001	Baseline preference positive
Index 1	–0.647	0.172	0.524	[0.374, 0.734]	< .001	Lower likelihood at low level of personalisation
Index 2	–0.469	0.179	0.626	[0.440, 0.890]	.009	Moderate decrease
Group 1 (*Neutral*)	–1.622	0.201	0.197	[0.133, 0.293]	< .001	Neutral framing reduces selection odds
Index 1×Group 1	1.738	0.248	5.687	[3.499, 9.243]	< .001	Strong positive interaction effect
Index 2×Group 1	0.889	0.256	2.433	[1.472, 4.022]	.001	Positive interaction under neutral framing and short-term

Note. Probability distribution = multinomial; link = generalised logit.
Target: Selection (*dependent variable*)

→ **Interpretation**: Higher personalisation levels (especially under neutral framing) significantly increased the odds of selection, indicating systematic variation in choice probabilities consistent with deeper engagement preferences.

Table A.B 4*: Random Effects Summary – Between-Participant Variation*

Effect	**Estimate**	**SE**	**Z**	**p**	**95 % CI**
Var(Intercept) – Selection 1	0.183	0.085	2.143	.032	[0.073, 0.456]
Var(Intercept) – Selection 2	0.126	0.080	1.567	.117	[0.036, 0.440]
Var(Intercept) – Selection 3	0.126	0.096	1.307	.191	[0.028, 0.564]

→ **Interpretation**: The significant random intercept for Selection 1 ($p = .032$) suggests between-person variability in baseline choice preferences, validating the model's inclusion of random effects for repeated measures.

Model 1: Unconditional Baseline Findings

Model 1 was used as an unconditional linear mixed model, estimating the overall change in goal strength over time without including experimental predictors. As shown in **Table A.B.5**, both the intercept and time effects are statistically significant, indicating a general upward trend in goal strength across the three waves. **Table A.B.6** reports the fixed and random effects of the intercept-only model, highlighting *between-person* variance in baseline levels (intercepts) and *within-person* variability in slopes across time points. These results confirm the suitability of a multilevel growth modeling approach and establish a foundational trajectory pattern used to inform the subsequent models.

Table A.B 5*: Model 1 - Type III Tests of Fixed Effects for the Unconditional Model of Goal Strength*

Effect	**df (num)**	**df (den)**	**F**	**p**
Intercept	1	1395.822	21687.09	< .001
Time	2	1178.864	21.416	< .001

Note. Dependent variable: Goal Strength. Model tested time as a fixed effect with repeated measures across three waves.

***Table A.B 6**: Model 1 - Linear Mixed Model (Model 0): Intercept-only Model of Goal Strength*

Fixed effects	**Estimate (β)**	***SE***	***p***	**95% CI**
Intercept	30.510	0.288	< .001	[29.945, 31.074]
Time = Wave 2 (10 days)	1.986	0.325	< .001	[1.347, 2.624]
Time = Wave 3 (5 months)	1.912	0.392	< .001	[1.142, 2.681]
Time = Wave 1 (Baseline)	*Reference*			
Random effects *(Variance components)*	**Estimate**	***SE***	***p***	**95% CI**
Intercept (subject = ID)	50.714	-	-	-
UN (1,1) *variance at Time = 0 (wave 3)*	41.936	4.462	< .001	[34.042, 51.661]
UN (2,2) *variance at Time = 1 (wave 2)*	58.521	4.367	< .001	[50.559, 67.737]
UN (3,3) *variance at Time = 2 (wave 1)*	68.047	4.437	< .001	[59.884, 77.324]
UN (2,1) *covariance [wave2, wave3]*	-19.869	3.455	< .001	[-26.641, -13.097]
UN (3,1) *covariance [wave3, wave1]*	-26.185	3.518	< .001	[-33.080, -19.291]
UN (2,3) covariance [wave2, wave1]	-5.236	3.375	.121	[-11.852, 1.380]
Model Fit Indices	**Value**			
-2-Log Likelihood (-2LL)	26,147.67			
Akaike's Information Criterion (AIC)	26161.67			
Schwarz's Bayesian Criterion (BIC)	26204.82			

Note. UN (i, j) parameters in *Table A.B.1* refer to the *unstructured covariance matrix* estimates between measurement occasions, used for repeated measure *Time.*

Furthermore, the spaghetti plots were used as supplementary visuals to explore intra-individual goal strength trajectories over time. In support of the main analysis described in Chapter 4 (*section 4.4.4.1),* the following figures provide a comparative view of linear versus quadratic time trends across a random sample of 100 participants. These visual diagnostics illustrate the observed variability in growth patterns and justify the use of fixed and random effects in subsequent mixed model estimations. Differences between experimental groups are also visualised to support model selection decisions (*section 4.4.3).*

Figure A.B.1 illustrates growth patterns under a quadratic time trend to assess potential non-linearity. Some individual patterns exhibit a curvilinear pattern (some showing recovery after a decline), most of the participants appears to follow approximately linear, steady paths. Although not statistically significant, the findings reinforce the decision to proceed with linear model for clarity. These visual diagnostics help guide model selection and justify the use of fixed and random effects in subsequent models.

Figures A.B.2 and **A.B.3** further compare experimental groups, showing that Group A (*control*) displayed a decline in Goal Strength over time, while Group B (*negative framing group*) showed a smoother, more positive upward trend over time. This preliminary visual analysis of sample data confirms the need for a model that can capture individual personal trajectories and group-level patterns. *Model 1*, as a baseline model, captures these insights, which is presented and proven by its findings in **Chapter 5** (refer to *section 5.1.1*).

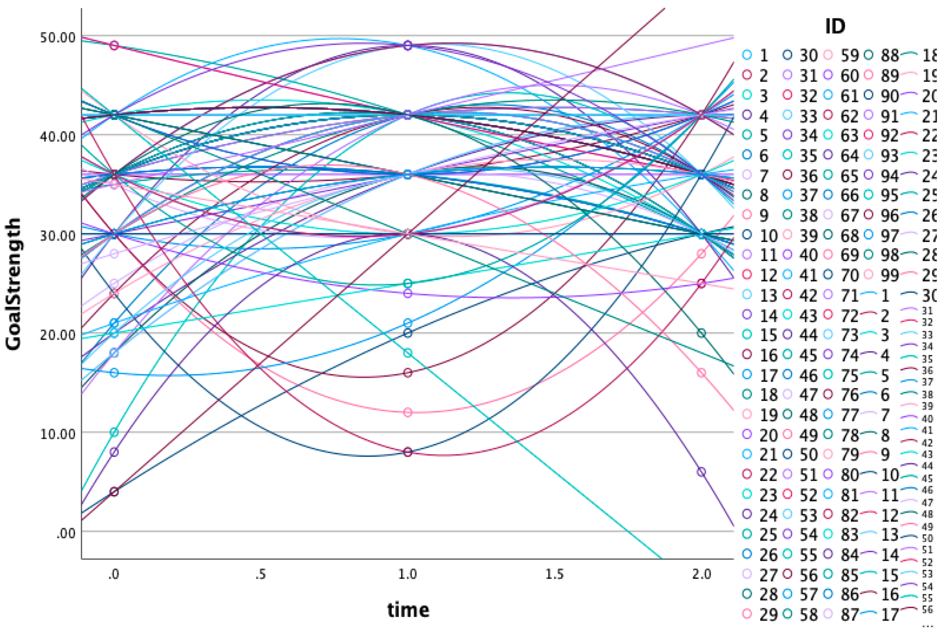


***Figure A.B 1**: Spaghetti Plot of Intra-Individual Quadratic Goal Strength Trajectories over time [100 random participants]*

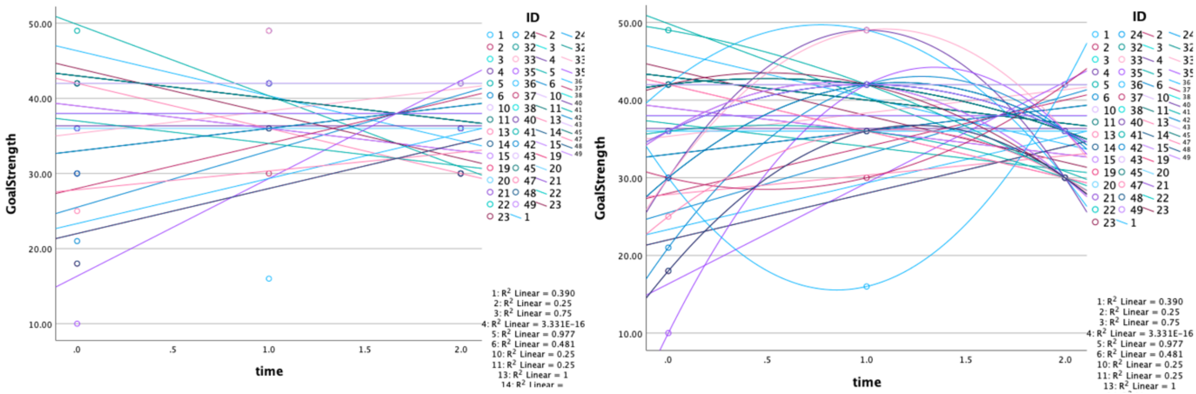


Figure A.B 2*: Spaghetti Plot of Intra-Individual Linear/Quadratic Goal Strength Trajectories of Group A over time [100 random participants]*

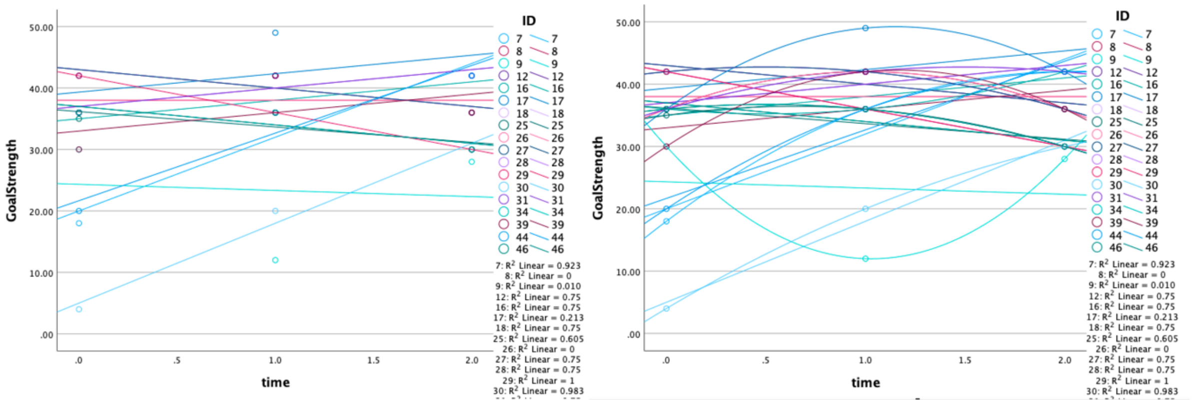


Figure A.B 3*: Spaghetti Plot of Intra-Individual Linear/Quadratic Goal Strength Trajectories of Group B over time [100 random participants]*

Model 2: Theoretical Hypothesis Findings

Model 2 was built as a linear mixed-effects model (LMM) using time as specified as a linear mixed-effects model with time entered as a categorical fixed effect, and grand-mean personalisation (calculated across all three time points) entered as a between-person fixed predictor. A random intercept was included for each participant (ID) to account for individual differences in baseline goal strength. This model structure isolates trait-level variation in perceived personalisation and its effect on average goal strength across the study duration.

Table A.B 7*: Model 2 - Type III Tests of Fixed Effects for the Theoretical Hypothesis Model of Goal Strength*

Effect	**df (num)**	**df (den)**	**F**	**p**
Intercept	1	1431.713	21017.044	< .001
Time	2	1184.877	19.137	< .001
Group	1	1431.713	1.364	.243
*Time * Group*	2	1184.877	13.612	< .001
Grand_SelectionMean	1	1518.932	13.267	< .001
Centered_Selection	1	2023.743	.616	.433
*Group * Grand_SelectionMean*	1	1518.932	.135	.713
*Group * Centered_Selection*	1	2023.743	4.890	.027
*Time * Centered_Selection*	2	2004.234	.679	.507
*Time * Group * Centered_Selection*	2	2004.234	2.773	.063

Note. Dependent variable: Goal Strength. Model tested time as a fixed effect with repeated measures across three waves.

Table A.B 8: *Model 2 - Linear Mixed Model Fixed Effects for Goal Strength (Hypothesis 1 and Hypothesis 2)*

Fixed effects	**Estimate (*β*)**	***SE***	**df**	***t***	***p***	**95% CI**
Intercept	30.944	0.422	1437.363	73.317	< .001	[30.116, 31.772]
Time = Wave 2 ***(10 days)***	.712	0.469	1351.165	1.518	.148	[-.208, 1.632]
Time = Wave 3 ***(5 months)***	2.552	0.576	1116.863	4.434	< .001	[1.423, 3.682]
Time = Wave 1 ***(Baseline)***	*Reference*					
Group = 1 ***(Group A - Neutral)***	−0.844	0.583	1437.930	−1.447	.148	[−1.988, 0.300]
Group = 2 (*Group B – Risk-framed*)	*Reference*					
Time=1 * Group=1 ***(10 days, Group A)***	2.327	0.652	1358.658	3.567	<.001	[1.047, 3.606]
*Time=0 * Group=1* ***(5 months, Group A)***	*-1.330*	0.798	1126.250	-1.667	.096	[-2.896, .235]
Grand-Mean Personalisation ***(Between-person)***	1.072	0.396	1467.719	2.704	.007	[0.294, 1.849]
Centered_Selection ***(Within-person)***	.089	.491	1493.612	.180	.857	[-.874, 1.051]

Fixed effects	Estimate (*β*)	*SE*	df	*t*	*p*	95% CI
*Time = 1 * CenteredSelection* ***(At 10 days)***	-.680	.775	2489.818	-.877	.381	[-2.200, .840]
*Time = 0 * CenteredSelection* ***(At 5 months)***	-.344	.720	1601.362	-.478	.633	[-1.756, 1.068]
*Group = 1 * Grand_SelectionMean* ***(Group A, Neutral)***	-.196	.533	1519.222	-.367	.713	[-1.245, .852]
*Group = 1 * Centered_Selection* ***(Group A, Neutral)***	-.289	.677	1504.072	-.427	.670	[-1.618, 1.040]
*Time = 1 * Group = 1 * Centered_Selection* ***(Group A At 10 days***	2.471	1.072	2439.547	2.305	.021	[.369, 4.574]
*Time = 0 * Group = 1 * Centered_Selection* ***(Group A At 5 months)***	.747	1.012	1610.221	.738	.461	[-1.238, 2.731]
Random effects *(Variance components)*	**Estimate**	***SE***	***p***			**95% CI**
Intercept (subject = ID)	47.753	-	-			-
UN (1,1) *variance at Time = 0 (wave 3)*	44.202	4.445	< .001			[36.295, 53.830]
UN (2,2) *variance at Time = 1 (wave 2)*	58.822	4.275	< .001			[51.012, 67.827]
UN (3,3) *variance at Time = 2 (wave 1)*	71.053	4.449	< .001			[62.848, 80.331]
UN (2,1) *covariance [wave2, wave3]*	-15.720	3.458	< .001			[-22.498, -8.942]
UN (3,1) *covariance [wave3, wave1]*	-23.854	3.515	< .001			[-30.743, -16.965]
UN (3,2) covariance [wave2, wave1]	-2.632	3.346	.431			[-9.190, 3.926]
Model Fit Indices	**Value**					

Fixed effects	**Estimate (*β*)**	***SE***	**df**	***t***	***p***	**95% CI**
-2-Log Likelihood (-2LL)	26,086.97					
Akaike's Information Criterion (AIC)	26,100.97					
Schwarz's Bayesian Criterion (BIC)	26,144.099					

Note. Time = 2 coded for wave 0 is the baseline reference for Time. Group B (Negative Privacy Framing) is the reference for Group. Grand mean centered hyper-personalisation (Grand_Mean_Selection) is centered at sample grand mean M = 2.486. Person-mean centered hyper-personalisation (*CenteredSelection*) is calculated as each participant's *Selection - GrandMean_Selection.*

Model 3: Post-Hoc Exploratory Findings

Model 3 presents a post-hoc exploratory analysis conducted to examine how perceived importance of hyper-personalisation interacts with hyper-personalised content selection patterns over time. This model builds on earlier fixed effects by incorporating both *person-mean centered* (within-person variation) and *grand-mean centered* (between-person variation) measures of hyper-personalisation selection, in conjunction with participants' *perceived importance* of hyper-personalisation.

As shown in **Tables A.B.9** and **A.B.10**, the analysis highlights the main effects of these variables and their interaction effects (e.g., Time × Perceived Importance) to detect whether personal valuation moderates temporal changes in *Goal Strength*. These results are exploratory in nature and serve to identify potential patterns that could be tested in future confirmatory models.

Table A.B 9*: Model 3 - Type III Tests of Fixed Effects for the Post-hoc Model of Goal Strength*

Effect	**df (num)**	**df (den)**	**F**	**p**
Intercept	1	1253.069	417.097	< .001
Time	2	1106.722	106.244	< .001
Group	1	1307.366	.264	.243
PersonalisedImportance	1	1255.303	358.688	< .001
*Grand_SelectionMean * PersonalisedImportance*	1	1536.908	17.521	< .001

*Centered_Selection * PersonalisedImportance*	1	2152.635	1.287	.257
*Time * PersonalisedImportance*	2	1107.999	89.037	< .001
*Group * PersonalisedImportance*	1	1317.885	.663	.416
*Time * Group * PersonalisedImportance*	2	1172.698	15.764	< .001

Note. Dependent variable: Goal Strength. Model tested time as a fixed effect with repeated measures across three waves.

***Table A.B 10**: Model 3 - Linear Mixed Model Fixed Effects for Goal Strength*

Fixed effects	**Estimate (β)**	***SE***	**df**	***t***	***p***	**95% CI**
Intercept	4.364	1.355	1751.258	3.220	.001	[1.706, 7.022]
Time = Wave 2 ***(10 days)***	15.923	1.323	1289.322	12.037	< .001	[13.328, 18.519]
Time = Wave 3 ***(5 months)***	19.881	1.559	1030.831	12.751	< .001	[16.821, 22.941]
Time = Wave 1 ***(Baseline)***	*Reference*					
Group = 1 **(*Group A - Neutral*)**	0.829	1.612	1307.366	.514	.607	[−2.334, 3.993]
Group = 2 **(*Group B – Risk-framed*)**	*Reference*					
PersonalisedImportance	4.784	0.240	1745.157	19.939	<.001	[4.313, 5.254]
*Grand_SelectionMean * PersonalisedImportance*	.171	.041	1536.908	4.186	<.001	[.091, .251]
*Centered_Selection * PersonalisedImportance*	.034	0.030	2152.635	1.135	.257	[-.025, .092]
*Time = 1 * PersonalisedImportance* ***(At 10 days)***	- 2.727	.239	1291.586	-11.388	<.001	[-3.196, -2.257]
*Time = 0 * CenteredSelection* ***(At 5 months)***	-3.084	.283	1034.793	-10.904	<.001	[-3.639, -2.529]
*Group = 1 * PersonalisedImportance* ***(Group A, Neutral)***	-.255	.289	1413.487	-.882	.378	[-.823, .312]
*Time = 1 * Group = 1 * PersonalisedImportance*	.392	.111	1337.990	3.548	<.001	[.175, .609]

Fixed effects	Estimate (*β*)	*SE*	df	*t*	*p*	95% CI
(Group A At 10 days						
*Time = 0 * Group = 1 * PersonalisedImportance* ***(Group A At 5 months)***	-.323	.134	1088.706	-2.409	.016	[-.585, -.060]
Random effects *(Variance components)*	**Estimate**	***SE***	***p***			**95% CI**
Intercept (subject = ID)	40.235	-	-			-
UN (1,1) *variance at Time = 0 (wave 3)*	48.005	4.287	< .001			[40.298, 57.186]
UN (2,2) *variance at Time = 1 (wave 2)*	59.459	4.006	< .001			[52.104, 67.853]
UN (3,3) *variance at Time = 2 (wave 1)*	42.188	3.084	< .001			[36.557, 48.686]
UN (2,1) *covariance [wave2, wave3]*	-13.962	4.287	< .001			[-20.379, -7.545]
UN (3,1) *covariance [wave3, wave1]*	-27.704	3.884	< .001			[-33.356, -22.052]
UN (3,2) covariance [wave2, wave1]	-11.715	2.637	< .001			[-16.883, -6.547]
Model Fit Indices	**Value**					
-2-Log Likelihood (-2LL)	25,591.3465					
Akaike's Information Criterion (AIC)	25,605.3465					
Schwarz's Bayesian Criterion (BIC)	25,648.4781					

Note. Time = 2 coded for wave 0 is the baseline reference for Time. Group B (Negative Privacy Framing) is the reference for Group. Grand mean centered hyper-personalisation (Grand_Mean_Selection) is centered at sample grand mean M = 2.486.

References

Abid, M.F., Shamim, A., Thaichon, P., Quach, S., Siddique, J., and Awan, M.I. (2025) 'Holistic customer experience: interplay between retail experience quality, customer in-shop emotion valence and in-shop involvement valence', *Marketing Intelligence and Planning*, *43*(5), pp. 912-933. https://doi.org/10.1108/MIP-09-2023-0478

Abdul, S., Adeghe, E. P., Adegoke, B. O., Adegoke, A. A., and Udedeh, E. H. (2024) 'Mental health management in healthcare organizations: Challenges and strategies-a review', *International Medical Science Research Journal*, *4*(5), pp. 585-605. https://doi.org/10.51594/imsrj.v4i5.1157

Abrahams, T.O., Ewuga, S.K., Kaggwa, S., Uwaoma, P.U., Hassan, A.O. and Dawodu, S.O. (2023) 'Review of strategic alignment: Accounting and cybersecurity for data confidentiality and financial security', *World Journal of Advanced Research and Reviews*, *20*(3), pp. 1743 – 1756. http://doi.org/10.30574/wjarr.2023.20.3.2691

Acquisti, A., Brandimarte, L. and Loewenstein, G. (2015) 'Privacy and human behavior in the age of information', *Science*, *347*(6221), pp.509-514. https://doi.org/10.1126/science.aaa1465

Acquisti, A., Brandimarte, L. and Loewenstein, G., (2020) 'Secrets and Likes: The Drive for Privacy and the Difficulty of Achieving It in the Digital Age', *Journal of Consumer Psychology*, *30*(4), pp.736–758. https://doi.org/10.1002/jcpy.1191

Adaga, E.M., Egieya, Z.E., Ewuga, S.K., Abdul, A.A., and Abrahams, T.O. (2024) 'A comprehensive review of ethical practices in banking and finance', *Finance & Accounting Research Journal*, *6*(1), pp. 1-20.

Adefemi, A., Daudu, C.D., Okoli, C.E., Ayorinde, O.B., Adekoya, O.O. and Ibeh, C.V., (2024) 'Reviewing the impact of LNG technology advancements on global energy markets', *Engineering Science & Technology Journal*, *5*(1), pp. 128-151.

Adjerid, I., Acquisti, A., and Loewenstein, G. (2019) 'Choice Architecture, Framing, and Cascaded Privacy Choices', *Management Science*, 65(5), pp. 1949-2443. https://doi.org/10.1287/mnsc.2018.3028.

Agarwal, S. and Modanwal, P. (2025) 'AI-Driven Personal Finance Assistants: Enhancing Customization Through Behavioural Insights', *International Journal of Engineering Development and Research*, *13*(2), pp.425-432.
Available: https://rjwave.org/IJEDR/papers/IJEDR2502168.pdf

Agrawal, N., and Wan, E.W. (2009) 'Regulating risk or risking regulation? Construal levels and depletion effects in the processing of health messages', *Journal of Consumer Research*, *36*(3), pp. 448–462. https://doi.org/10.1086/597331

Aguirre, E., Mahr, D., Grewal, D., De Ruyter, K. and Wetzels, M. (2015) 'Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness', *Journal of retailing*, *91*(1), pp.34-49. https://doi.org/10.1016/j.jretai.2014.09.005

Ajiga, D.I., Ndubuisi, N.L., Asuzu, O.F., Owolabi, O.R., Tubokirifuruar, T.S. and Adeleye, R.A. (2024) 'AI-Driven Predictive Analytics in Retail: A Review of Emerging Trends and Customer Engagement Strategies', *International Journal of Management & Entrepreneurship Research*, 6(2), pp. 307-321.
https://doi.org/10.51594/ijmer.v6i2.772

Ajzen, I. (1991) 'The theory of planned behavior', *Organizational Behavior and Human Decision Processes*, *50*(2), pp. 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2012) 'The theory of planned behaviour', In P. A. M. van Lange, A. W. Kruglanski, and E. T. Higgins (Eds.), Handbook of theories of social psychology (Vol. 1, pp. 438–459). Sage. https://doi.org/10.4135/9781446249215

Ajzen, I. and Fishbein, M. (1970) 'The prediction of behavior from attitudinal and normative variables', *Journal of experimental social Psychology*, *6*(4), pp. 466-487. https://doi.org/10.1016/0022-1031(70)90057-0

Ajzen. I., and Fishbein, M. (1980) *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, NJ: Prentice-Hall.

Ajzen, I., and Kruglanski, A. W. (2019) 'Reasoned action in the service of goal pursuit', *Psychological Review*, *126*(5), pp. 774–786. https://doi.org/10.1037/rev0000155

Ajzen, I. and Schmidt, P. (2020) 'Theory of Reasoned Goal Pursuit: A new theory linking intentions and goal achievement', *Journal of Business and Psychology*, [Online] Springer. Available at: https://link.springer.com/article/10.1007/s10869-025-10009-8.

Akaka, M.A. and Vargo, S.L. (2015) 'Extending the context of service: from encounters to ecosystems', *Journal of Services Marketing*, *29*(6/7), pp.453-462. https://doi.org/10.1108/JSM-03-2015-0126

Akdim, K. and Casaló, L.V. (2023) 'Perceived value of AI-based recommendations service: the case of voice assistants', *Service Business*, *17*(1), pp. 81-112, https://doi.org/10.1007/s11628-023-00527-x.

Akinc, D., Street, D.J. and Vandebroek, M. (2024) 'Varying choice set sizes in discrete choice experiments', *Journal of choice modelling*, *52*, p.100493. https://doi.org/10.1016/j.jocm.2024.100493

Alberts, L., Lyngs, U., and Lukoff, K. (2024) 'Designing for sustained motivation: a review of Self-Determination Theory in behaviour change technologies', *Interacting with Computers*, iwae040, pp. 1-22. https://doi.org/10.1093/iwc/iwae040

Alcañiz, M., Parra, E., and Giglioli, I.A.C. (2018) 'Virtual reality as an emerging methodology for leadership assessment and training', *Frontiers in Psychology*, *9*, pp. 1658, https://doi.org/10.3389/fpsyg.2018.01658.

Alexander, M., Jaakkola, E. and Hollebeek, L. (2018) 'Zooming out: actor engagement beyond the dyadic', *Journal of Service Management*, 29(3), pp. 333-351. https://doi.org/10.1108/JOSM-08-2016-0237

Alderson, W. and Martin, M.W. (1965) 'Toward a formal theory of transactions and transvections', *Journal of Marketing Research*, *2*(2), pp.117-127. https://doi.org/10.1177/002224376500200201

Amarnath, D. D., and Jaidev, U. P. (2020) 'Toward an integrated model of consumer reactance: A literature analysis', *Management Review Quarterly*, 71(1), pp. 41–90. https://doi.org/10.1007/s11301-020-00180-y

Amatulli, C., Deangelis, M., Peluso, A., Soscia, I., Guido, G. (2019) 'The Effect of Negative Message Framing on Green Consumption: An Investigation of the Role of Shame', *Journal of Business Ethics*. 157. https://doi.org/10.1007/s10551-017-3644-x

Ameen, N., Hosany, S. and Tarhini, A. (2021) 'Consumer interaction with cutting-edge technologies: Implications for future research', *Computers in Human Behavior*, *120*, p.106761. https://doi.org/10.1016/j.chb.2021.106761

Amoo, O.O., Osasona, F., Atadoga, A., Ayinla, B.S., Farayola, O.A., and Abrahams, T.O. (2024) 'Cybersecurity threats in the age of IoT: A review of protective measures', *International Journal of Science and Research Archive*, *11*(1), pp. 1304-1310. https://doi.org/10.30574/ijsra.2024.11.1.0217

Anderson, J.R. (1983) 'A spreading activation theory of memory', *Journal of verbal learning and verbal behavior*, *22*(3), pp.261-295. https://doi.org/10.1016/S0022-5371(83)90201-3

Anderson J. C., Narus J. A. (1998) ‘Business marketing: Understand what customers value’, *Harvard Business Review*, 76, pp. 53–58.

Anderson, J. and Rainie, L. (2018) ‘*The Future of Well-Being in a Tech-Saturated World: Expert Perspectives*’, Pew Research Center: Internet, Science & Tech. United States of America. Retrieved from https://coilink.org/20.500.12592/wswbkg on 31 Jul 2025. https://coilink.org/20.500.12592/wswbkg

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., Van Boven, L., Weber, B. and Yang, H. (2018) ‘Consumer choice and autonomy in the age of artificial intelligence and big data’, *Customer needs and solutions*, *5*(1), pp.28-37. https://doi.org/10.1007/s40547-017-0085-8

Anica-Popa, I., Anica-Popa, L., Rădulescu, C. and Vrîncianu, M. (2021) ‘The integration of artificial intelligence in retail: benefits, challenges and a dedicated conceptual framework’, *Amfiteatru Economic*, *23*(56), pp.120-136.

Anker, T.B., Sparks, L., Moutinho, L. and Grönroos, C. (2015) ‘Consumer dominant value creation: A theoretical response to the recent call for a consumer dominant logic for marketing’, *European Journal of Marketing*, *49*(3/4), pp. 532-560. https://doi.org/10.1108/EJM-09-2013-0518

Anker, T.B., Gordon, R. and Zainuddin, N. (2022) ‘Consumer-dominant social marketing: a definition and explication’, *European journal of marketing*, *56*(1), pp.159-183. https://doi.org/10.1108/EJM-08-2020-0618

Areeb, Q.M., Nadeem, M., Sohail, S.S., Imam, R., Doctor, F., Himeur, Y., Hussain, A. and Amira, A. (2023) ‘Filter bubbles in recommender systems: Fact or fallacy—A systematic review’, *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(6), p.e1512. https://doi.org/10.1002/widm.1512

Arnold, M., Goldschmitt, M. and Rigotti, T. (2023) ‘Dealing with information overload: a comprehensive review’, *Frontiers in psychology*, *14*, p.1122200. https://doi.org/10.3389/fpsyg.2023.1122200

Arora, N., Dreze, X., Ghose, A., Hess, J.D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S.A., Sajeesh, S., Su, M., Syam, N.B., Thomas, J., and Zhang, Z.J. (2008) 'Putting one-to-one marketing to work: personalization, customization, and choice', *Marketing Letters*, 19, pp. 305–321. https://doi.org/10.1007/s11002-008-9056-z

Atkinson, J. W. (1957) 'Motivational determinants of risk-taking behavior', *Psychological Review, 64*(6, Pt.1), pp. 359–372. https://doi.org/10.1037/h0043445

Austin, J. T., and Vancouver, J. B. (1996) 'Goal constructs in psychology: Structure, process, and content', *Psychological Bulletin, 120*(3), pp. 338–375. https://doi.org/10.1037/0033-2909.120.3.338

Awad, N.F. and Krishnan, M.S. (2006) 'The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization', *MIS quarterly*, pp.13-28. https://doi.org/10.2307/25148715

Baars, B. J. (1986). *The Cognitive Revolution in Psychology*. Guilford.

Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., and Ogundipe, D. O. (2024) 'The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies', *International Journal of Management & Entrepreneurship Research*, 6(3), pp. 936-949.

Bagozzi, R.P. and Dholakia, U. (1999) 'Goal setting and goal striving in consumer behavior', *Journal of Marketing*, *63*(4_suppl1), pp.19-32. https://doi.org/10.1177/00222429990634s104

Balasubramanian, G. (2024) 'The Role of AI in Enhancing Personalization in E-commerce: A Study on Customer Engagement and Satisfaction', *Asian and Pacific Economic Review*, *17*(2), Article 2.

Balducci, B., and Marinova, D. (2018) ‘Unstructured data in marketing’, *Journal of the Academy of Marketing Science*, *46*(4), pp. 557-590. https://doi.org/10.1007/s11747-018-0581-x.

Bandara, R., Fernando, M., and Akter, S. (2020) ‘Explicating the privacy paradox: A qualitative inquiry of online shopping consumers’, *Journal of Retailing and Consumer Services*, *52*, p.101947. https://doi.org/10.1016/j.jretconser.2019.101947

Bandhu, D., Mohan, M.M., Nittala, N.A.P., Jadhav, P., Bhadauria, A. and Saxena, K.K., (2024) ‘Theories of motivation: A comprehensive analysis of human behavior drivers’, *Acta Psychologica*, *244*, p.104177. https://doi.org/10.1016/j.actpsy.2024.104177

Bargh, J.A. (1990) ‘Goal and intent: Goal-directed thought and behavior are often unintentional’, *Psychological Inquiry*, *1*(3), pp. 248-251. https://doi.org/10.1207/s15327965pli0103_14

Bargh, J. A., and Gollwitzer, P. M. (1994) ‘Environmental control of goal-directed action: Automatic and strategic contingencies between situations and behavior’, In W. D. Spaulding (Ed.), *Integrative views of motivation, cognition, and emotion* (pp. 71–124). University of Nebraska Press.

Bargh, J. A., Gollwitzer, P., Lee-Chai, A., Barndollar, K., and Troetschel, R. (2001) ‘The automated will: Nonconscious activation and pursuit of behavioral goals’, *Journal of Personality and Social Psychology*, *81*, pp. 1014–1027. https://doi.org/10.1037/0022-3514.81.6.1014

Bargh, J.A. (2022) ‘The hidden life of the consumer mind’, *Consumer Psychology Review*, *5*(1), pp.3-18. https://doi.org/10.1002/arcp.1075

Barney-McNamara, B., Peltier, J., Chennamaneni, P.R. and Niedermeier, K.E. (2021) ‘A conceptual framework for understanding the antecedents and consequences of social selling: a theoretical perspective and research agenda’, *Journal of Research in Interactive Marketing*, *15*(1), pp.147-178. https://doi.org/10.1108/JRIM-05-2020-0108

Barth, S., and de Jong, M. D. T. (2017) 'The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review', *Telematics and Informatics, 34*(7), pp. 1038–1058. https://doi.org/10.1016/j.tele.2017.04.013

Bassey, K.E., (2023) 'Solar energy forecasting with deep learning technique', *Engineering Science & Technology Journal*, *4*(2), pp. 18-32.

Bastani, H., Harsha P., Perakis G., and Singhvi D. (2022) 'Learning personalized product recommendations with customer disengagement', *Manufacturing and Service Operations Management*, *24*(4), pp. 2010–2028. https://doi.org/10.1287/msom.2021.1047

Basu, B., Chakraborty, D., and Kar, A.K. (2024) 'How can we improve buyer experiences for the operations of e-grocery platforms? Towards a unified framework for digital service operations', *International Journal of Production Economics*, *278*, 109417. https://doi.org/10.1016/j.ijpe.2024.109417.

Barbopoulos, I. and Johansson, L.O. (2017) 'The Consumer Motivation Scale: Development of a multi-dimensional and context-sensitive measure of consumption goals', *Journal of Business Research*, *76*, pp.118-126. https://doi.org/10.1016/j.jbusres.2017.03.012

Becker, L. and Jaakkola, E. (2020) 'Customer experience: fundamental premises and implications for research', *Journal of the academy of marketing science*, *48*(4), pp.630-648. https://doi.org/10.1007/s11747-019-00718-x

Becker, L., Jaakkola, E. and Halinen, A. (2020) 'Toward a goal-oriented view of customer journeys', *Journal of Service Management*, *31*(4), pp.767-790. https://doi.org/10.1108/JOSM-11-2019-0329

Behera, R.K., Bala, P.K., Rana, N.P., Algharabat, R.S. and Kumar, K. (2024) 'Transforming customer engagement with artificial intelligence E-marketing: an E-retailer perspective in the era of retail 4.0', *Marketing Intelligence & Planning*, 42(7), pp. 1141-1168. https://doi.org/10.1108/MIP-04-2023-0145.

Bélanger-Gravel, A., Godin, G. and Amireault, S. (2013) 'A meta-analytic review of the effect of implementation intentions on physical activity', *Health psychology review*, *7*(1), pp.23-54. https://doi.org/10.1080/17437199.2011.560095

Ben-Akiva, M.E. and Lerman, S.R. (1985) *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Ben Gamra Zinelabidine, B., Touzani, L., Ben Dahmane, N. and Touzani, M. (2018) 'How off-track tourists create their own event: A customer-dominant logic perspective', *Qualitative Market Research: An International Journal*, *21*(4), pp.549-566. https://doi.org/10.1108/QMR-01-2017-0037

Bhattarai, A. (2023) 'Exploring customer engagement through generative AI innovative strategies in digital marketing campaigns', *Quarterly Journal of Emerging Technologies and Innovations*, *8*(12), pp.1-9.

Bianchi, C. (2019) 'Value co-creation behaviours from customer-to-customer interactions (CCIs) in recreational social tango experiences', *Leisure Studies*, *38*(5), pp.666-681. https://doi.org/10.1080/02614367.2019.1614209

Billard, E., and Lakshmivarahan, S. (1999) 'Learning in multilevel games with incomplete information. I', *IEEE Transactions on Systems, Man, and Cybernetics, Part B* (Cybernetics), *29*(3), pp. 329–339. http://dx.doi.org/10.1109/3477.764864.

Bitra, S.K. (2025) 'The convergence of generative AI and hyper-personalization: Transforming customer experience at scale', *World Journal of Advanced Research and Reviews*, *26*(02), pp.669–678. https://doi.org/10.30574/wjarr.2025.26.2.1648

Blasco-Arcas, L., Lee, H.H.M., Kastanakis, M.N., Alcañiz, M. and Reyes-Menendez, A., (2022) 'The role of consumer data in marketing: A research agenda. *Journal of business research*, *146*, pp. 436-452. https://doi.org/10.1016/j.jbusres.2022.03.054

Bleier, A., Goldfarb, A. and Tucker, C. (2020) ‘Consumer privacy and the future of data-based innovation and marketing’, *International Journal of Research in Marketing*, *37*(3), pp.466-480. https://doi.org/10.1016/j.ijresmar.2020.03.006

Bjørlo, L., Moen, Ø. and Pasquine, M. (2021) ‘The role of consumer autonomy in developing sustainable AI: A conceptual framework’, *Sustainability*, *13*(4), p.2332. https://doi.org/10.3390/su13042332

Boerman, S.C., Kruikemeier, S. and Zuiderveen Borgesius, F.J. (2017) ‘Online behavioral advertising: A literature review and research agenda’, *Journal of advertising*, *46*(3), pp.363-376. https://doi.org/10.1080/00913367.2017.1339368

Bolos, L.A., Lagerkvist, C.J., Edenbrant, A.K. and Nayga, R.M., (2022) ‘Consumer preferences for visually sub-optimal food: Role of information framing and personal goals’, *Resources, Conservation and Recycling*, *184*, p.106426. https://doi.org/10.1016/j.resconrec.2022.106426

Bolton, R., N., Gustafsson, A., McColl-Kennedy, J., J. Sirianni, N. and K. Tse, D. (2014) ‘Small details that make big differences: A radical approach to consumption experience as a firm's differentiating strategy’, *Journal of Service Management*, *25*(2), pp.253-274. https://doi.org/10.1108/JOSM-01-2014-0034

Bolton, R. N., McColl-Kennedy, J. R., Cheung, L., Gallan, A., Orsingher, C., Witell, L., and Zaki, M. (2018) ‘Customer experience challenges: Bringing together digital, physical and social realms’, *Journal of Service Management*, *29*(5), pp. 776–808. https://doi.org/10.1108/JOSM-04-2018-0113

Bolton, R.N. (2020) ‘Commentary: future directions of the service discipline’, *Journal of Services Marketing*, *34*(3), pp.279-289. https://doi.org/10.1108/JSM-02-2020-0067

Bonezzi, A., Brenda, C. M., and De Angelis, M. (2011) ‘Stuck in the Middle: The Psychophysics of Goal Pursuit’, *Psychological Science*, *22*(5), 607–12. https://doi.org/10.1177/0956797611404899

Böttger, T., Rudolph, T., Evanschitzky, H. and Pfrang, T. (2017) 'Customer inspiration: Conceptualization, scale development, and validation', *Journal of Marketing*, *81*(6), pp. 116-131. https://doi.org/10.1509/jm.15.0007

Brandstätter, V. and Bernecker, K. (2022) 'Persistence and disengagement in personal goal pursuit', *Annual Review of Psychology*, *73*(1), pp.271-299. https://doi.org/10.1146/annurev-psych-020821-110710

Brinson, N.H., Eastin, M.S. and Bright, L.F. (2019) 'Advertising in a quantified world: a proposed model of consumer trust, attitude toward personalized advertising and outcome expectancies", *Journal of Current Issues & Research in Advertising*, *40*(1), pp. 54-72. https://doi.org/10.1080/10641734.2018.1503108.

Brodie, R., Ranjan, K. R., Verreynne, M. L., Jiang, Y. and Previte, J. (2021) 'Coronavirus crisis and health care: learning from a service ecosystem perspective', *Journal of Service Theory and Practice*, *31*(2), pp. 225-246. https://doi.org/10.1108/JSTP-07-2020-0178

Burböck, B., Kubli, V., Maček, A., Bobek, V. (2019) 'Effects of different types of framing in advertising messages on human decision behaviour', *International Journal of Diplomacy and Economy*, https://doi.org/5.27.10.1504/IJDIPE.2019.10020206.

Burr, C., and Floridi, L. (2020) 'The ethics of digital well-being: A multidisciplinary perspective', In Burr C., Floridi L. (Eds.), *Ethics of digital well-being* (pp. 1–29). Springer. https://doi.org/10.1007/978-3-030-50585-1_1

Byun, H., Shin, J., Lee, C.-Y. (2018) 'Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles', *Energy*, *144*, pp. 312-321. https://doi.org/10.1016/j.energy.2017.12.035

Čaić, M., Solsona Caba, N. and Mattelmäki, T. (2025), 'Viewpoint: advancing service design with practitioners' insights', *Journal of Services Marketing*, *39*(10), pp. 83-96. https://doi.org/10.1108/JSM-11-2024-0602

Čaić, M., Holmlid, S., Mahr, D. and Odekerken-Schroder, G. (2019) 'Beneficiaries' view of actor networks: Service resonance for pluralistic actor networks', *International Journal of Design*, *13*(3), pp.69-88. http://www.ijdesign.org/index.php/IJDesign/article/viewFile/3106/873

Callaway, F., Lieder, F., Das, P., Gul, S. and Krueger, P.M. (2018) 'A resource-rational analysis of human planning', In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 40).

Carver, C.S., and Scheier, M. F. (1998) *On the self-regulation of behavior*. New York: Cambridge University Press.

Carver, C.S. and Scheier, M.F. (2001) 'Optimism, pessimism, and self-regulation', In E. C. Chang (Ed.), *Optimism & pessimism: Implications for theory, research, and practice* (pp. 31–51). American Psychological Association. https://doi.org/10.1037/10385-002

Chalmers Thomas, T., Price, L. L., and Schau, H. J. (2013) 'When Differences Unite: Resource Dependence in Heterogeneous Consumption Communities', *Journal of Consumer Research*, *39*(5), pp. 1010–1033. https://doi.org/10.1086/666616

Calder, B. J., Isaac, M. S. and Malthouse, E. C. (2016) 'How to capture consumer experiences: A context-specific approach to measuring engagement: Predicting consumer behavior across qualitatively different experiences', *Journal of Advertising Research*, *56*(1), pp. 39-52. https://doi.org/10.2501/JAR-2015-028

Cao, L. (2021) 'Artificial intelligence in retail: applications and value creation logics', *International Journal of Retail & Distribution Management*, *49*(7), pp. 958-976. https://doi.org/10.1108/IJRDM-09-2020-0350

Capponi, A., Olafsson, S. and Zariphopoulou, T. (2022) 'Personalized robo-advising: Enhancing investment through client interaction', *Management Science*, *68*(4), pp. 2485-2512. https://doi.org/10.1287/mnsc.2021.4014

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y.J. and Mavrommatis, A. (2020) 'From data to action: how marketers can leverage AI', *Business Horizons*, *63*(2), pp. 227-243. https://doi.org/10.1016/j.bushor.2019.12.002

Cerdan Chiscano, M. (2024) 'Co-creating family-inclusive leisure experiences: A study of Barcelona's Gran Teatre del Liceu opera house', *Journal of Leisure Research*, *55*(1), pp.25-45. https://doi.org/10.1080/00222216.2023.2187265

Chan, E.K. (2019) 'The role of personal relevance in the value creation process of edutainment consumption', *Journal of consumer behaviour*, *18*(3), pp. 190-204. https://doi.org/10.1002/cb.1757

Chang, T.-S. and Bau, D.-Y. (2024) 'eXplainable artificial intelligence (XAI) in business management research: a success/failure system perspective', *Journal of Electronic Business & Digital Economics*, 4(1), pp. 36-53. https://doi.org/10.1108/JEBDE-07-2024-0019

Chang C., and Dibb S. (2012) 'Reviewing and conceptualising customer-perceived value', *The Marketing Review*, 12(3), pp. 253–274. https://doi.org/10.1362/146934712x13420906885395

Chartrand, T. L., and Bargh, J. A. (1996) 'Automatic activation of impression formation and memorization goals: Nonconscious goal priming reproduces effects of explicit task instructions', *Journal of Personality and Social Psychology, 71*(3), pp. 464–478. https://doi.org/10.1037/0022-3514.71.3.464

Chatterjee, S., Rana, N.P., Khorana, S., Mikalef, P. and Sharma, A. (2023) 'Assessing organizational users' intentions and behavior to AI integrated CRM systems: A meta-UTAUT approach', *Information Systems Frontiers*, *25*(4), pp.1299-1313. https://doi.org/10.1007/s10796-021-10181-1

Chavare, S.R., Awati, C.J., Shirgave, S.K. (2021) 'Smart Recommender System Using Deep Learning', *In Proceedings of the 6th IEEE International Conference on Inventive Computation Technologies (ICICT)*, pp. 590–594. https://doi.org/10.1109/ICICT50816.2021.9358580

Chen, C.F. and Wang, J.P. (2016) 'Customer participation, value co-creation and customer loyalty–A case of airline online check-in system', *Computers in Human Behavior*, *62*, pp.346-352. https://doi.org/10.1016/j.chb.2016.04.010

Chen, X., Latham, G. P., Piccolo, R. F., and Itzchakov, G. (2021) 'An enumerative review and a meta-analysis of primed goal effects on organizational behavior', *Applied Psychology: An International Review*, *70*(1), pp. 216–253. https://doi.org/10.1111/apps.12239

Chen, X., Sun, J., and Liu, H. (2022a) 'Balancing web personalization and consumer privacy concerns: Mechanisms of consumer trust and reactance', *Journal of Consumer Behaviour*, *21*(3), pp. 572–582. https://doi.org/10.1002/cb.1947

Chen, H.Y., Lombardi, G., Li, S.C. and Hare, T.A. (2022b) 'Older adults process the probability of winning sooner but weigh it less during lottery decisions', *Scientific Reports*, *12*(1), p.11381. https://doi.org/10.1038/s41598-022-15432-y

Chen, J., Zhang, Y. and Liu, Z. (2025) 'Unlocking the power of algorithmic recommendations: the effect of recommendation characteristics on users' willingness to value co-creation', *Current Psychology, 44*, pp. 1492–1510. https://doi.org/10.1007/s12144-024-07175-y

Cheung, M.F. and To, W.M. (2016) 'Service co-creation in social media: An extension of the theory of planned behavior', *Computers in Human Behavior*, *65*, pp.260-266. https://doi.org/10.1016/j.chb.2016.08.031

Choi, J., Lee, H.J. and Kim, H.-W. (2017) 'Examining the effects of personalized app recommender systems on purchase intention: a self and social-interaction perspective', *Journal of Electronic Commerce Research*, 18(1), pp. 73-102.

Choi, W.J. and Jerath, K. (2022) 'Privacy and consumer empowerment in online advertising', *Foundations and Trends® in Marketing*, *15*(3), pp.153-212. http://dx.doi.org/10.1561/1700000053

Choi, W.J., Jerath, K. and Sarvary, M. (2023) 'Consumer privacy choices and (un) targeted advertising along the purchase journey', *Journal of Marketing Research*, *60*(5), pp.889-907. https://doi.org/10.1177/00222437221140052

Chaudhry, B.M., Dasgupta, D. and Chawla, N. (2022) 'Formative evaluation of a tablet application to support goal-oriented care in community-dwelling older adults', *Proceedings of the ACM on Human-Computer Interaction*, *6*(MHCI), Article 208, pp.1-21. https://doi.org/10.1145/3546743.

Christensen, C.M., Hall, T., Dillon, K. and Duncan, D.S. (2016) 'Know your customers' jobs to be done', *Harvard Business Review*, 94(9), pp. 54-62.

Chulef, A.S., Read, S.J. and Walsh, D.A. (2001) 'A hierarchical taxonomy of human goals.', *Motivation and Emotion*, *25*(3), pp.191-232. https://doi.org/10.1023/A:1012225223418

Cicek, M., Gursoy, D. and Lu, L. (2025) 'Adverse impacts of revealing the presence of "Artificial Intelligence (AI)" technology in product and service descriptions on purchase intentions: the mediating role of emotional trust and the moderating role of perceived risk', *Journal of Hospitality Marketing & Management*, *34*(1), pp.1-23. https://doi.org/10.1080/19368623.2024.2368040

Ciuchita, R., Medberg, G., Penttinen, V., Lutz, C. and Heinonen, K. (2022)' Affordances advancing user-created communication (UCC) in service: interactivity, visibility and anonymity', *Journal of Service Management*, *33*(4/5), pp.688-704. https://doi.org/10.1108/JOSM-10-2021-0407

Clasen, D.R. and Brown, B.B. (1985) 'The multidimensionality of peer pressure in adolescence', *Journal of youth and adolescence*, *14*(6), pp.451-468. https://doi.org/10.1007/BF02139520

Cloarec, J., Meyer-Waarden, L., and Munzel, A. (2022). The personalization-privacy paradox at the nexus of social exchange and construal level theories. Psychology & Marketing, 39(3), 647–661. https://doi.org/10.1002/mar.21587

Cloarec, J., Meyer-Waarden, L. and Munzel, A. (2024) 'Transformative privacy calculus: Conceptualizing the personalization-privacy paradox on social media', *Psychology & Marketing*, *41*(7), pp.1574-1596. https://doi.org/10.1002/mar.21998

Concari, A., Kok, G., and Martens, P. (2020) 'A Systematic Literature Review of Concepts and Factors Related to Pro-Environmental Consumer Behaviour in Relation to Waste Management Through an Interdisciplinary Approach', *Sustainability*, 12(11). https://doi.org/10.3390/su12114452

Concari, A., Kok, G., and Martens, P. (2022) 'Recycling behaviour: Mapping knowledge domain through bibliometrics and text mining', Journal of Environmental Management, *303*, p. 114160. https://doi.org/10.1016/j.jenvman.2021.114160

Crawford, K. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

Costa, E., Montemurro, D. and Giuliani, D. (2019) 'Consumers' willingness to pay for green cars: a discrete choice analysis in Italy', *Environment, Development and Sustainability*, *21*(5), pp.2425-2442. https://doi.org/10.1007/s10668-018-0141-z.

Crews, F. (2017). Freud: The Making of an Illusion. Henry Holt.

Crusius, J. and Mussweiler, T. (2012) 'To achieve or not to achieve? Comparative mindsets elicit assimilation and contrast in goal priming', *European Journal of Social Psychology*, *42*(6), pp.780-788. https://doi.org/10.1002/ejsp.873

Cruz-Cárdenas, J., Guadalupe-Lanas, J. and Velín-Fárez, M. (2019) 'Consumer value creation through clothing reuse: A mixed methods approach to determining influential factors', *Journal of Business Research*, *101*, pp. 846-853. https://doi.org/10.1016/j.jbusres.2018.11.043

Cukier, K. (2020) 'Commentary: How AI Shapes Consumer Experiences and Expectations', *Journal of Marketing*, *85*(1), 152-155. https://doi.org/10.1177/0022242920972932.

Curran, P.J. and Bauer, D.J. (2011) 'The disaggregation of within-person and between-person effects in longitudinal models of change', *Annual review of psychology*, *62*(1), pp. 583-619. https://doi.org/10.1146/annurev.psych.093008.100356

Curran, P. J., Howard, A. L., Bainter, S. A., Lane, S. T., and McGinley, J. S. (2014) 'The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals', *Journal of Consulting and Clinical Psychology, 82*(5), pp. 879–894. https://doi.org/10.1037/a0035297

Curran, M., Komesidou, R. and Hogan, T.P. (2022) 'Less is more: Implementing the minimal intervention needed for change approach to increase contextual fit of speech-language interventions', *Language, Speech, and Hearing Services in Schools*, *53*(2), pp. 317-328. https://doi.org/10.1044/2021_LSHSS-21-00050

Custers, R., Vermeent, S. and Aarts, H. (2019) '15 Does Goal Pursuit Require Conscious Awareness?', *The Oxford handbook of human motivation*, p.269.

Dachler, H.P. and Mobley, W.H. (1973) 'Construct validation of an instrumentality-expectancy-task-goal model of work motivation: Some theoretical boundary conditions', *Journal of Applied Psychology*, *58*(3), pp.397–418.

https://doi.org/10.1037/h0036297

Dahl, A.J., Peltier, J.W. and Swan, E.L. (2023) 'Anticipatory value-in-use in early-stage digital health service transformations: How consumers assess value propositions before and after abrupt, exogenous shocks.', *Journal of Business Research*, *163*, p.113910. https://doi.org/10.1016/j.jbusres.2023.113910

Danaf, M., Becker, F., Song, X., Atasoy, B. and Ben-Akiva, M. (2019) 'Online discrete choice models: Applications in personalized recommendations', *Decision Support Systems*, *119*, pp.35-45. https://doi.org/10.1016/j.dss.2019.02.003

Danaf, M., Guevara, C.A. and Ben-Akiva, M. (2023) 'A control-function correction for endogeneity in random coefficients models: The case of choice-based recommender systems', *Journal of choice modelling*, *46*, p.100399. https://doi.org/10.1016/j.jocm.2022.100399

Darmody, A. and Zwick, D. (2020) 'Manipulate to empower: Hyper-relevance and the contradictions of marketing in the age of surveillance capitalism', *Big Data & Society*, *7*(1), https://doi.org/10.1177/2053951720904112

Davenport, T.H. (2023) 'Hyper-personalization for customer engagement with artificial intelligence', *Management and Business Review*, *3*(1-2), pp. 29-3. https://doi.org/10.1177/2694105820230301006

Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS quarterly*, 13(3), pp.319-340. https://doi.org/10.2307/249008

de Bekker-Grob, E.W., Donkers, B., Bliemer, M.C., Veldwijk, J. and Swait, J.D. (2020) 'Can healthcare choice be predicted using stated preference data?', *Social Science & Medicine*, *246*, p.112736. https://doi.org/10.1016/j.socscimed.2019.112736

Decock, S., De Clerck, B., Lybaert, C. and Plevoets, K. (2020) 'Testing the various guises of conversational human voice: the impact of formality and personalization on customer outcomes in online complaint management', *Journal of Internet Commerce*, 20(1), pp. 1-24, http://doi.org/10.1080/15332861.2020.1848060

De Keyzer, F., Dens, N. and De Pelsmacker, P. (2022a) 'How and when personalized advertising leads to brand attitude, click, and WOM intention', *Journal of Advertising*, *51*(1), pp. 39-56.

De Keyzer, F., Dens, N. and De Pelsmacker, P. (2022b) 'Let's get personal: Which elements elicit perceived personalization in social media advertising?', *Electronic Commerce Research and Applications*, 55, 101183.
https://doi.org/10.1016/j.elerap.2022.101183

Delporte, M., Aerts, M., Verbeke, G. and Molenberghs, G. (2025) 'Analysing matched continuous longitudinal data: A review', *Statistical Methods in Medical Research*, *34*(1), pp.170-179. https://doi.org/10.1177/09622802241300823

Desai, D. (2022) 'Hyper-personalization: an AI-enabled personalization for customer-centric marketing', in Singh, S. (Ed), Adoption and Implementation of AI in Customer Relationship Management, *IGI Global*, pp. 40-53. https://doi.org/10.4018/978-1-7998-7959-6.ch003.

Di, C., Li, F., Xu, P., Guo, Y., Chen, C. and Shu, M. (2023) 'Learning automata-accelerated greedy algorithms for stochastic submodular maximization', *Knowledge-Based Systems*, *282*, p.111118. https://doi.org/10.1016/j.knosys.2023.111118

Difallah, D., Filatova, E., and Ipeirotis, P. (2018) 'Demographics and Dynamics of Mechanical Turk Workers', In Proceedings of WSDM 2018: The Eleventh ACM International Conference on Web Search and Data Mining, Marina Del Rey, CA, USA, February 5–9, 2018 (WSDM 2018), 9 pages.
https://doi.org/10.1145/3159652.3159661

Divya, R.P. and Vajraveli, D. (2025) 'A study exploring AI-driven hyper-personalization in e-commerce', *Kronika*, June. Available at: https://www.researchgate.net/publication/398227560 (Accessed: 12 July 2025).

Donkers, T. and Ziegler, J. (2021) ‘The dual echo chamber: Modeling social media polarization for interventional recommending’, In *Proceedings of the 15th ACM conference on recommender systems* (pp. 12-22). https://doi.org/10.1145/3460231.3474261

Drucker, P.F. (1974) *Management: Tasks, Responsibility, Practices*, Harper & Row, New York, NY.

Du, C., Hori, K., and Miyazaki, Y. (2025) ‘Two-Wave Models for Latent Changes: How Well Can They Recover the Parameters of the Three-Wave Growth Curve Model?’, *Structural Equation Modeling: A Multidisciplinary Journal*, *32*(4), pp. 565–578. https://doi.org/10.1080/10705511.2025.2462926

Duan, R., Jiang, C. and Jain, H.K. (2022) ‘Combining review-based collaborative filtering and matrix factorization: A solution to rating's sparsity problem’, *Decision Support Systems*, *156*, p.113748. https://doi.org/10.1016/j.dss.2022.113748

Dwivedi, Y.K., Hughes, L., Wang, Y., Alalwan, A.A., Ahn, S.J., Balakrishnan, J., Barta, S., Belk, R., Buhalis, D., Dutot, V., and Felix, R. (2023) ‘Metaverse marketing: How the metaverse will shape the future of consumer research and practice’, *Psychology & Marketing*, *40*(4), pp.750-776. https://doi.org/10.1002/mar.21767

Eagly, A. H., and Chaiken, S. (1993) *The psychology of attitudes*: Harcourt Brace Jovanovich College Publishers.

Ed-Daakouri, I. and Alla, L. (2025) ‘Generative AI Solutions for Unlocking Customer Loyalty and Retention Strategies in Emerging Markets.’, In M. Aarabe, N. Ben Khizzou, L. Alla, & A. Benjelloun (Eds.), *AI Innovations for Customer Experience Optimization in the Service Sector* (pp. 105-154). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-0918-7.ch004.

Edvardsson, B., Frow, P., Jaakkola, E., Keiningham, T.L., Koskela-Huotari, K., Mele, C. and Tombs, A. (2018) 'Examining how context change foster service innovation', *Journal of Service Management*, *29*(5), pp.932-955. https://doi.org/10.1108/JOSM-04-2018-0112

Eletxigerra, A., Barrutia, J. M., and Echebarria, C. (2021) 'Tourist expertise and pre-travel value co-creation: Task-related processes and beyond', *Tourism Management Perspectives*, *37*, pp. 1–11. https://doi.org/10.1016/j.tmp.2020.100772

Eklund, O. (2022) 'Custom thumbnails: The changing face of personalisation strategies on Netflix.', *Convergence*, *28*(3), pp. 737-760. https://doi.org/10.1177/13548565211064520

Elkhani, N. and Bakri, A. (2012) 'Review on 'expectancy disconfirmation theory' (EDT) model in B2C E-commerce', *Journal of Information Systems Research and Innovation*, 2(12), pp. 95-102. http://seminar.utmspace.edu.my/myaisprint/

Enders, C. K. (2022). *Applied missing data analysis* (2nd ed.). The Guilford Press.

Epp, A. M., and Price, L. L. (2011) 'Designing Solutions around Customer Network Identity Goals', *Journal of Marketing*, *75*(2), pp. 36-54. https://doi.org/10.1509/jm.75.2.36

Etkin, J., (2019) 'Time in relation to goals', *Current Opinion in Psychology*, *26*, pp. 32–36. https://doi. org/10.1016/j.copsyc.2018.04.013.

Falk, A. and Ichino, A. (2003) 'Clean evidence on peer pressure', *Working paper/Institute for Empirical Research in Economics*, *144*. https://doi.org/10.3929/ethz-a-004491926

Fan D. X. F., Hsu C. H. C., Lin B. (2020) 'Tourists' experiential value co-creation through online social contacts: Customer-dominant logic perspective', *Journal of Business Research*, *108*, pp. 163–173. https://doi.org/10.1016/j.jbusres.2019.11.008

Fan, D. X. F., Buhalis, D., Fragkaki, E., Tsai, Y.-R. (2025) ‘Achieving Senior Tourists’ Active Aging Through Value Co–creation: A Customer-Dominant Logic Perspective’, *Journal of Travel Research*, *64*(2), pp. 427-443. https://doi.org/10.1177/00472875231214733

Fang, J. and Fan, Q., (2022) ‘Research on Collaborative Filtering Recommendation Algorithm based on Item Feature Clustering’, *International Core Journal of Engineering*, *8*(9), pp. 294-302. https://doi.org/10.6919/ICJE.202209_8(9).0041

Fang, C., Samaradivakara, Y., Maes, P., Nanayakkara, S. (2025) ‘Mirai: A Wearable Proactive AI "Inner-Voice" for Contextual Nudging’, 10.48550/arXiv.2502.02370.

Farahani, M.G., Torkestani, J.A. and Rahmani, M. (2022) ‘Adaptive personalized recommender system using learning automata and items clustering’, *Information systems*, *106*, p.101978. https://doi.org/10.1016/j.is.2021.101978

Farahani, M. and Payandeh, R. (2025) ‘Echoes of Privacy: Deciphering Consumer Voices in the Data Deluge’, *Journal of Consumer Behaviour*, 24(4), pp. 1930-1949. https://doi.org/10.1002/cb.2495

Faraji, A., Tavakoli, M., Kismihók, G. (2022) ‘Goal-Driven Lifelong Learning through Personalized Search and Recommendation Services’, In *INRA/IWILDS@ SIGIR*, pp. 94-100.

Feather, N. T. (1962) ‘The study of persistence’, *Psychological Bulletin, 59*(2), pp. 94–115. https://doi.org/10.1037/h0042645

Feldman, J., Zhang, D.J., Liu, X. and Zhang, N. (2022) ‘Customer choice models vs. machine learning: Finding optimal product displays on Alibaba’, *Operations Research*, *70*(1), pp.309-328. https://doi.org/10.1287/opre.2021.2158

Ferguson, M. L., and Bargh, J. A. (2004) ‘Liking is for doing: The effects of goal pursuit on automatic evaluation’, *Journal of Personality and Social Psychology*, *87*, pp. 557–572. https://doi.org/10.1037/0022-3514.87.5.557

Ferguson, M. J. (2008) 'On becoming ready to pursue a goal you don't know you have: Effects of nonconscious goals on evaluative readiness', *Journal of Personality and Social Psychology*, *95*, pp. 1268–1294. https://doi.org/10.1037/a0013263

Fernandez, K., Hamilton, R., Cabrera, L., and Medaglia, J.D. (2022) 'Context-dependent risk & benefit sensitivity mediate judgments about cognitive enhancement', *AJOB neuroscience*, *13*(1), pp.73-77. https://doi.org/10.1080/21507740.2021.2001077

Fishbein, M., and Ajzen, I. (1975) '*Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*', Reading, MA, USA: Addison-Wesley.
Fishbein, M., and Ajzen, I. (2010) 'Predicting and changing behavior: The reasoned action approach'. Psychology Press. https://doi.org/10.4324/9780203838020

Fishbach, A., and Dhar, R. (2005) 'Goals as excuses or guides: The liberating effect of perceived goal progress on choice', *Journal of Consumer Research, 32*, pp. 370-377. https://doi.org/10.1086/497548

Fishbach, A., and Ferguson, M.J. (2007) 'The goal construct in social psychology', *Social psychology: Handbook of basic principles*, *2*, pp.490-515.

Fishbach, A. and Choi, J. (2012) 'When thinking about goals undermines goal pursuit', *Organizational Behavior and Human Decision Processes*, *118*(2), pp.99-107. https://doi.org/10.1016/j.obhdp.2012.02.003

Fishbach, A. and Woolley, K. (2022) 'The structure of intrinsic motivation', *Annual Review of Organizational Psychology and Organizational Behavior*, *9*(1), pp.339-363. https://doi.org/10.1146/annurev-orgpsych-012420-091122

Finsterwalder, J. (2018) 'A 360-degree view of actor engagement in service co-creation', *Journal of Retailing and Consumer Services*, *40*, pp. 276-278. https://doi.org/10.1016/j.jretconser.2016.08.005

Flavián, C., Ibáñez-Sánchez, S. and Orús, C. (2019) 'The impact of virtual, augmented and mixed reality technologies on the customer experience', *Journal of business research*, *100*, pp.547-560. https://doi.org/10.1016/j.jbusres.2018.10.050

Font, X., English, R., Gkritzali, A. and Tian, W.S. (2021) 'Value co-creation in sustainable tourism: A service-dominant logic approach', *Tourism management*, *82*, p.104200. https://doi.org/10.1016/j.tourman.2020.104200

Ford, J., Jain, V., Wadhwani, K., and Gupta, D. G. (2023). AI advertising: An overview and guidelines, *Journal of Business Research*, *166*, 114124.

Fournier, S., and Avery, J. (2011) 'The uninvited brand', *Business horizons*, *54*(3), pp.193-207. https://doi.org/10.1016/j.bushor.2011.01.001

Francis, D.J., Fletcher, J.M., Stuebing, K.K., Davidson, K.C., and Thompson, N.M. (1991) 'Analysis of change: modeling individual growth', *Journal of Consulting Clinical Psychology*, 59(1), pp. 27–37. https://doi.org/10.1037/10109-041

Frémal, S., and Lecron, F. (2017) 'Weighting strategies for a recommender system using item clustering based on genres', *Expert Systems with Applications*, *77*, pp. 105–113, http://dx.doi.org/10.1016/j.eswa.2017.01.031.

Friedman, E.M., Savary, J. and Dhar, R. (2018) 'Apples, oranges, and erasers: The effect of considering similar versus dissimilar alternatives on purchase decisions', *Journal of consumer research*, *45*(4), pp.725-742.
https://doi.org/10.1093/jcr/ucy023

Galekop, M.M.J., Veldwijk, J., Uyl-de Groot, C.A. and Redekop, W.K. (2024) 'Preferences and willingness to pay for personalized nutrition interventions: Discrete choice experiments in Europe and the United States', *Food Quality and Preference*, *113*, p.105075. https://doi.org/10.1016/j.foodqual.2023.105075

Gallarza, M. G., Arteaga F., and Gil-Saura I. (2019) 'Customer value in tourism and hospitality: Broadening dimensions and stretching the value-satisfaction-loyalty chain', *Tourism Management Perspectives*, *31*, pp. 254–268. https://doi.org/10.1016/j.tmp.2019.05.011

Ganuthula, V.R.R., Balaraman, K.K. and Vohra, N., (2025) 'Hedonic Adaptation in the Age of AI: A Perspective on Diminishing Satisfaction Returns in Technology Adoption', *arXiv preprint arXiv:2503.08074*. https://doi.org/10.48550/arXiv.2503.08074

Gao, Y., and Liu, H. (2022) 'Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective', *Journal of Research in Interactive Marketing, 17*(5), pp.663–680. https://doi.org/10.1108/JRIM-01-2022-0023

Gao, J., Rong, Y., Tian, X. and Yao, Y. (2023) 'Improving convenience or saving face? An empirical analysis of the use of facial recognition payment technology in retail', *Information Systems Research*, 35 (1), pp. 16-27, https://doi.org/10.1287/isre.2023.1205

García-Fernández, J., Gálvez-Ruiz, P., Vélez-Colon, L., Ortega-Gutiérrez, J. and Fernández-Gavira, J., (2018) 'Exploring fitness centre consumer loyalty: differences of non-profit and low-cost business models in Spain', *Economic research-Ekonomska istraživanja*, *31*(1), pp.1042-1058. https://doi.org/10.1080/1331677X.2018.1436455

Geiger, J. L., Steg, L., van der Werff, E., and Unal, A. B. (2019) 'A meta-analysis of factors related to recycling', *Journal of Environmental Psychology*, *64*, pp. 78-97. https://doi.org/10.1016/j.jenvp.2019.05.004

Gibbons, R.D., Hedeker, D. and DuToit, S. (2010) 'Advances in analysis of longitudinal data', *Annual review of clinical psychology*, *6*(1), pp.79-107. https://doi.org/10.1146/annurev.clinpsy.032408.153550

Gil de Zúñiga, H., Goyanes, M. and Durotoye, T., (2024) 'A scholarly definition of artificial intelligence (AI): advancing AI as a conceptual framework in communication research', *Political communication*, *41*(2), pp.317-334. https://doi.org/10.1080/10584609.2023.2290497

Gironda, J.T. and Korgaonkar, P.K. (2018) 'iSpy? Tailored versus invasive ads and consumers' perceptions of personalized advertising', *Electronic commerce research and applications*, *29*, pp.64-77. https://doi.org/10.1016/j.elerap.2018.03.007

Goli, A. (2020) '*Personalized versioning: Product strategies constructed from experiments on pandora*', The University of Chicago.

Gollwitzer, P. M. (1999) 'Implementation intentions: Strong effects of simple plans', *American Psychologist*, *54*, pp. 493–503. https://doi.org/10.1037/0003-066X.54.7.493

Gollwitzer, P.M. and Oettingen, G. (2012) 13 Goal Pursuit. *The Oxford handbook of human motivation*, p.208.

Gottfredson, N.C. (2019) 'A straightforward approach for coping with unreliability of person means when parsing within-person and between-person effects in longitudinal studies', *Addictive Behaviors*, *94*, pp.156-161. https://doi.org/10.1016/j.addbeh.2018.09.031

Greene, Travis; Shmueli, Galit; and Ray, Soumya (2023) 'Taking the Person Seriously: Ethically Aware IS Research in the Era of Reinforcement Learning-Based Personalization', *Journal of the Association for Information Systems*, 24(6), pp. 1527-1561. https://doi.org/10.17705/1jais.00800

Grönroos C. (1990) *Service management and marketing: Managing the moments of truth in service competition*. Lexington Books.

Grönroos C. (2006) 'Adopting a service logic for marketing', *Marketing Theory*, *6*(3), pp. 317–333. https://doi.org/10.1177/1470593106066794

Grönroos, C. (2008) 'Service logic revisited: who creates value? And who co-creates?', *European business review*, *20*(4), pp. 298-314. https://doi.org/10.1108/09555340810886585

Grönroos C., and Voima P. (2013) 'Critical service logic: Making sense of value creation and co-creation', *Journal of the Academy of Marketing Science*, 41(2), pp. 133–150. https://doi.org/10.1007/s11747-012-0308-3

Grönroos, C., and Gummerus, J. (2014) 'The service revolution and its marketing implications: Service logic vs service-dominant logic', *Managing Service Quality, 24*(3), pp. 206–229. https://doi.org/10.1108/MSQ-03-2014-0042

Guan, J., Wu, J., Li, J.N., Cheng, C. and Wu, W. (2025) 'A Survey on Personalized Alignment--The Missing Piece for Large Language Models in Real-World Applications', arXiv preprint arXiv:2503.17003.

Guha, A., Grewal, D., Kopalle, P.K., Haenlein, M., Schneider, M.J., Jung, H., Moustafa, R., Hegde, D.R. and Hawkins, G. (2021) 'How artificial intelligence will affect the future of retailing.', *Journal of Retailing*, *97*(1), pp.28-41. https://doi.org/10.1007/s12144-025-07925-6

Gujar, V. (2024) 'AI Camera: Unique Technique to Hyper AI Personalization for Malls', *International Journal of Science and Research (IJSR), 13*(4), pp. 455-460. https://doi.org/0.21275/SR24406112210

Gummesson, E. (2006) 'Many-to-many marketing as grand theory: a Nordic school contribution', in Lusch, R.F. and Vargo, S.L. (Eds), *The Service-Dominant Logic of Marketing: Dialog, Debate, and Directions Armonk*, M.E. Sharpe, New York, NY, pp. 339-353.

Gunning, D., and Aha, D. W. (2019) 'DARPA's explainable artificial intelligence program', AI Magazine, 40(2), 44–58. https://doi.org/10.1609/aimag.v40i2.2850

Guo, J. and An, F. (2025) 'Exploring the impact of cognitive and affective components within the attitude construct on students' deep approach to learning in technology-enhanced learning.', *Current Psychology.*, *44*, pp. 1-16. https://doi.org/10.1007/s12144-025-07925-6

Hackney, C. H. (2024) 'Positive psychology in a secular age: Exploring the influence of secularization on the ideological underpinnings of the positive psychology movement', *International Journal of Applied Positive Psychology*, 9(3), pp. 1–13. https://doi.org/10.1007/s41042-023-00131-4

Haenlein, M. and Kaplan, A. (2019) 'A brief history of artificial intelligence: on the past, present, and future of artificial intelligence', *California Management Review*, *61*(4), pp. 5-14. https://doi.org/10.1177/0008125619864925

Hagger, M. S., and Hamilton, K. (2020) '*Changing behaviour using integrated theories'*, In M. S. Hagger, L. D. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), The handbook of behavior change (pp. 208–224). Cambridge University Press.

Hagger, M. S., Cheung, M. W. -L., Ajzen, I., and Hamilton, K. (2022) 'Perceived behavioral control moderating effects in the theory of planned behavior: A meta-analysis', *Health Psychology, 41*(2), pp. 155–167. https://doi.org/10.1037/hea0001153

Haghani, M., Bliemer, M.C., Rose, J.M., Oppewal, H. and Lancsar, E. (2021) 'Hypothetical bias in stated choice experiments: Part II. Conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods', *Journal of choice modelling*, *41*, p.100322. https://doi.org/10.1016/j.jocm.2021.100322

Hamilton, R. and Price, L.L. (2019) 'Consumer journeys: Developing consumer-based strategy', *Journal of the Academy of Marketing Science*, *47*(2), pp.187-191. https://doi.org/10.1007/s11747-019-00636-y

Hamilton, K., Phipps, D.J., Schmidt, P., Bamberg, S. and Ajzen, I. (2024) ‘First test of the theory of reasoned goal pursuit: predicting physical activity’, *Psychology & Health*, *39*(1), pp.24-41. https://doi.org/10.1080/08870446.2022.2026946

Han, J.J. and Broniarczyk, S.M. (2022) ‘The complexities of consumer empowerment in the modern consumption environment’, *Current Opinion in Psychology*, *46*, 101333. https://doi.org/10.1016/j.copsyc.2022.101333.

Han, Z., Kang, E.Y. and Sok, S. (2023) The complexity epistemology and ontology in second language acquisition: A critical review. *Studies in second language acquisition*, *45*(5), pp.1388-1412. https://doi.org/10.1017/S0272263122000420

Hassan, N., Abdelraouf, M. and El-Shihy, D. (2025) ‘The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce.’, *Future Business Journal*, *11*(1), p.66. https://doi.org/10.1186/s43093-025-00476-z.

Hardcastle, K., Vorster, L. and Brown, D. M. (2025) ‘Understanding Customer Responses to AI-Driven Personalized Journeys: Impacts on the Customer Experience’, *Journal of Advertising*, *54*(2), pp. 176–195. https://doi.org/10.1080/00913367.2025.2460985

Harshavardhan, K., Sharma, R., and Gupta, P. (2024) ‘Leveraging AI for personalized recommendations: Case studies of Amazon and Netflix’, *Journal of Digital Innovation*, *9*(2), pp. 101-115. http://dx.doi.org/10.35629/8028-1309131136.

Hartmann, N.N., Wieland, H., and Vargo, S.L. (2018) ‘Converging on a new theoretical foundation for selling, Journal of Marketing, 82(2), pp. 1–18. https://doi.org/10.1509/jm.16.0268

Hawkins, R.P., Kreuter, M., Resnicow, K., Fishbein, M. and Dijkstra, A. (2008) ‘Understanding tailoring in communicating about health.’, *Health education research*, *23*(3), pp. 454-466. https://doi.org/10.1093/her/cyn004

Hazrati, N. and Ricci, F. (2024) 'Choice models and recommender systems effects on users' choices', *User Modeling and User-Adapted Interaction*, *34*(1), pp.109-145. https://doi.org/10.1007/s11257-023-09366-x

Heinonen, K., Strandvik, T., Mickelsson, K., Edvardsson, B., Sundström, E., and Andersson, P. (2010) 'A customer-dominant logic of service', *Journal of Service Management*, *21*(4), pp. 531–548. https://doi.org/10.1108/09564231011066088

Heinonen, K., Strandvik, T., and Voima, P. (2013) 'Customer dominant value formation in service', *European Business Review*, *25*(2), pp. 104–123. https://doi.org/10.1108/09555341311302639

Heinonen, K. and Strandvik, T. (2015) 'Customer-dominant logic: foundations and implications', *Journal of Services Marketing*, *29*(6/7), pp. 472–484. https://doi.org/10.1108/JSM-02-2015-0096.

Heinonen, K. (2018) 'Positive and negative valence influencing consumer engagement', *Journal of Service Theory and Practice*, *28*(2), pp. 147–169. https://doi.org/10.1108/JSTP-02-2016-0020

Heinonen, K., and Strandvik, T. (2018) 'Reflections on customers' primary role in markets', *European Management Journal*, *36*(1), pp. 1–11. https://doi.irg/10.1016/j.emj.2017.09.005.

Heinonen, K., Campbell, C. Lord Ferguson, S. (2019) 'Strategies for creating value through individual and collective customer experiences', *Business Horizons*, *62*(1), pp. 95–104. https://doi.org/10.1016/j.bushor.2018.09.002.

Heinonen, K. and Strandvik, T. (2020) 'Customer-dominant service logic', *The Routledge Handbook of Service Research Insights and Ideas*, Routledge.

Heinonen, K., and Strandvik, T. (2021) 'Reframing service innovation: COVID-19 as a catalyst for imposed service innovation', *Journal of Service Management*, *32*(1), pp. 101–112. https://doi.org/10.1108/josm-05-2020-0161

Heinonen, K. and Strandvik, T., (2022) ‘Reframing service logic: Integrating value facilitation and customer context’, *Journal of Service Theory and Practice*, 32(3), pp.350–368. https://doi.org/10.1108/JSTP-11-2021-0265

Heinonen K., and Strandvik T. (2022) ‘Viewpoint: applying pragmatism to stimulate service research and practice: AA European perspective’, *Journal of Services Marketing’*, *36*(4), pp. 467–475. https://doi.org/10.1108/jsm-06-2021-0211

Heinonen, K. (2023) ‘Characterizing Ex situ Value: A Customer-Dominant Perspective on Value’, *Journal of Travel Research*, *62*(8), pp. 1707–1721. https://doi.org/10.1177/00472875221139489

Heinonen, K., and Lipkin, M. (2023) ‘Ordinary customer experience: Conceptualization, characterization, and implications’, *Psychology and Marketing*, *40*(9), pp. 1720–1736. doi:10.1002/mar.21830.

Heinonen, K. (2024) ‘Editorial: Embracing the future of services marketing’, *Journal of Services Marketing*, 38(10), pp. 66–69. doi:10.1108/JSM-08-2024-0384.

Heinrich, C.J. and Lynn, L.E., Jr. (2001) ‘Means and ends: a comparative study of empirical methods for investigating governance and performance’, *Journal of Public Administration Research Theory, 11*(1), pp. 109–138. https://doi.org/10.1093/oxfordjournals.jpart.a003490

Helkkula, A., and Kelleher, C. (2010) ‘Circularity of customer service experience and customer perceived value’, *Journal of Customer Behaviour*, *9*(1), pp. 37–53. https://doi.org/10.1362/147539210X497611

Helkkula, A. (2011) ‘Characterising the concept of service experience’, *Journal of Service Management*, *22*(3), pp. 367-389. https://doi.org/10.1108/09564231111136872

Helkkula, A. and Kelleher, C. (2011) ‘Experiences and practices: challenges and opportunities for value research’, In *Naples Forum on Service-Service Dominant logic, network & system theory and service science: integrating three perspectives for a new service agenda, 14th-17th June, Capri, Italy*.

Helkkula, A., Kelleher, C. and Pihlström, M. (2012) ‘Characterizing value as an experience: implications for service researchers and managers’, *Journal of service research*, *15*(1), pp.59-75. https://doi.org/10.1177/1094670511426897

Henkens, B., Verleye, K. and Larivière, B. (2021) ‘The smarter, the better?! Customer well-being, engagement, and perceptions in smart service systems’, *International Journal of Research in Marketing*, 38(2), pp. 425-447. https://doi.org/10.1016/j.ijresmar.2020.09.006.

Hensher, D.A. and Ho, C. (2016) ‘Identifying a behaviourally relevant choice set from stated choice data’, *Transportation*, *43*(2), pp.197-217. https://doi.org/10.1007/s11116-014-9572-z

Herlocker, J.L., Konstan, J.A., Terveen, L.G., and Riedl, J.T. (2004) ‘Evaluating collaborative filtering recommender systems’, *ACM Transactions on Infomation Systems*, *22*(1), pp. 5–53. https://doi.org/10.1145/963770.963772

Higgins, S.F., Mulvenna, M.D., Bond, R.B., McCartan, A., Gallagher, S. and Quinn, D. (2018) ‘Multivariate testing confirms the effect of age–gender congruence on click-through rates from online social network digital advertisements’, *Cyberpsychology, Behavior, and Social Networking*, *21*(10), pp.646-654. https://doi.org/10.1089/cyber.2018.0197

Higgins, E.T., Nakkawita, E., Cornwell, J.F.M. (2020) ‘Beyond outcomes: How regulatory focus motivates consumer goal pursuit processes’, *Consumer Psychology, Review*, *3*(1), pp. 76-90.

Hill, W., Stead, L., Rosenstein, M. and Furnas, G., (1995) ‘Recommending and evaluating choices in a virtual community of use’, In *Proceedings of the SIGCHI* *conference on Human factors in computing systems,* pp. 194-201. https://doi.org/10.1108/09564231111136872

Hill, S. E., & Durante, K. M. (2011) 'Courtship, competition, and the pursuit of attractiveness: Mating goals facilitate health-related risk taking and strategic risk suppression in women', *Personality and Social Psychology Bulletin*, *37*, pp. 383–394. https://doi.org/10.1177/0146167210395603

Hirschprung, R. S., Tayro, S., and Reznik, E. (2022) 'Optimising technological literacy acquirement to protect privacy and security', *Behaviour & Information Technology*, *41*(5), pp. 922–933. https://doi.org/10.1080/0144929X.2020.1842907

Hoffman, L. (2021) *Longitudinal Analysis: Modeling Within-Person Fluctuation and Change*. Routledge.

Hoffman, L., and Walters, R. W. (2022) 'Catching up on multi-level modeling', *Annual Review of Psychology*, *73*(1), pp. 659–689. https://doi.org/10.1146/annurev-psych-020821-103525.

Hoffman, L. (2025) 'Disaggregating Associations of Between-Person Differences in Change over Time from Within-Person Associations in Longitudinal Data', *Multivariate behavioral research*, pp.1-19. https://doi.org/10.1080/00273171.2025.2519348

Holbrook M. B. (1994) 'The nature of customer value: An axiology of services in the consumption experience', In Rust R. T., Oliver R. L. (Eds.), *Service quality: New directions in theory and practice* (pp. 21–71). SAGE. https://doi.org/10.4135/9781452229102.n2

Holbrook M. B. (2006) 'Consumption experience, customer value, and subjective personal introspection: An illustrative photographic essay', *Journal of Business Research*, 59(6), pp. 714–725. https://doi.org/10.1016/j.jbusres.2006.01.008

Hollebeek, L., Malthouse, E., and Block, M. (2016) 'Sounds of music: Exploring consumers' musical engagement', *Journal of Consumer Marketing*, 33(6), pp. 417-427. https://doi.org/10.1108/JCM-02-2016-1730

Hori, K., and Miyazaki, Y. (2023) 'Cross-level covariance approach to the disaggregation of between-person effect and within-person effect', *Psychological Methods,* 30(2), pp. 340–373. https://doi.org/10.1037/met0000548

Holmes, T.P., Adamowicz, W.L., Carlsson, F. (2017) 'Choice Experiments', In: Champ, P., Boyle, K., Brown, T. (eds) A Primer on Nonmarket Valuation. The Economics of Non-Market Goods and Resources, vol 13. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-7104-8_5

Horiuchi, Y., Markovich, Z. and Yamamoto, T. (2022) 'Does Conjoint Analysis Mitigate Social Desirability Bias?', *Political Analysis*, *30*(4), pp. 535–549. https://doi.org/10.1017/pan.2021.30.

Hox, J. J. (2010). *Multilevel analysis: Techniques and applications* (2nd ed.). New York: Routledge.

Hox, J., Moerbeek, M. and Van de Schoot, R., (2017) *Multilevel analysis: Techniques and applications*. Routledge.

Hoy, M.G. and Milne, G., (2010) 'Gender differences in privacy-related measures for young adult Facebook users.', *Journal of interactive advertising*, *10*(2), pp.28-45. https://doi.org/10.1080/15252019.2010.10722168

Hoyer, W.D., Kroschke, M., Schmitt, B., Kraume, K. and Shankar, V. (2020) 'Transforming the customer experience through new technologies', *Journal of interactive marketing*, *51*(1), pp.57-71. https://doi.org/10.1016/j.intmar.2020.04.001

Hsu, C. L. (2023) 'Enhancing brand love, customer engagement, brand experience, and repurchase intention: Focusing on the role of gamification in mobile apps', *Decision Support Systems*, 114020. https://doi.org/10.1016/j.dss.2023.114020

Hu, X., Qian, M., Cheng, B., Cheung, Y.K. (2021) ‘Personalized Policy Learning using Longitudinal Mobile Health Data’, *Journal of the American Statistical Association*, *116*(534), pp. 410-420. https://doi.org/10.1080/01621459.2020.1785476

Huang, K.H., Teixeira, J.G., Patrício, L., Constantine, L. and Nóbrega, L.A. (2013) ‘Model-driven service design toolkit: From co-design to implementation’, In *The 5th international congress IASDR 2013*. IASDR.

Huang, J.Y. and Bargh, J.A. (2014) ‘The selfish goal: Autonomously operating motivational structures as the proximate cause of human judgment and behavior’, *Behavioral and Brain Sciences*, *37*(2), pp.121-135. ‘https://doi.org/10.1017/S0140525X13000290

Huang, M.H. and Rust, R.T. (2018) ‘Artificial intelligence in service’, *Journal of Service Research*, *21*(2), pp. 155-172.

Huang, M. H., and Rust, R. T. (2021) ‘A strategic framework for artificial intelligence in marketing’, *Journal of the Academy of Marketing Science*, *49*, pp. 30-50. https://doi.org/10.1007/s11747-020-00749-9

Huang, J.H. (2023) ‘The Effectiveness of Collaborative Learning on Developing Communicative Strategies in English for Specific Purpose Tour Guide Language Training Course at Tertiary Level’, *International Journal of Educational Methodology*, *9*(4), pp.619-630.

Husairi, M. A., and P. Rossi. (2024). Delegation of Purchasing Tasks to AI: The Role of Perceived Choice and Decision Autonomy. *Decision Support Systems*, 179: 114166. https://doi.org/10.1016/j.dss.2023.114166

Hussein, A.H., Kharma, Q.M., Taweel, F.M., Abualhaj, M.M. and Shambour, Q.Y. (2022) ‘A Hybrid Multi-Criteria Collaborative Filtering Model for Effective Personalized Recommendations’, *Intelligent Automation & Soft Computing*, *31*(1), pp. 661. https://doi.org/10.32604/iasc.2022.020132

Hutmacher, F. and Appel, M. (2023) 'The psychology of personalization in digital environments: From motivation to well-being–a theoretical integration.', *Review of General Psychology*, *27*(1), pp.26-40. https://doi.org/10.1177/10892680221105663

Igwama, G. T., Olaboye, J. A., Maha, C. C., Ajegbile, M. D., and Abdul, S. (2024) 'Big data analytics for epidemic forecasting: Policy Frameworks and technical approaches', *International Journal of Applied Research in Social Sciences*, *6*(7), pp. 1449-1460. https://doi.org/10.51594/ijarss.v6i7.1334

Ijaiya, H., (2024) 'Balancing Data Privacy and Technology Advancements: Navigating Ethical Challenges and Shaping Policy Solutions', *International Journal of Research Publication and Reviews, 5*(11), pp. 8118-8130. https://doi.org/10.55248/gengpi.5.1224.3549

Inzlicht, M., Werner, K.M., Briskin, J.L. and Roberts, B.W. (2021) 'Integrating models of self-regulation', Annual *review of psychology*, *72*(1), pp.319-345. https://doi.org/10.1146/annurev-psych-061020-105721

Isayama, D., Ishiyama, M., Relator, R. and Yamazaki, K. (2016) 'Computer science education for primary and lower secondary school students: Teaching the concept of automata', *ACM Transactions on Computing Education (TOCE)*, *17*(1), pp.1-28. https://doi.org/10.1145/2940331

Iyelolu, T. V., Agu, E. E., Idemudia, C., & Ijomah, T. I. (2024). Leveraging artificial intelligence for personalized marketing campaigns to improve conversion rates. International *Journal of Engineering Research and Development*, 20(8), pp. 253-270.

Jaakkola, E., Helkkula, A., and Aarikka-Stenroos, L. (2015) 'Service experience co-creation: Conceptualization, implications, and future research directions', *Journal of Service Management*, *26*(2), pp.182–205. https://doi.org/10.1108/JOSM-12-2014-0323

Jaaz, Z.A., Ansari, M.D., JosephNg, P.S. and Gheni, H.M. (2022) 'Optimization technique based on cluster head selection algorithm for 5G-enabled IoMT smart healthcare framework for industry *Paladyn', Journal of Behavioral Robotics*, *13*(1), pp.99-109. https://doi.org/10.1515/pjbr-2022-0101

Jadhav, S.L. and Mali, M.P. (2016) 'Pre-recommendation clustering and review based approach for collaborative filtering based movie recommendation. *International Journal of Information Technology and Computer Science*, *8*(7), pp.72-80. https://doi.org/10.5815/ijitcs.2016.07.10

Jain, G., Paul, J. and Shrivastava, A., (2021) 'Hyper-personalization, co-creation, digital clienteling and transformation', *Journal of Business Research*, *124*, pp.12-23. https://doi.org/10.1016/j.jbusres.2020.11.034

Janaka, N., Cai, R., Ram, A., Zhu, L., Zhao, S. and Yong, K.Q. (2024) 'Pilotar: Streamlining pilot studies with ohmds from concept to insight', *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(3), pp.1-35. https://doi.org/10.1145/3678576

Jara-Ettinger, J. (2019) 'Theory of mind as inverse reinforcement learning', *Current Opinion in Behavioral Sciences*, *29*, pp. 105–110. https://doi.org/10.1016/j.cobeha.2019.04.010

Jayasinghe, L M R, Kasthurirathna, D., (2022). A Goal-driven Personalized Educational Content Recommendation System for Self-Learning., *International Journal of Innovative Science and Research Technology* (IJISRT), 7(11), pp. 1556-1563. https://doi.org/10.5281/zenodo.7467422

Jesse, M., and Jannach, D. (2021) 'Digital nudging with recommender systems: survey and future directions', *Computers in Human Behavior Reports*, *3*, 100052. https://doi.org/10.1016/j.chbr.2020.100052

Jiang, H., Qi, X. and Sun, H. (2014) 'Choice-based recommender systems: a unified approach to achieving relevancy and diversity', *Operations Research*, *62*(5), pp.973-993. https://doi.org/10.1287/opre.2014.1292

Jin, C., and Pan, W. (2025) ‘A hybrid model based on learning automata and cuckoo search for optimizing test item selection in computerized adaptive testing’, *Scientific Reports, 15*, 18218. https://doi.org/10.1038/s41598-025-01115-x

Joseph O.O., Akintola A.S., Offiong E., Olajuwon, O.O., Offia, U. I., and Faniyan, A.A. (2025) ‘AI-Enhanced Consumer Insights: Leveraging Behavioural Analytics for Hyper-Personalised Marketing Strategies’, *Journal of Artificial Intelligence Machine Learning & Data Science*, *3*(1), pp. 2361-2368. https://doi.org/10.51219/JAIMLD/Omotoso-Oluwayomi-Joseph/511

Ju, B., Stewart, J.B., Park, S. and Walker, J.J. (2025) ‘Artificial intelligence (AI) powered chatbots: factors in uptake among early adopters’, *Aslib Journal of Information Management*. https://doi.org/10.1108/AJIM-12-2024-0994

Juechems, K. and Summerfield, C. (2019) ‘Where does value come from?’, *Trends in cognitive sciences*, *23*(10), pp.836-850.

Kabadayi, S. and Tsiotsou, R.H. (2022) ‘Guest editorial: the Triple-A framework for serving humanity with service research’, *Journal of Services Marketing*, *36*(7), pp. 865-872. https://doi.org/10.1108/JSM-07-2022-0234.

Kahneman, D., and Tversky, A. (1979) ‘Prospect Theory: An Analysis of Decision under Risk’, *Econometrica*, *47*(2), pp. 263–291. https://doi.org/10.2307/1914185.

Kahneman, D. and Tversky, A. (1984) ‘Choices, values, and frames’, *American psychologist*, *39*(4), pp. 341–350. https://doi.org/10.1037/0003-066X.39.4.341

Kahneman, D., and Tversky, A. (2013) ‘Prospect theory: An analysis of decision under risk’, In *Handbook of the fundamentals of financial decision making: Part I*, pp. 99-127. https://doi.org/10.1142/9789814417358_0006

Kaine, G., and Stronge, D. (2024) ‘An idiographic approach to measuring subjective well-being’, *Applied Research in Quality of Life*, *19*(6), pp. 3253–3277. https://doi.org/10.1007/s11482-024-10370-5

Kang, J.W. and Namkung, Y. (2019) ‘The role of personalization on continuance intention in food service mobile apps’, *International Journal of Contemporary Hospitality Management*, *31*(2), pp. 734-752. https://doi.org/10.1108/ijchm-12-2017-0783.

Kannan, P.K. (2017) ‘Digital marketing: A framework, review and research agenda’, *International Journal of Research in Marketing*, *34*(1), pp.22-45. https://doi.org/10.1016/j.ijresmar.2016.11.006

Kannan, P.K. and Kulkarni, G. (2022) ‘The impact of Covid-19 on customer journeys: implications for interactive marketing’, *Journal of Research in Interactive Marketing*, *16*(1), pp. 22-36. https://doi.org/10.1108/JRIM-03-2021-0078

Kapuściński, G., Richards, B. (2016). News framing effects on destination risk perception, *Tourism Management*, 57, 234-244. https://doi.org/10.1016/j.tourman.2016.06.017

Kaspar, K., Weber, S. L., and Wilbers, A.-K. (2019) ‘Personally relevant online advertisements: Effects of demographic targeting on visual attention and brand evaluation’, *PLoS ONE, 14*(2), Article e0212419. https://doi.org/10.1371/journal.pone.0212419

Katarya, R. (2018) ‘Movie recommender system with metaheuristic artificial bee’, *Neural Computing & Applications, 30*, pp. 1983–1990. https://doi.org/10.1007/s00521-017-3338-4

Kelleher, C., Helkkula, A., and Holmlund, M. (2010) ‘Customer-Centric Co-Creation of Value Propositions’, I A. Dibley (Red.), *18th International Colloquium in Relationship Marketing. University of Reading, Henley Business School, Reading, UK, September 27-30, 2010*

Kelleher, C., O'Loughlin, D., Gummerus, J. and Peñaloza, L. (2020) 'Shifting arrays of a kaleidoscope: the orchestration of relational value cocreation in service systems', *Journal of Service Research*, *23*(2), pp.211-228. https://doi.org/10.1177/1094670519882495

Kelly, S.P., Corbett, E.A. and O'Connell, R.G. (2021) 'Neurocomputational mechanisms of prior-informed perceptual decision-making in humans', *Natural Human Behavior, 5*, pp. 467–481. https://doi.org/10.1038/s41562-020-00967-9

Kim, D., and Park, B.J.R. (2017) 'The Moderating Role of Context in the Effects of Choice Attributes on Hotel Choice: A Discrete Choice Experiment', *Tourism Management*, *63*, pp. 439–451. https://doi.org/10.1016/j.tourman.2017.07.014

Kim, H.Y., Song, J.H. and Lee, J.-H. (2019) 'When are personalized promotions effective? The role of consumer control', *International Journal of Advertising*, 38(4), pp. 628-647. https://doi.org/10.1080/02650487.2019.1593721.

Kim, B., Fernandez, K. and Medaglia, J. (2025) 'The Dynamics of Neuroethical Decisions Depend on Psychological Traits. Available At: https://osf.io/54kfy/download

Kim, S.Y., and Kim, J. (2025) 'The impact of AI recommendation quality on service satisfaction: the moderating roles of standardization and customization', *Journal of Services Marketing*, *39*(4), pp. 365–386. https://doi.org/10.1108/JSM-05-2024-0214

Kim, J. and Park, S. (2025) 'Empowering individual preferences in mobile notifications: a balanced approach to cognitive load and information needs', *IEEE Access*, *13*, pp. 44936-44950. https://doi.org/10.1109/ACCESS.2025.3549033.

Kivetz, R., Urminsky, O., and Zheng, Y., (2006) 'The goal-gradient hypothesis resurrected: purchase acceleration, illusionary goal progress, and customer retention', *Journal of Marketing Research*, pp. 39–58. https://doi.org/0.1509/jmkr.43.1.39.

Klar, S., Leeper, T., Robison. J. (2020). Studying identities with Experiments: Weighing the risk of posttreatment bias against priming effects. *Journal of Experimental Political Science*, 7 (1): 56–60. https://doi.org/10.1017/XPS.2019.26.

Kleinaltenkamp, M., Plewa, C., Gudergan, S., Karpen, I.O. and Chen, T. (2017) 'Usage center–value cocreation in multi-actor usage processes', *Journal of Service Theory and Practice*, *27*(4), pp.721-737. https://doi.org/10.1108/JSTP-04-2016-0074

Khalik, M.F., Mohammad, W., Zilfana, Z. and Themba, O.S. (2023) 'The Influence of Service Personalization, Customer Satisfaction, and Customer Retention in the Telecommunications Industry on Data-Driven Marketing', *West Science Information System and Technology*, *1*(02), pp.55-62. https://doi.org/10.58812/wsist.v1i02.476

Khurana, D. and Dhingra, S. (2021) 'An improved hybrid and knowledge based recommender system for accurate prediction of movies', In *2021 8th International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 881-886). IEEE.

Kohtamäkia, M., Parida, V., Oghazi, P., Gebauer, H. and Baines, T. (2019) 'Digital servitization business models in ecosystems: a theory of the firm', *Journal of Business Research*, *104*(11), pp. 380-392. https://doi.org/10.1016/j.jbusres.2019.06.027

Kokolakis, S. (2017) 'Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon', *Computers and Security*, *64*, pp. 122–134. https://doi.org/10.1016/j.cose.2015.07.002

Kolotylo-Kulkarni, M., Xia, W., and Dhillon, G. (2021) 'Information disclosure in e-commerce: A systematic review and agenda for future research', *Journal of Business Research, 126*, pp. 221–238. https://doi.org/10.1016/j.jbusres.2020.12.006

Kolb, D.A. and Boyatzis, R.E. (1970) 'Goal-setting and self-directed behavior change', *Human Relations*, *23*(5), pp.439-457.
https://doi.org/10.1177/001872677002300506

Köpetz, C., Faber, T., Fishbach, A., and Kruglanski, A. W. (2011) 'The multifinality constraints effect: How goal multiplicity narrows the means set to a focal end', *Journal of Personality and Social Psychology, 100*(5), pp. 810–826. https://doi.org/10.1037/a0022980

Kopetz, C.E., Kruglanski, A.W., Arens, Z.G., Etkin, J. and Johnson, H.M. (2012) 'The dynamics of consumer behavior: A goal systemic perspective', *Journal of Consumer Psychology*, *22*(2), pp.208-223. https://doi.org/10.1016/j.jcps.2011.03.001

Köpetz C., Woerner J. I., MacPherson L., Lejuez C. W., Nelson C. A., Zeanah C. H., Fox N. A. (2019) 'Early psychosocial deprivation and adolescent risk-taking: The role of motivation and executive control', *Journal of Experimental Psychology: General*, 148, pp. 388–399. https://doi.org/10.1037/xge0000486

Köpetz, C. and Woerner, J.I. (2021) 'People downplay health risks to fulfill their goals: a motivational framework for guiding behavioral policy. *Policy insights from the behavioral and brain sciences*, *8*(1), pp.92-100. https://doi.org/10.1177/2372732220980093

Korneeva, E., Salge, T. O., Cichy, P., Antons, D. (2024) 'How Users Assess Privacy Risks in the Internet of Things: The Role of Framing, Comparing, and Educating', *Business and Society*, *63*(8), pp. 1794-1841. https://doi.org/10.1177/00076503241255082

Kotler, P. and Keller, K.L. (2006) 'Identifying market segments and targets', *Marketing management, 12th edition, Pearson Education Singapore, 234.*

Kozlowski, A.J., Pretz, C.R., Dams-O'Connor, K., Kreider, S. and Whiteneck, G. (2013) 'An introduction to applying individual growth curve models to evaluate change in rehabilitation: a National Institute on Disability and Rehabilitation Research Traumatic Brain Injury Model Systems report', *Archives of physical medicine and rehabilitation*, *94*(3), pp. 589-596. https://doi.org/10.1016/j.apmr.2012.08.199

Krafft, M., Kumar, V., Harmeling, C., Singh, S., Zhu, T., Chen, J., Duncan, T., Fortin, W., and Rosa, E. (2021) 'Insight is power: Understanding the terms of the consumer-firm data exchange', *Journal of Retailing*, *97*(1), pp. 133-149. https://doi.org/10.1016/j.jretai.2020.11.001

Krause, T., and Oosterhuis, H. (2025) 'A Non-Parametric Choice Model That Learns How Users Choose Between Recommended Options', *arXiv preprint arXiv:2507.20035*. https://doi.org/10.48550/arXiv.2507.20035

Krishna, S. K., and Prathapkumar, K. S. (2024). Study on impact of artificial intelligence on personalised marketing. *International Journal of Science and Research Archive*, 13(01), pp. 3211–3223. https://doi.org/10.30574/ijsra.2024.13.1.2042

Kruglanski, A. W. (1996) 'Motivated social cognition: Principles of the interface', In E. T. Higgins and A. W. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 493–520). The Guilford Press.

Kruglanski, A. W., Shah, J. Y., Fishbach, A., Friedman, R., Chun, W. Y., and Sleeth-Keppler, D. (2002) 'A theory of goal systems, In M. P. Zanna (Ed.), Advances in experimental social psychology (Vol. 34, pp. 331–378). Academic Press. https://doi.org/10.1016/S0065-2601(02)80008-9

Kruglanski, A.W. and Kopetz, C. (2009) *What is so special (and nonspecial) about goals?: A view from the cognitive perspective*. Guilford Press.

Kruglanski, A.W., Chernikova, M., Rosenzweig, E. and Kopetz, C. (2014) 'On motivational readiness', *Psychological Review*, *121*(3), pp. 367–388. https://doi.org/10.1037/a0037013

Kruglanski, A.W., Chernikova, M., Babush, M., Dugas, M. and Schumpe, B.M. (2015) 'The architecture of goal systems: Multifinality, equifinality, and counterfinality in means—end relations, In *Advances in motivation science* (Vol. 2, pp. 69-98). Elsevier. https://doi.org/10.1016/bs.adms.2015.04.001

Kruglanski, A.W., Shah, J.Y., Fishbach, A., Friedman, R., Chun, W.Y. and Sleeth-Keppler, D., (2018) '*A theory of goal systems*', In: A.J. Elliot, ed., The Motivated Mind, 1st ed. London: Routledge, pp.207–250.

Kruglanski, A. W., and Szumowska, E. (2020) 'Habitual Behavior Is Goal-Driven', *Perspectives on Psychological Science*, *15*(5), pp. 1256-1271. https://doi.org/10.1177/1745691620917676

Kruglanski, A.W., Fishbach, A., Kopetz, C., and Kopetz, C.E. eds., (2023) '*Goal systems theory: Psychological processes and applications*', Oxford University Press.

Kumar, V., Ramachandran, D. and Kumar, B. (2020) 'Influence of new-age technologies on marketing: a research agenda', *Journal of Business Research*, *1*(7), pp. 1-14. https://doi.org/10.1016/j.jbusres.2020.01.007

Kumar, H. (2024) 'Virtual worlds, real opportunities: A review of marketing in the metaverse', *Acta Psychologica*, *250*, 104517. https://doi.org/10.1016/j.actpsy.2024.104517

Kuper, N., Andresen, P. K., Beck, E. D., Costantini, G., Hamaker, E. L., Wright, A. G., Zimmermann, J. (2024) 'From persons to general principles: Methodological decisions for idiographic and nomothetic research', *European Journal of Personality*, *39*(4), pp. 635-661. https://doi.org/10.1177/08902070241278020

Kuuru, T. K. (2022) 'Embodied knowledge in customer experience: Reflections on yoga', *Consumption Markets & Culture*, *25*(3), pp. 231–251. https://doi.org/10.1080/10253866.202 2.2025783

Kylkilahti, E., Syrjälä, H., Autio, J., Kuismin, A. and Autio, M. (2016) 'Understanding co-consumption between consumers and their pets', *International Journal of Consumer Studies*, *40*(1), pp.125-131. https://doi.org/10.1111/ijcs.12230

Lahindah, L., and Sudriman, I. D. (2023) 'Classification Approach to Predict Customer Decision Between Product Brands Based on Customer Profile and Transaction', *Journal of Theoretical and Applied Information Technology, 101(9),* pp. 3362-3370. http://repository.ithb.ac.id/id/eprint/82

Lang, G., Farsi, M., Lanz, B. and Weber, S. (2021) 'Energy efficiency and heating technology investments: Manipulating financial information in a discrete choice experiment', *Resource and Energy Economics*, *64*, p.101231. https://doi.org/10.1016/j.reseneeco.2021.101231

Latham, G.P. and Locke, E.A. (2006) 'Enhancing the benefits and overcoming the pitfalls of goal setting', *Organizational dynamics*, *35*(4), pp.332-340. https://doi.org/10.1016/j.orgdyn.2006.08.008

Le, C., Zhang, Z., and Liu, Y. (2024) 'Research on Privacy Disclosure Behavior of Mobile App Users from Perspectives of Online Social Support and Gender Differences.', *International Journal of Human–Computer Interaction*, *41*(2), pp. 861–875. https://doi.org/10.1080/10447318.2024.2305988

Ledermann, T., and Kenny, D. A. (2017) 'Analyzing dyadic data with multilevel modeling versus structural equation modeling: A tale of two methods', *Journal of Family Psychology*, *31*, pp. 442–452.

Lee, J. and Chu, W. (2022) 'The effect of adding focal-goal similar versus dissimilar attributes on convergence product purchase decision: The role of relational and item-specific elaboration style', *Journal of Consumer Behaviour*, *21*(2), pp.296-309. https://doi.org/10.1002/cb.2002

Lederrey, G., Lurkin, V., Hillel, T. and Bierlaire, M. (2021) 'Estimation of discrete choice models with hybrid stochastic adaptive batch size algorithms', Journal of choice modelling, 38, p.100226. https://doi.org/10.1016/j.jocm.2020.100226

Lemmink, J., Franzelova, I., Sääksjärvi, M. and Heinonen, K. (2019) 'Customer-dominant logic and the need for exploring app usage in different customer contexts’, *Journal of Indian Business Research*, *11*(1), pp.50-59. https://doi.org/10.1108/JIBR-05-2018-0137

Liang, X., Chen, T., Nguyen, Q.V.H., Li, J. and Yin, H. (2023) ‘Learning compact compositional embeddings via regularized pruning for recommendation’, In *2023 IEEE International Conference on Data Mining (ICDM)* (pp. 378-387). IEEE. https://doi.org/10.1109/ICDM58522.2023.00047

Liang, C., Jiang, P., Takii, K., and Ogata, H. (2025) ‘Data-driven peer recommendation in higher education: A pilot study on academic reading’, *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.10411

Lieder, F., Chen, O.X., Krueger, P.M., and Griffiths, T.L. (2019) ‘Cognitive prostheses for goal achievement’, *Nature human behaviour*, *3*(10), pp.1096-1106. https://doi.org/10.1038/s41562-019-0672-9

Lamberton, C. and Stephen, A.T. (2016) ‘A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry’, *Journal of marketing*, *80*(6), pp.146-172. https://doi.org/10.1509/jm.15.0415

Liberman, N. and Trope, Y. (1998) ‘The role of feasibility and desirability considerations in near and distant future decisions: A test of temporal construal theory’, *Journal of personality and social psychology*, *75*(1), pp.5–18. https://doi.org/10.1037/0022-3514.75.1.5

Lieder, F., and Griffiths, T.L. (2020) ‘Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources’, *Behavioral and brain sciences*, *43*, p.e1. https://doi.org/10.1017/S0140525X1900061X

Leischnig, A., Kasper-Brauer, K. and Thornton, S.C. (2018) ‘Spotlight on customization: an analysis of necessity and sufficiency in services’, *Journal of Business Research*, *89*, pp. 385-390, https://doi.org/10.1016/j.jbusres.2017.12.038.

Lemon, K. N., and Verhoef, P. C. (2016) 'Understanding customer experience throughout the customer journey', *Journal of Marketing*, *80*(6), pp. 69–96. https://doi.org/10.1509/jm.15.0420

Levitt, T. (1960) *Marketing Myopia*, Harvard Business Review July. August, 26, p.37.

Li, C. (2016) 'When does web-based personalization really work? The distinction between actual personalization and perceived personalization', *Computers in Human Behavior*, *54*, pp. 25–33. https://doi.org/10.1016/j.chb.2015.07.049.

Li, L.P., Juric, B. and Brodie, R.J. (2018) 'Actor engagement valence: conceptual foundations, propositions and research directions', *Journal of Service Management*, *29*(3), pp. 491-516. http://doi.org/10.1108/josm-08-2016-0235.

Li, Y., Li, G., Tayi, G.K. and Cheng, T.C.E. (2019). Omni-channel retailing: Do offline retailers benefit from online reviews?, *International Journal of Production Economics*, 218, pp.43–61. https://doi.org/10.1016/j.ijpe.2019.04.006

Li, H., Majumdar, R., Chen, M.R.A., Ogata, H. (2021a) 'Goal-oriented active learning (GOAL) system to promote reading engagement, self-directed learning behavior, and motivation in extensive reading', *Computers and Education*, *171*, pp. 104-239. https://doi.org/10.1016/j.compedu.2021.104239.

Li, Y., Yang, D., Liu, Y. (2021b). The Effect of Message Framing on Consumers' Intentions to Purchase Recycling-Aiding Products in China. *Sustainability*, *13*(12), 6966. https://doi.org/10.3390/su13126966

Li, C., and Zhang, L.J. (2023) 'The Development of Accuracy and Fluency in Second Language (L2) Speaking Related to Self-Efficacy Through Online Scaffolding: A Latent Growth Curve Modeling Analysis', *Journal of Psycholinguist Research, 52*, pp. 1371–1395. https://doi.org/10.1007/s10936-023-09950-7

Li, Y., Chen, D. and Deng, X., (2024) 'The impact of digital educational games on student's motivation for learning: The mediating effect of learning engagement and the moderating effect of the digital environment', *PloS one*, *19*(1), p.e0294350. https://doi.org/10.1371/journal.pone.0294350

Li, X., Jia, P., Xu, D., Wen, Y., Zhang, Y., Zhang, W., Wang, W., Wang, Y., Du, Z., Li, X. and Liu, Y., (2025) 'A survey of personalization: From rag to agent', *arXiv preprint arXiv:2504.10147*. https://doi.org/10.48550/arXiv.2504.10147

Liao, P., Klasnja, P. and Murphy, S. (2021) 'Off-policy estimation of long-term average outcomes with applications to mobile health', *Journal of the American Statistical Association*, *116*(533), pp. 382-391.
https://doi.org/10.1080/01621459.2020.1807993

Liberali, G. and Ferecatu, A. (2022) 'Morphing for consumer dynamics: Bandits meet hidden Markov models', *Marketing Science*, *41*(4), pp. 769-794. https://doi.org/10.1287/mksc.2021.1346

Lieberman, S. (2021) 'Commentary: managing human experience as a core marketing capability', *Journal of Marketing*, *85*(1), pp. 219-222.
https://doi.org/10.1177/0022242920973035.

Lipkin, M. (2016) 'Customer experience formation in today's service landscape', *Journal of Service Management*, *27*(5), pp. 678–703.
https://doi.org/10.1108/JOSM-06-2015-0180

Lipkin, M. (2020) '*Exploring Customer Experiences with Smart Self-service: A Customer Ecosystem Approach*', *Hanken School of Economics*, University of Helsinki. https://helda.helsinki.fi/dhanken/handle/10227/346321

Lipkin, M., and Heinonen, K. (2022) 'Customer ecosystems: Exploring how ecosystem actors shape customer experience', *Journal of Services Marketing*, *36*(9), pp. 1–17. https://doi.org/10.1108/jsm-03-2021-0080

Liu, S. Q., Mattila, A. S. (2016) ‘Using Comparative Advertising to Promote Technology-Based Hospitality Services’, *Cornell Hospitality Quarterly*, *57*(2), pp. 162-171. https://doi.org/10.1177/1938965516630424

Liu, J., Liu, W., Allechy, F.B., Zheng, Z., Liu, R., and Kouadio, K.L. (2024) ‘Machine learning-based techniques for land subsidence simulation in an urban area.’, *Journal of Environmental Management*, *352*, 120078.

Lobato R (2019) Netflix Nations: The Geography of Digital Distribution. New York, NY: New York University Press.

Locke, E.A., Frederick, E., Lee, C. and Bobko, P. (1984) ‘Effect of self-efficacy, goals, and task strategies on task performance’, *Journal of applied psychology*, *69*(2), pp. 241–251. https://doi.org/10.1037/0021-9010.69.2.241

Locke, E.A. and Latham, G.P. (1990) ‘*A theory of goal setting & task performance*’, Prentice-Hall, Inc.

Locke, E.A. and Latham, G.P. (2019) ‘The development of goal setting theory: A half century retrospective’, *Motivation science*, *5*(2), p.93-105.

Loomes, G. and Sugden, R. (1982) ‘Regret theory: An alternative theory of rational choice under uncertainty’, *The economic journal*, *92*(368), pp.805-824. https://doi.org/10.2307/2232669

Lombardi, G., and Hare, T. (2021) ‘Piecewise constant averaging methods allow for fast and accurate hierarchical Bayesian estimation of drift diffusion models with time-varying evidence accumulation rates’. https://doi.org/10.31234/osf.io/5azyx

Loureiro, S.M.C., Romero, J. and Bilro, R.G. (2020) ‘Stakeholder engagement in co-creation processes for innovation: A systematic literature review and case study’, *Journal of Business Research*, *119*, pp. 388-409. https://doi.org/10.1016/j.jbusres.2019.09.038

Lu, J., Bradlow, E.T. and Hutchinson, J.W., (2022) 'Testing theories of goal progress in online learning', *Journal of Marketing Research*, 59(1), pp.1–21. https://doi.org/10.1177/0022243721991100

Luke, D. (2020) *Multilevel modeling: second edition*. SAGE Publications, Inc., https://doi.org/10.4135/9781544310305

Lukoff, K., Lyngs, U. and Alberts, L. (2022) 'Designing to support autonomy and reduce psychological reactance in Digital Self-Control Tools', In *Self-Determination Theory in HCI: Shaping a Research Agenda. Workshop at the ACM CHI Conference on Human Factors in Computing Systems (CHI'22)* (Vol. 6).

Lumbreras, S. (2018) 'Getting Ready for the Next Step: Merging Information Ethics and Roboethics—A Project in the Context of Marketing Ethics', *Information*, *9*(8), p.195. https://doi.org/10.3390/info9080195

Luo, R., Wang, T., Deng, J. and Wan, P. (2023) 'Mcm: A multi-task pre-trained customer model for personalization', In *Proceedings of the 17th ACM Conference on Recommender Systems* (pp. 637-639). https://doi.org/10.1145/3604915.3608868

Lutz, C., and Hoffmann, C.P. (2017) 'The dark side of online participation: exploring non-, passive and negative participation', *Information, Communication & Society*, *20*(6), pp.876-897. https://doi.org/10.1080/1369118X.2017.1293129

Ma, L. and Sun, B. (2020) 'Machine learning and AI in marketing – connecting computing power to human insights', *International Journal of Research in Marketing*, *37*(3), pp. 481-504. https://doi.org/10.1016/j.ijresmar.2020.04.005

Ma, R. and Wang, W. (2021) 'Smile or pity? Examine the impact of emoticon valence on customer satisfaction and purchase intention', *Journal of Business Research*, *134*, pp. 443-456, http://doi: 10.1016/j.jbusres.2021.05.057

Macdonald, E.K., Kleinaltenkamp, M. and Wilson, H.N. (2016) 'How business customers judge solutions: Solution quality and value in use', *Journal of Marketing*, *80*(3), pp. 96-120. https://doi.org/10.1509/jm.15.0109

Mangham, L.J., Hanson, K. and McPake, B. (2009) 'How to do (or not to do)... Designing a discrete choice experiment for application in a low-income country', *Health policy and planning*, *24*(2), pp.151-158. https://doi.org/10.1093/heapol/czn047

Mahadevan, D., Shainesh, G. (2024) 'Conceptualizing customer experience in multi-actor platforms', *AMS Review*, 14(1), pp. 83–103. https://doi.org/10.1007/s13162-023-00272-4

Malfacini, K. (2025) 'The impacts of companion AI on human relationships: risks, benefits, and design considerations', *AI & Society*, pp. 1-14. https://doi.org/10.1007/s00146-025-02318-6

Malter, M.S., Holbrook, M.B., Kahn, B.E., Parker, J.R. and Lehmann, D.R. (2020) 'The past, present, and future of consumer research', *Marketing Letters*, *31*(2), pp.137-149. https://doi.org/10.1007/s11002-020-09526-8

Malone, S., McKechnie, S., and Tynan, C. (2018) 'Tourists' emotions as a resource for customer value creation, cocreation, and destruction: A customer-grounded understanding', *Journal of Travel Research*, 57(7), pp. 843–855. https://doi.org/10.1177/0047287517720118

Mani, Z., and Chouk, I. (2018) 'Consumer Resistance to Innovation in Services: Challenges and Barriers in the Internet of Things Era', *The Journal of Product Innovation Management*, *35*(5), pp. 780–807. https://doi.org/10.1111/jpim.12463

Manser Payne, E. H., Peltier, J., and Barger, V. A. (2021) 'Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms', *Journal of Research in Interactive Marketing*, *15*(1), pp. 68–85. https://doi.org/10.1108/JRIM-10-2020-0214

Mariel, P., Campbell, D., Sandorf, E.D., Meyerhoff, J., Vega-Bayo, A., Blevins, R. (2025) ‘Steps of a Discrete Choice Experiment’, In: Environmental Valuation with Discrete Choice Experiments in R. The Economics of Non-Market Goods and Resources, vol 17. Springer, Cham. https://doi.org/10.1007/978-3-031-89338-4_2

Marr, M. J. (2009) ‘The natural selection: Behavior analysis as a natural science’, *European Journal of Behavior Analysis, 10*, pp. 105-120. https://doi.org/10.1080/15021149.2009.11434313

Marr, M. J., and Zilio, D. (2013) ‘No island entire of itself: Reductionism and behavior analysis’, *European Journal of Behavior Analysis*, *14*(2), pp.241-257. https://doi.org/10.1080/15021149.2013.11434458

Martin, K.D. and Murphy, P.E. (2017) ‘The role of data privacy in marketing’, *Journal of the Academy of Marketing Science*, *45*(2), pp.135-155. https://doi.org/10.1007/s11747-016-0495-4

Martin K. (2020) ‘Breaking the privacy paradox: The value of privacy and associated duty of firms’, *Business Ethics Quarterly*, 30(1), pp. 65–96. https://doi.org/10.1017/beq.2019.24

Martin, K.D., Kim, J.J., Palmatier, R.W., Steinhoff, L., Stewart, D.W., Walker, B.A., Wang, Y. and Weaven, S.K. (2020) ‘Data privacy in retail’, *Journal of Retailing*, *96*(4), pp.474-489. https://doi.org/10.1016/j.jretai.2020.08.003

Matz, S.C., Teeny, J.D., Vaid, S.S., Peters, H., Harari, G.M. and Cerf, M. (2024) ‘The potential of generative AI for personalized persuasion at scale’, *Scientific Reports*, *14*(1), p.4692. https://doi.org/10.1038/s41598-024-53755-0

Mas-Herrero, E., Sescousse, G., Cools, R. and Marco-Pallarés, J. (2019) ‘The contribution of striatal pseudo-reward prediction errors to value-based decision-making’, *NeuroImage*, *193*, pp.67-74. https://doi.org/10.1016/j.neuroimage.2019.02.052

Maslowska, E., Smit, E.G. and Van den Putte, B. (2016) ‘It is all in the name: A study of consumers' responses to personalized communication’, *Journal of Interactive Advertising*, *16*(1), pp. 74-85. https://doi.org/10.1080/15252019.2016.1161568

Maslowska, E., Malthouse, E.C. and Hollebeek, L.D. (2022) ‘The role of recommender systems in fostering consumers' long-term platform engagement’, *Journal of Service Management*, *33*(4/5), pp. 721-732. https://doi.org/10.1108/JOSM-12-2021-0487

Mazhar, M., Hooi Ting, D., Zaib Abbasi, A., Nadeem, M.A. and Abbasi, H.A. (2022) ‘Gauging customers’ negative disconfirmation in online post-purchase behaviour: the moderating role of service recovery’, *Cogent Business and Management*, 9(1), 2072186. https://doi.org/10.1080/23311975.2022.2072186.

McCabe, C.J., Kim, D.S, King, K.M. (2018) ‘Improving Present Practices in the Visual Display of Interactions’, *Advances in Methods and Practices in Psychological Science*, *1*(2), pp. 147-165. https://doi.org/10.1177/2515245917746792.

McColl-Kennedy, J. R., Cheung, L., and Coote, L. V. (2020) ‘Tensions and trade-offs in multi-actor service ecosystems’, *Journal of Business Research*, *121*, pp. 655–666. https://doi.org/10.1016/j.jbusres.2020.06.055

McFadden, D. (2001) ‘Economic choices’, *American economic review*, *91*(3), pp.351-378. https://doi.org/10.1257/aer.91.3.351

McKee, K. M., Dahl, A. J., & Peltier, J. W. (2024). Gen Z’s personalization paradoxes: A privacy calculus examination of digital personalization. Journal of Consumer Behaviour. https://doi.org/10.1002/cb.2199

McNeish, D. and Matta, T. (2018) ‘Differentiating between mixed-effects and latent-curve approaches to growth modeling’, *Behavior Research Methods*, 50(4), pp.1398-1414. https://doi.org/10.3758/s13428-017-0976-5

Medberg, G., and Heinonen, K. (2014) ‘Invisible value formation: a netnography in retail banking’, *International Journal of Bank Marketing*, 32(6), 590–607. https://doi.org/10.1108/IJBM-03-2014-0041

Medberg, G. and Grönroos, C. (2020) ‘Value-in-use and service quality: do customers see a difference?’, *Journal of Service Theory and Practice*, *30*(4/5), pp. 507-529. https://doi.org/10.1108/JSTP-09-2019-0207

Mehmood, K., Verleye, K., De Keyser, A. and Larivière, B. (2023) ‘Piloting personalization research through data-rich environments: a literature review and future research agenda’, *Journal of Service Management*, *34*(3), pp. 520-552. https://doi.org/10.1108/JOSM-10-2021-0405

Mehmood, K., Verleye, K., De Keyser, A. and Lariviere, B. (2024) ‘The transformative potential of AI-enabled personalization across cultures’, *Journal of Services Marketing*, *38*(6), pp. 711-730. https://doi.org/10.1108/JSM-08-2023-0286

Mehr, K. S., Geiser, A. E., Milkman, K. L., Duckworth, A. L. (2020) ‘Copy-paste prompts: A new nudge to promote goal achievement’, *Journal of the Association for Consumer Research*, 5(3), pp. 329-334. https://doi.org/10.1086/708880

Mejtoft T., Lindmark T., Söderström U., Cripps H. (2020) ‘The user experience of personalized content’, In Pucihar A., Kljajić Borštnar M., Bons R., Cripps H., Sheombar A., Vidmar D. (Eds.), *33rd bled eConference – enabling technology for a sustainable society* (pp. 147–158). University of Maribor University Press. https://doi.org/10.18690/978-961-286-362-3.10

Melnikoff, D. E., and Bailey, A. H. (2018) ‘Preferences for moral vs. immoral traits in others are conditional’, *Proceedings of the National Academy of Sciences*, *115*, pp. 592–600. https://doi.org/10.1073/pnas.1714945115

Melnikoff, D.E. and Strohminger, N. (2020) ‘The automatic influence of advocacy on lawyers and novices’, *Nature Human Behaviour*, *4*(12), pp.1258-1264. https://doi.org/10.1038/s41562-020-00943-3

Menard, P., and Bott, G. J. (2025) ‘Artificial intelligence misuse and concern for information privacy: New construct validation and future directions’, Information Systems Journal, 35(1),322–367. https://doi.org/10.1111/isj.12544

Mende, M., Scott, M.L., Ubal, V.O., Hassler, C.M., Harmeling, C.M. and Palmatier, R.W. (2024) ‘Personalized communication as a platform for service inclusion? Initial insights into interpersonal and AI-based personalization for stigmatized consumers’, *Journal of Service Research*, *27*(1), pp. 28-48. https://doi.org/10.1177/10946705231188676

Meteyard, L. and Davies, R.A. (2020) ‘Best practice guidance for linear mixed-effects models in psychological science’, *Journal of Memory and Language*, *112*, p.104092. https://doi.org/10.1016/j.jml.2020.104092

Mickelsson, J., Särkikangas, U., Strandvik, T. and Heinonen, K. (2022) ‘User-defined ecosystems in health and social care’, *Journal of Services Marketing*, *36*(9), pp.41-56. https://doi.org/10.1108/JSM-03-2021-0090

Micu, A., Capatina, A., Cristea, D.S., Munteanu, D., Micu, A.E. and Sarpe, D.A., (2022) ‘Assessing an on-site customer profiling and hyper-personalization system prototype based on a deep learning approach.’, *Technological Forecasting and Social Change*, *174*, pp. 121-289. https://doi.org/10.1016/j.techfore.2021.121289

Miller, G. A., Galanter, E., and Pribram, K. H. (1960) ‘The integration of plans’, In G. A. Miller, E. Galanter, and K. H. Pribram, *Plans and the structure of behavior* (pp. 95–102). Henry Holt and Co. https://doi.org/10.1037/10039-007

Milne, G.R., Kaplan, B., Walker, K.L. and Zacharias, L. (2021) ‘Connecting with the future: The role of science fiction movies in helping consumers understand privacy-technology trade-offs’, *Journal of Consumer Affairs*, *55*(3), pp.737-762. https://doi.org/10.1111/joca.12366

Milyavskaya, M., and Werner, K. M. (2018) ‘Goal pursuit: Current state of affairs and directions for future research’, *Canadian Psychology/psychologie canadienne*, 59(2), 163.

Milyavskaya, M. and Werner, K.M. (2025) ‘An integrative model of personal goal pursuit’, *Advances in Motivation Science*. https://osf.io/preprints/psyarxiv/qydpv_v2

Mishra, A. R., Rai, A., Nandan, D., Kshirsagar, U., & Singh, M. K. (2025) ‘Unveiling emotions: NLPbased mood classification and well-being tracking for enhanced mental health awareness’, *Mathematical Modelling of Engineering Problems*, *12*(2), pp. 1–10. https://doi.org/10.18280/mmep.120228

Mogaji, E., Dwivedi, Y.K. and Raman, R., (2024) ‘Fashion marketing in the metaverse’, *Journal of Global Fashion Marketing*, *15*(1), pp.115-130. https://doi.org/10.1080/20932685.2023.2249483

Moore, J.F. (1993) ‘Predators and prey: a new ecology of competition’, *Harvard business review*, *71*(3), pp.75-86.

Moran, D. (2002). *Introduction to Phenomenology*. Routledge.

Moshontz, H. and Hoyle, R.H. (2021) ‘Resisting, recognizing, and returning: A three-component model and review of persistence in episodic goals’, *Social and Personality Psychology Compass*, *15*(1), p.e12576. https://doi.org/10.1111/spc3.12576

Movafegh, Z. and Rezapour, A. (2023) ‘Improving collaborative recommender system using hybrid clustering and optimized singular value decomposition’, *Engineering Applications of Artificial Intelligence*, *126*, p.107109. https://doi.org/10.1016/j.engappai.2023.107109

Mu, Y., and Wu, Y. (2023) ‘Multimodal Movie Recommendation System Using Deep Learning’, *Mathematics*, 11, 895. https://doi.org/10.3390/math1104089

Mugil, H. and Kenzie, F., (2025) ‘The Shift from Traditional to New Media: How Media Evolution Shapes Audience Engagement’, *Journal of Artificial Intelligence, Machine Learning and Data Science*, *35*, pp.1-10.

Mund, M., Park, Y. and Nestler, S. (2024) ‘Disentangling between-and within-person variation in relationship science’, *Journal of Marriage and Family*, *86*(5), pp.1495-1518. https://doi.org/10.1111/jomf.12999

Mustafa, A. S., Ali, N.A., Dhillon, J. S., Alkawsi, G. and Baashar, Y. (2022) ‘User engagement and abandonment of mHealth: a crosssectional survey’, Healthcare, *10*(2), 221. https://doi.org/10.3390/healthcare10020221

Naeem, M. and Ozuem, W., (2025) ‘Understanding social motivation in scan and go technology’, *Journal of Computer Information Systems*, pp.1-18. https://doi.org/10.1080/08874417.2024.2445007

Nahum-Shani, I., Smith, S.N., Spring, B.J., Collins, L.M., Witkiewitz, K., Tewari, A. and Murphy, S.A. (2016) ‘Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support’, *Annals of behavioral medicine*, *52*, pp. 1-17. https://doi.org/10.1007/s12160-016-9830-8

Nakata C., Izberk-Bilgin E., Sharp L., Spanjol J., Cui A. S., Crawford S. Y., Xiao Y. (2019) ‘Chronic illness medication compliance: A liminal and contextual consumer journey’, *Journal of the Academy of Marketing Science*, 47(2), pp. 192–215. https://doi.org/10.1007/s11747-018-0618-1

Nassar, N., Jafar, A. and Rahhal, Y. (2020) ‘A novel deep multi-criteria collaborative filtering model for recommendation system’, *Knowledge-Based Systems*, *187*, p.104811. https://doi.org/10.1016/j.knosys.2019.06.019

Neely, J. H. (1977) ‘Semantic priming and retrieval from lexical memory: Roles of inhibitionless spreading activation and limited-capacity attention’, *Journal of Experimental Psychology: General, 106*(3), pp. 226–254. https://doi.org/10.1037/0096-3445.106.3.226

Neglur, I. S., and PS, R. (2024) 'Keeping viewers hooked: Netflix's innovative strategies for reducing churn', *Journal of Information Technology Teaching Cases*, 0(0). https://doi.org/10.1177/20438869241296895

Neisser, U. (1967) *Cognitive Psychology*. Prentice-Hall.

Newans T, Bellinger P, Drovandi C, Buxton S, Minahan C. (2022) 'The utility of mixed models in sport science: a call for further adoption in longitudinal data sets', *International Journal of Sports Physiology and Performance*, *17*(8), pp. 1285-1289. https://doi.org/10.1123/ijspp.2021-0496

Newell S., Marabelli M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *The Journal of Strategic Information Systems*, 24(1), pp. 3–14. https://doi.org/10.1016/j.jsis.2015.02.001

Nguyen, T.C., Le, H.T., Nguyen, H.D., Ngo, M.T. and Nguyen, H.Q. (2021) 'Examining ordering effects and strategic behaviour in a discrete choice experiment', *Economic Analysis and Policy*, *70*, pp.394-413. https://doi.org/10.1016/j.eap.2021.03.005

Nguyen, N. B., and Menezes, J. (2024) 'An Extensive Framework of Customer-to-Customer Value Co-creation Practices: A Study in a Running Event Context', *Services Marketing Quarterly*, *45*(2), 182–224. https://doi.org/10.1080/15332969.2024.2323288

Nier, J.A., Gaertner, S.L., Dovidio, J.F., Banker, B.S., Ward, C.M. and Rust, M.C. (2001) 'Changing interracial evaluations and behavior: The effects of a common group identity', *Group Processes & Intergroup Relations*, *4*(4), pp.299-316. https://doi.org/10.1177/1368430201004004001

Nira, R.A. (2025) 'AI-Driven Hyper-Personalization in Hospitality: Application, Present and Future Opportunities, Challenges, and Guest Trust Issues', *International Journal of Research and Innovation in Social Science*, *9*(4), pp. 5562-5573. https://doi.org/10.47772/IJRISS.2025.90400397

Niu, S., Vishnuvardhan, D., and Punnam, V. S. R. (2025) ‘Chat with the 'For You' Algorithm: An LLM-Enhanced Chatbot for Controlling Video Recommendation Flow’, In Proceedings of the 7th ACM Conference on Conversational User Interfaces (CUI '25). *Association for Computing Machinery*, New York, NY, USA, Article 54, pp. 1–16. https://doi.org/10.1145/3719160.3736628.

Nöjd, S., Trischler, J.W., Otterbring, T., Andersson, P.K. and Wästlund, E., (2020) ‘Bridging the valuescape with digital technology: A mixed methods study on customers’ value creation process in the physical retail space’, *Journal of Retailing and Consumer Services*, 56, 102161.https://doi.org/10.1016/j.jretconser.2020.102161

Norberg, P.A., Horne, D.R. and Horne, D.A. (2007) ‘The privacy paradox: Personal information disclosure intentions versus behaviors’, *Journal of consumer affairs*, *41*(1), pp.100-126. https://doi.org/10.1111/j.1745-6606.2006.00070.x

Normann, R. and Ramirez, R. (1993) ‘From value chain to value constellation: Designing interactive strategy. *Harvard business review*, *71*(4), pp.65-77.

Nwanna M, Offiong E, Ogidan T, Fagbohun, O., Ifaturoti, A., Oladotun, F. (2025). AI-Driven Personalisation: Transforming User Experience Across Mobile Applications. *Journal of Artificial Intelligence Machine Learning & Data Science*, 3(1), pp. 1920-1929. DOI: doi.org/10.51219/JAIMLD/maxwell-nwanna/425.

Obiegbu, C. J., and Larsen, G. (2024) ‘Algorithmic personalization and brand loyalty: An experiential perspective.’, *Marketing Theory*, *25*(2), pp. 199-219. https://doi.org/10.1177/14705931241230041

O'Connell, R.G., and Kelly, S.P. (2021) ‘Neurophysiology of human perceptual decision-making’, *Annual review of neuroscience*, *44*(1), pp.495-516. https://doi.org/10.1146/annurev-neuro-092019-100200

Oettingen, G., Bulgarella, C., Henderson, M. and Gollwitzer, P.M. (2004) ‘The self-regulation of goal pursuit’, In *Motivational Analyses of Social Behavior* (pp. 225-244). Psychology Press.

Okur, N., and Saricam, C. (2025) ‘Digital Markets and E-Commerce Applications in Fashion Retailing’, In: Changing Textile and Apparel Consumption in Transformative Era of Sustainability and Digitalization Sustainable Textiles: Production, Processing, Manufacturing & Chemistry. Springer, Cham. https://doi.org/10.1007/978-3-031-97419-9_3

Paliński, M., Jusypenko, B. and Hardy, W. (2025) ‘Behind the screens. Privacy and advertising preferences in VoD—the role of privacy concerns, persuasion knowledge, and experience’, *Journal of Retailing and Consumer Services*, *84*, p.104233. https://doi.org/10.1016/j.jretconser.2025.104233

Park, K. and Young Yoon, H. (2025) ‘AI algorithm transparency, pipelines for trust not prisms: mitigating general negative attitudes and enhancing trust toward AI’, *Humanities and Social Sciences Communications*, *12*(1), pp.1-13. https://doi.org/10.1057/s41599-025-05116-z

Parsons, S., and McCormick, E. M. (2024) ‘Limitations of two time point data for understanding individual differences in longitudinal modeling – What can difference reveal about change?’, *Developmental Cognitive Neuroscience*, *66*, 101353. https://doi.org/10.1016/j.dcn.2024.101353

Paschen, U., Pitt, C., and Kietzmann, J. (2020) ‘Artificial intelligence: Building blocks and an innovation typology’, *Business Horizons*, *63*(2), pp. 147-155. https://doi.org/10.1016/j.bushor.2019.10.004

Patil, D. (2024) ‘Artificial Intelligence for Personalized Marketing and Consumer Behaviour Analysis: Enhancing Engagement and Conversion Rates’ (November 19, 2024). Available at https://doi.org/10.2139/ssrn.5057436.

Patnaik, P. (2022) ‘Personalized Product Recommendation and User Satisfaction: Theory and Application’, In M. Pejic-Bach & Ç. Doğru (Eds.), *Management Strategies for Sustainability, New Knowledge Innovation, and Personalized Products and Services* (pp. 35-67). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-7998-7793-6.ch002.

Patrício, L., Fisk, R. P., Falcão e Cunha, J., and Constantine, L. (2011) ‘Multilevel service design: From customer value constellation to service experience blueprinting’, *Journal of Service Research*, *14*(2), pp. 180–200. https://doi. org/10.1177/1094670511401901

Patrício, L., Gustafsson, A. and Fisk, R. (2018) ‘Upframing service design and innovation for research impact’, *Journal of Service Research*, *21*(1), pp. 3-16. https://doi.org/10.1177/1094670517746780

Patrício, L., Sangiorgi, D., Mahr, D., Čaić, M., Kalantari, S. and Sundar, S. (2020) ‘Leveraging service design for healthcare transformation: Toward people-centered, integrated, and technology-enabled healthcare systems’, *Journal of Service Management*, *31*(5), pp.889-909. https://doi.org/10.1108/JOSM-11-2019-0332

Paul, J., Ueno, A., Dennis, C., Alamanos, E., Curtis, L., Foroudi, P., Kacprzak, A., Kunz, W.H., Liu, J., Marvi, R., Sreekumaran Nair, S.L., Ozdemir, O., Pantano, E., Papadopoulos, T., Petit, O., Tyagi, S. and Wirtz, J. (2024) ‘Digital transformation: A multidisciplinary perspective and future research agenda’, I*nternational Journal of Consumer Studies*, *48*(3), pp. 1 – 20. https://doi.org/10.1111/ijcs.13015

Payne, E.M., Dahl, A.J. and Peltier, J. (2021). Digital servitization value co-creation framework for AIservices: a research agenda for digital transformation in financial service ecosystems, *Journal of Research in Interactive Marketing*, *15*(2), pp. 200-222.

Paz, A., Arteaga, C., Cobos, C. (2019) ‘Specification of mixed logit models assisted by an optimization framework’, *Journal of Choice Modelling*, *30*, pp. 50–60.

Peltier, J. W., Piquet, J., and Dahl, A. J. (2020) ‘A hierarchical model of personalized advertising effects on consumer brand engagement’, *Journal of Business Research*, *109*, pp. 62–73. https://doi.org/10.1016/j.jbusres.2019.11.052

Peer E., Vosgerau J., and Acquisti A. (2014) ‘Reputation as a sufficient condition for data quality on Amazon Mechanical Turk’, Behavioural Research Methods, 46, pp. 1023–1031. https://doi.org/10.3758/s13428-013-0434-y

Pfiffelmann, J., Dens, N., and Soulez, S., (2020) ‘Personalized advertisements with integration of names and photographs: An eye-tracking experiment’, *Journal of Business Research*, 196–207 https://doi.org/10.1016/j.jbusres.2019.08.017.

Piccirillo, M. L., and Rodebaugh, T. L. (2019) ‘Foundations of idiographic methods in psychology and applications for psychotherapy’, *Clinical Psychology Review*, *71*, pp. 90–100. https://doi.org/10.1016/j.cpr.2019.01.002

Pizzi, G., Scarpi, D. and Pantano, E., (2021) ‘Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?’, *Journal of Business Research*, *129*, pp. 878-890.

Poku-Boansi, M., Tetteh, N. and Adarkwa, K.K. (2023) ‘Preferences for rental housing in urban Ghana: A discrete choice experiment’, *Habitat International*, *138*, p.102853. https://doi.org/10.1016/j.habitatint.2023.102853

Polushkina-Merchanskaya, O., Sorochan Armstrong, M.D, Gómez-Llorente, C., Ferrer, P., Fernandez-Gonzalez, S., Perez-Cruz, M., Gómez-Roig, M. D., Camacho, J. (2025) ‘Considerations for missing data, outliers and transformations in permutation testing for ANOVA with multivariate responses’, *Chemometrics and Intelligent Laboratory Systems*, *258*(1), 105320.
https://doi.org/10.1016/j.chemolab.2025.105320

Polyportis, A., 2024. A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education. *Frontiers in Artificial Intelligence*, *6*, p.1324398.
https://doi.org/10.3389/frai.2023.1324398

Powers, W., Clark, R.K. and MacFarland, R.L., (1960) ‘A General Feedback Theory of Human Behavior’, *General Systems-Yearbook of the Society for General Systems Research*, pp.63-83. https://doi.org/10.2466/pms.1960.11.1.71

Prasetyo, P. K., Achananuparp, P., and Lim, E. P. (2020). ‘Foodbot: a goal-oriented just-in-time healthy eating interventions chatbot’, In *Proceedings of the 14th EAI*

International Conference on Pervasive Computing Technologies for Healthcare Association for Computing Machinery, New York, NY, USA, pp. 436–439. https://doi.org/10.1145/3421937.3421960

Prebensen, N.K. and Xie, J. (2017) 'Efficacy of co-creation and mastering on perceived value and satisfaction in tourists' consumption', *Tourism management*, *60*, pp.166-176. https://doi.org/10.1016/j.tourman.2016.12.001

Price, L.L. and Epp, A.M. (2015) 'The heterogeneous and open-ended project of assembling family', Assembling Consumption: Researching Actors, Networks and Markets, Routledge, New York, NY (2015), pp. 59-76, pp.59-76. https://doi.org/10.4324/9781315743608

Pu, Z., Beam, M. A. (2021) 'Information Overload and user satisfaction: Balance between reliance on recommendations and deliberate news selection', *CEUR Workshop Proceedings*, [Online] Vol. *3143*. Available at: https://ceur-ws.org/Vol-3143/paper5.pdf.

Pu, Z., Beam, M. A. (2024) 'The impacts of relevance of recommendations and goal commitment on user experience in news recommender design', *User Modeling and User-Adapted Interaction*, *34*(4), pp. 925-953. https://doi.org/10.1007/s11257-024-09405-1

Pukas, A. (2022) 'Hyper-personalization as a customer relationship management tool in a SMART organization', *Problemy Zarządzania*, *20*(3 (97)), pp. 95-108.

Puneet, S. (2023) 'AI-Driven Personalization in Telecom Customer Support: Enhancing User Experience and Loyalty', *Distributed Learning and Broad Applications in Scientific Research*, *9*, Available at: http://dx.doi.org/10.2139/ssrn.5196189

Puntoni, S., Reczek, R.W., Giesler, M. and Botti, S. (2021) 'Consumers and artificial intelligence: an experiential perspective', *Journal of Marketing*, *85*(1), pp. 131-151. https://doi.org/10.1177/0022242920953847

Qi, T., Wu, F., Wu, C., Sun, P., Wu, L., Wang, X., Huang, Y. and Xie, X. (2022) 'ProFairRec: Provider fairness-aware news recommendation', In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 1164-1173). https://doi.org/10.1145/3477495.3532046

Qin, Z.T., Zhang, M. (2021) 'Towards a Personalized Movie Recommendation System: A Deep Learning Approach'. In 2021 2nd International Conference on Artificial Intelligence and Information Systems (ICAIIS 2021). *Association for Computing Machinery*, New York, NY, USA, Article 216, pp. 1–5. https://doi.org/10.1145/3469213.3470423

Qin, K., (2023) 'Revisiting Automatic Goal Pursuit: Exploring the Value of Goals in Cue-Based Behavior', https://doi.org/10.33540/1856

Quach, S., Thaichon, P., Martin, K.D., Weaven, S., and Palmatier, R.W. (2022) 'Digital technologies: tensions in privacy and data', *Journal of the Academy of Marketing Science*, *50*(6), pp. 1299-1323, doi: 10.1007/s11747-022-00845-y.

Qureshi, N., Edelen, M., Hilton, L., Rodriguez, A., Hays, R. D., and Herman, P. M. (2022) 'Comparing Data Collected on Amazon's Mechanical Turk to National Surveys', American journal of health behavior, 46(5), 497–502. https://doi.org/10.5993/AJHB.46.5.1

Raeside, R., Jia, S.S., Todd, A., Hyun, K., Singleton, A., Gardner, L.A., Champion, K.E., Redfern, J. and Partridge, S.R. (2024) 'Are digital health interventions that target lifestyle risk behaviors effective for improving mental health and wellbeing in adolescents? A systematic review with meta-analyses', *Adolescent Research Review*, *9*(2), pp. 193-226. https://doi.org/10.1007/s40894-023-00224-w

Rafieian, O. (2022) 'Optimizing User Engagement Through Adaptive Ad Sequencing', *Marketing Science*, *42*(5), pp. 910-933. https://doi.org/10.1287/mksc.2022.1423

Rafieian, O. and Yoganarasimhan, H. (2023) ‘AI and Personalization’, *Artificial Intelligence in Marketing*, *20*(1), pp. 77-102. https://doi.org/10.1108/S1548-643520230000020004

Rafieian, O., and Zuo, Si (2024) ‘Personalization, Algorithmic Dependence, and Learning’ (November 28, 2024). Cornell SC Johnson College of Business Research Paper (forthcoming), Available at http://dx.doi.org/10.2139/ssrn.5037671

Rai, N. and Pandey, A., (2024) ‘Marketing Cues in Industry 5.0: Journey to Hyper Personalization’, *Interantional journal of scientific research in engineering and management*, *8*, pp.1-13.

Ramachandran, R., Pillai, S., and Dahal, R.K. (2025) ‘The Transformative Role of AI in Advertising and Marketing: From Data-Driven Practices to Virtual Experiences’, *Interdisciplinary Journal of Innovation in Nepalese Academia*, *4*(1), pp. 27-45. https://doi.org/10.32674/2q7y1a35

Randall, D.M. and Wolff, J.A. (1994) ‘The time interval in the intention-behaviour relationship: Meta-analysis’, *British Journal of Social Psychology*, *33*(4), pp.405-418. https://doi.org/10.1111/j.2044-8309.1994.tb01037.x

Raudenbush, S. W., and Bryk, A. S. (2002) *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Newbury Park, CA: Sage.

Raza, S. and Ding, C. (2022) ‘News recommender system: a review of recent progress, challenges, and opportunities. *Artificial Intelligence Review*, *55*(1), pp.749-800. https://doi.org/10.1007/s10462-021-10043-x

Renjilian, D.A., Perri, M.G., Nezu, A.M., McKelvey, W.F., Shermer, R.L. and Anton, S.D. (2001) ‘Individual versus group therapy for obesity: effects of matching participants to their treatment preferences’, *Journal of consulting and clinical psychology*, *69*(4), p.717-721. https://doi.org/10.1037/0022-006X.69.4.717

Ribas-Fernandes, J.J., Shahnazian, D., Holroyd, C.B. and Botvinick, M.M. (2019) ‘Subgoal-and goal-related reward prediction errors in medial prefrontal cortex’, *Journal of cognitive neuroscience*, *31*(1), pp.8-23. https://doi.org/10.1162/jocn_a_01341

Rihova, I., Buhalis D., Gouthro M. B., Moital M. (2018) ‘Customer-to-customer co-creation practices in tourism: Lessons from customer-dominant logic’, *Tourism Management*, 67, 362–375. https://doi.org/10.1016/j.tourman.2018.02.010

Rindell, A. (2013) ‘Time in corporate images: Introducing image heritage and image-in-use’, *Qualitative Market Research: An International Journal*, 16 (2), pp. 197-213. https://doi.org/10.1108/13522751311317594

Robinson, N. L., Kavanagh, D. J. (2021) ‘A social robot to deliver a psychotherapeutic treatment: Qualitative responses by participants in a randomized controlled trial and future design recommendations’, *International Journal of Human-Computer Studies*, 155, 102700, ISSN 1071-5819, https://doi.org/10.1016/j.ijhcs.2021.102700.

Rodrigues, F., Ortelli, N., Bierlaire, M., Pereira, F. (2022) ‘Bayesian automatic relevance determination for utility function specification in discrete choice models’, IEEE *Transactions on Intelligent Transportation Systems*, *23*(4), pp. 3126-3136. https://doi.org/10.1109/TITS.2020.3031965.

Rosenbaum, M.S., Ramirez, G.C., Campbell, J., and Klaus, P. (2021) ‘The product is me: hyper-personalized consumer goods as unconventional luxury’, *Journal of Business Research*, *129*(1), pp. 446-454, Doi: 10.1016/j. jbusres.2019.05.017.

Rosenbaum, M.S., Ramírez, G.C., Edwards, K., Kim, J., Campbell, J.M., and Bickle, M.C. (2017) ‘The digitization of health care retailing’, *Journal of Research in Interactive Marketing*, *11*(4), pp. 432-446, Doi: 10.1108/JRIM07-2017-0058.

Rowe, F. (2020) ‘Contact tracing apps and values dilemmas: A privacy paradox in a neo-liberal world’, *International Journal of Information Management*, *55*, pp. 102178–102178. https://doi.org/10.1016/j.ijinfomgt.2020.102178

Rumelhart, D. E., and Ortony. A. (1977) 'Representation of knowledge', In J. R. Anderson, R, J. Spiro, and W. E. Montague (Eds.), Schooling and the acquisition of knowledge. HiIlsdale, NJ: Erlbaum.

Ryan, R. M., and Deci, E. L. (2020) 'Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions', *Contemporary Educational Psychology*, *61*. https://doi.org/10.1016/j.cedpsych.2020.101860

Ryan, R.M., Duineveld, J.J., Di Domenico, S.I., Ryan, W.S., Steward, B.A. and Bradshaw, E.L. (2022) 'We know this much is (meta-analytically) true: A meta-review of meta-analytic findings evaluating self-determination theory', *Psychological Bulletin*, *148*(11-12), pp. 813–842. https://doi.org/10.1037/bul0000385

Sahhar, Y., and Loohuis, R. (2022) 'Characterizing the spaces of consumer value experience in value co-creation and value codestruction', *European Journal of Marketing*, *56*(13), pp. 105–136. https://doi.org/10.1108/ejm-04-2020-0313

Sallami, D., Ben Salem, R. and Aïmeur, E. (2023) 'Trust-based recommender system for fake news mitigation. In *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization* (pp. 104-109). https://doi.org/10.1145/3563359.3597395

Sangaiah, A.K., Javadpour, A., Ja'fari, F., Zavieh, H. and Khaniabadi, S.M. (2023) 'SALA-IoT: Self-reduced internet of things with learning automaton sleep scheduling algorithm', *IEEE Sensors Journal*, 23(18), pp.20737-20744. https://doi.org/10.1109/JSEN.2023.3242759.

Sathya, A., Vignesh, A., Akash, M., Gokulakrishnan, S. (2024) 'Fitness Guide: A Holistic Approach for Personalized Health and Wellness Recommendation System', *In 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS)* (pp. 01-06). IEEE. https://doi.org/10.1109/ADICS.2024.00001

Schembri, S. (2006) ‘Rationalizing service logic, or understanding services as experience?’, *Marketing Theory*, *6*(3), pp. 381–392. https://doi.org/10.1177/1470593106066798

Schildmeijer, K., Frykholm, O., Kneck, Å. and Ekstedt, M. (2019) ‘Not a straight line – patients’ experiences of prostate cancer and their journey through the healthcare system’, *Cancer Nursing*, 42(1), pp. 36-43. https://doi.org/10.1097/NCC.0000000000000559

Schmidt-Kraepelin, M., Thiebes, S., Stepanovic, S., Mettler, T., and Sunyaev, A. (2019) ‘Gamification in health behavior change support systems—a synthesis of unintended side effects’, In Wirtschaftsinformatik. 14th International Conference on Wirtschaftsinformatik, Siegen, Germany, pp. 1032–1046. https://api.semanticscholar.org/CorpusID:145042569

Schoettle, B., and Sivak, M. (2014) ‘A Survey of Public Opinion About Connected Vehicles in the U.S., the U.K., and Australia’, Ann Arbor, MI: *Transportation Research Institute*, University of Michigan.

Schwipper, S., Peche, S. and Schmitz, G. (2020) ‘Mobile location-based services’ value-in-use in inner cities: Do a customer’s shopping patterns, prior user experience, and sales promotions matter?’, *Schmalenbach business review*, *72*(4), pp.511-564. https://doi.org/10.1007/s41464-020-00103-0

Seppänen, K., Huiskonen, J., Koivuniemi, J. and Karppinen, H. (2017) ‘Revealing customer dominant logic in healthcare services’, *International Journal of Services and Operations Management*, *26*(1), pp.1-17. https://doi.org/10.1504/IJSOM.2017.080675

Serino, C. M., Furner C. P., Smatt C. (2005) ‘Making it personal: How personalization affects trust over time’, Proceedings of the 38th Annual Hawaii International Conference on System Sciences, Washington, DC, 3–6 January, 2005, (pp. 170). https://doi.org/10.1109/HICSS.2005.398

Sfeir, G., Rodrigues, F. and Abou-Zeid, M. (2022) ‘Gaussian process latent class choice models’, *Transportation Research Part C: Emerging Technologies*, *136*, p.103552. https://doi.org/10.1016/j.trc.2022.103552

Shah, J.Y. and Kruglanski, A.W., (2003) ‘When opportunity knocks: bottom-up priming of goals by means and its effects on self-regulation’, *Journal of personality and social psychology*, *84*(6), p.1109.

Shah, D., and Murthi, B.P.S. (2021) ‘Marketing in a data-driven digital world: Implications for the role and scope of marketing’, *Journal of Business Research*, *125*, pp. 772-779. https://doi.org/10.1016/j.jbusres.2020.06.062

Sharif, M.A. and Woolley, K. (2020) ‘The effect of categorization on goal progress perceptions and motivation’, *Journal of Consumer Research*, *47*(4), pp.608-630. https://doi.org/10.1093/jcr/ucaa022

Sheagley, G., and S. Clifford. (2023) ‘No evidence that measuring moderators alters treatment effects’, *American Journal of Political Science, 69*(1), pp. 49–63. https://doi.org/10.1111/ajps.12814.

Shen, L. and Li, S.S. (2023) ‘Quantifying emotional flow: Testing the emotional flow hypothesis from a longitudinal latent growth curve (LGC) modeling approach’, *Media Psychology*, *26*(4), pp.436-459. https://doi.org/10.1080/15213269.2022.2156886

Sheth, J., and Kellstadt, C.H. (2021) ‘Next frontiers of research in data driven marketing: Will techniques keep up with data tsunami?’, *Journal of Business Research*, *125*, pp. 780-784. https://doi.org/10.1016/j.jbusres.2020.04.050

Shin, D., Zaid, B., Biocca, F. and Rasul, A. (2022) ‘In platforms we trust? Unlocking the black-box of news algorithms through interpretable AI’, *Journal of Broadcasting & Electronic Media*, *66*(2), pp.235-256. https://doi.org/10.1080/08838151.2022.2057984

Siddique, J., Shamim, A., Nawaz, M., Faye, I. and Rehman, M. (2021) 'Co-creation or co-destruction: a perspective of online customer engagement valence', *Frontiers in Psychology*, *11*(1), pp. 591-753. Doi: 10.3389/fpsyg.2020.591753.

Sifringer, B., Lurkin, V. and Alahi, A. (2020) 'Enhancing discrete choice models with representation learning. *Transportation Research Part B: Methodological*, *140*, pp.236-261. https://doi.org/10.1016/j.trb.2020.08.006

Simester, D., Timoshenko, A. and Zoumpoulis, S.I., (2020) 'Targeting prospective customers: Robustness of machine-learning methods to typical data challenges', *Management Science*, *66*(6), pp. 2495-2522.

Sipos, D. (2025) 'The Effects of AI-Powered Personalization on Consumer Trust, Satisfaction, and Purchase Intent', *European Journal of Applied Science, Engineering and Technology*, *3*(2), pp. 14-24. https://doi.org/10.59324/ejaset.2025.3(2).02

Singer, J.D. (1998) 'Using SAS PROC MIXED to fit multilevel models, hierarchical models, and individual growth models', *Journal of Educational and Behavioral Statistics, 23(4)*, pp. 323–355. https://doi.org/10.3102/10769986023004323

Singer, J. D. and Willett, J. B. (2003) *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press, New York.

Singh, A. and Kakkar, A., (2025) 'Marketing in the age of hyper-personalisation: Lessons from analytics-driven brand success', *Applied Marketing Analytics*, *11*(1), pp. 72-86. https://doi.org/10.69554/XQVW6761

Sliwinski, M.J. (2011) 'Approaches to modeling intraindividual and interindividual facets of change for developmental research', *Handbook of life-span development*, *1*, pp.1-25.

Snijders, T., and Bosker, R. (2012).*Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.), London, England: Sage.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines', *Journal of Business Research*, 104, pp. 333 – 339. https://doi.org/10.1016/j.jbusres.2019.07.039

Sokol, K., and Flach, P. (2020) 'Explainability fact sheets. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency', January 27–30, 2020, Barcelona, Spain (pp. 56–67). ACM. https://doi.org/10.1145/3351095.3372870

Solgaard, H.S., Yang, Y. and Nguyen, T.T. (2023) 'An investigation of consumers' preference and willingness to pay for fish welfare in Denmark: A discrete choice modeling approach', *Aquaculture*, *574*, p.739652. https://doi.org/10.1016/j.aquaculture.2023.739652

Souiden, N., Ladhari, R. and Chiadmi, N.E. (2019) 'New trends in retailing and services', *Journal of Retailing and Consumer Services*, *50*, pp. 286-288. https://doi.org/10.1016/j.jretconser.2018.07.023

Spanakis, E. G., Santana S., Ben-David B., Marias K., Tziraki C. (2014) 'Persuasive technology for healthy aging and wellbeing. 4th International Conference on Wireless Mobile Communication and Healthcare, Athens, Greece, 3–5 November, 2014 (pp. 23). https://doi.org/10.4108/icst.mobihealth.2014.257499

Spiekermann, S., (2021) 'What to expect from IEEE 7000: The first standard for building ethical systems', *IEEE Technology and Society Magazine*, *40*(3), pp.99-100. https://doi.org/10.1109/MTS.2021.3104386.

Spiel, K., Kayali, F., Horvath, L., Penkler, M., Harrer, S., Sicart, M. and Hammer, J. (2018) 'Fitter, happier, more productive? The normative ontology of fitness trackers', In Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, (Montreal QC, Canada), (CHI EA '18), pp. 1–10. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3170427.3188401.

Storms, E., Alvarado, O. and Monteiro-Krebs, L. (2022) 'Transparency is Meant for Control and Vice Versa: Learning from Co-designing and Evaluating Algorithmic

News Recommenders', *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2), pp.1-24. https://doi.org/10.1145/3555130

Straiton, N., Hollings, M., Gullick, J., and Gallagher, R. (2023) 'Wearable Activity Trackers Objectively Measure Incidental Physical Activity in Older Adults Undergoing Aortic Valve Replacement', *Sensors (Basel), 23*(6), 3347.
https://doi.org/10.3390/s23063347.

Strandvik, T., Holmlund, M. and Edvardsson, B. (2012) 'Customer needing: a challenge for the seller offering, *Journal of business & industrial marketing*, *27*(2), pp.132-141. https://doi.org/10.1108/08858621211196994

Strandvik, T., Holmlund, M. and Lähteenmäki, I. (2018) '"One of these days, things are going to change!" How do you make sense of market disruption?', *Business Horizons*, *61*(3), pp.477-486. https://doi.org/10.1016/j.bushor.2018.01.014

Strandvik, T., Heinonen, K. and Vollmer, S. (2019) 'Revealing business customers' hidden value formation in service', *Journal of Business & Industrial Marketing*, 34(6), pp. 1145–1159. https://doi.org/10.1108/JBIM-11-2017-0259.

Sun, H., Chen, J. and Fan, M. (2021) 'Effect of live chat on traffic-to-sales conversion: Evidence from an online marketplace', *Production and Operations Management*, *30*(5), pp.1541–1561. https://doi.org/10.1111/poms.13320.

Sun, H., Xie, P., Sun, Y. (2025) 'The Inverted U-Shaped Effect of Personalization on Consumer Attitudes in AI-Generated Ads: Striking the Right Balance Between Utility and Threat', *Journal of Advertising Research*, *65*(2), pp. 237–258.
https://doi.org/10.1080/00218499.2025.2462405

Sundar, S. S., Marathe S. S. (2010) 'Personalization versus customization: The importance of agency, privacy, and power usage', *Human Communication Research*, 36(3), pp. 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x

Sundar, S. S. (2020) ‘Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII)’, *Journal of Computer-Mediated Communication*, *25*(1), pp. 74–88. https://doi.org/10.1093/jcmc/zmz026

Susser, D. (2025) ‘Exploitation in the Platform Age’ (January 03, 2025). In Beate Roessler and Valeries Steeves (ed.), *Being Human in the Digital World*. Cambridge University Press, forthcoming., http://dx.doi.org/10.2139/ssrn.5080971

Sutton, R. S., and Barto, A. G. (2018) Reinforcement Learning: An Introduction (2nd ed.). MIT Press.

Symasek, L., Yeazitzis, T., Weger, K., and Mesmer, B. (2025) ‘Recent Developments in Individual Difference Research to Inform the Adoption of AI Technology’, *Systems*, *13*(3), pp. 156. https://doi.org/10.3390/systems13030156

Taghipour, S., Akbari Torkestani, J. and Nazari, S. (2022) ‘A learning automata-based approach to improve the scalability of clustering-based recommender systems’, *Cybernetics and Systems*, *55*(7), pp. 1562-1593. https://doi.org/10.1080/01969722.2022.2145650

Talić, I., Winter, W., Renner, K.-H. (2023) ‘What works best for whom?: The effectiveness of positive psychology interventions on real-world psychological and biological stress and wellbeing is moderated by personality traits’, *Zeitschrift Für Psychologie*, *231*(4), 291–302. https://doi. org/10.1027/2151- 2604/ a0005 28.

Tax, S.S., McCutcheon, D. and Wilkinson, I.F. (2013) ‘The Service Delivery Network (SDN): a customer-centric perspective of the customer journey’, *Journal of Service Research*, 16(4), pp. 454-470. https://doi.org/10.1177/1094670513481108

Tazarv, A., Labbaf, S., Rahmani, A., Dutt, N., Levorato, M. (2023). Active Reinforcement Learning for Personalized Stress Monitoring in Everyday Settings. *In ACM/IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies* (CHASE ’23).

Teepapal, T. (2025) ‘AI-driven personalization: Unraveling consumer perceptions in social media engagement’, *Computers in Human Behavior*, 165, 108549. https://doi.org/10.1016/j.chb.2024.108549

Teixeira, J., Patrício, L., Nunes, N. J., Nóbrega, L., Fisk, R. P., and Constantine, L. (2012) ‘Customer experience modeling: From customer experience to service design’, *Journal of Service Management, 23*(3), pp. 362–376. https://doi.org/10.1108/09564231211248453

Tikkanen, H., Heinonen, K. and Ravald, A. (2023) ‘Smart Wearable Technologies as Resources for Consumer Agency in Well-Being’, *Journal of Interactive Marketing*, *58*(2/3), pp. 136–150. https://doi.org/10.1177/10949968221143351.

Tiwari, A. (2024) ‘Leveraging AI-Powered Hyper-Personalization and Predictive Analytics for Enhancing Digital Experience Optimization’, *International Journal of Research Science and Management*, *11*(9), pp. 9-23. https://ijrsm.com/index.php/journal-ijrsm/article/view/828

Theocharous, G., Thomas, P.S. and Ghavamzadeh, M., (2015) ‘Personalized ad recommendation systems for life-time value optimization’, In *Proceedings of the 24th international conference on world wide web* (pp. 1305-1310).

Thomaz, F., Salge, C., Karahanna, E. and Hulland, J. (2020) ‘Learning from the dark web: leveragingconversational agents in the era of hyper-privacy to enhance marketing’, *Journal of the Academy of Marketing Science*, *48*(1), pp. 43-63.

Thomas, T.C., Epp, A.M. and Price, L.L. (2020) ‘Journeying together: Aligning retailer and service provider roles with collective consumer practices’, *Journal of Retailing*, *96*(1), pp.9-24. https://doi.org/10.1016/j.jretai.2019.11.008

Thomas, B., Clegg, K.A., Holding, A.C. and Koestner, R. (2022) ‘From the good life to good living: A longitudinal study investigating the relationship between good-life coherence and motivation, goal progress and subjective well-being’, *Journal of*

Happiness Studies, *23*(5), pp.1887-1900. https://doi.org/10.1007/s10902-021-00476-0

Tong, S., Luo, X. and Xu, B. (2020) 'Personalized mobile marketing strategies', *Journal of the Academy of Marketing Science*, *48*(1), pp. 64-78. https://doi.org/10.1007/s11747-019-00693-3

Truong, K. (2017) 'Pilot Studies: When and how to conduct them when conducting user studies', *GetMobile: Mobile Computing and Communications, 20*(4), pp. 8–11. https://doi.org/10.1145/3081016.3081020

Tsay, C.H.H., Kofinas, A.K., Trivedi, S.K. and Yang, Y. (2020) 'Overcoming the novelty effect in online gamified learning systems: An empirical evaluation of student engagement and performance', *Journal of Computer Assisted Learning*, *36*(2), pp.128-146. https://doi.org/10.1111/jcal.12385

Tucker, C. (2019) 'Privacy, algorithms, and artificial intelligence', In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 423–437). London: University of Chicago Press.

Tufekci Z (2014) 'Engineering the public: Big data, surveillance and computational politics. [Big data; surveillance; public sphere; Political campaigns; persuasive communication]', *First Monday*, 19(7).

Tueanrat, Y., Papagiannidis, S. and Alamanos, E. (2021) 'Going on a journey: A review of the customer journey literature', *Journal of business research*, *125*, pp.336-353. https://doi.org/10.1016/j.jbusres.2020.12.028

Turetken, O., Grefen, P., Gilsing, R. and Adali, O.E. (2019) 'Service-dominant business model design for digital innovation in smart mobility', *Business and Information Systems Engineering*, *61*, pp. 9-29. https://doi.org/10.1007/s12599-018-0565-x

Tversky, A. and Kahneman, D. (1981) 'The framing of decisions and the psychology of choice', *science*, *211*(4481), pp.453-458. https://doi.org/10.1126/science.7455683

Tynan, C., McKechnie, S. and Hartley, S. (2014) ‘Interpreting value in the customer service experience using customer-dominant logic’, *Journal of Marketing Management*, *30*(9-10), pp.1058-1081. https://doi.org/10.1080/0267257X.2014.934269

Tyrväinen, O. and Karjaluoto, H. (2019) ‘A systematic literature review and analysis of mobile retailing adoption’, *Journal of Internet Commerce*, *18*(2), pp.221-247. https://doi.org/10.1080/15332861.2019.1595364

Udeh, E.O., Amajuoyi, P., Adeusi, K.B. and Scott, A.O. (2024) ‘AI-Enhanced Fintech communication: Leveraging Chatbots and NLP for efficient banking support’, *International Journal of Management & Entrepreneurship Research*, *6*(6), pp. 1768-1786.

Valdez Mendia, J. M., and Flores-Cuautle, J. J. A. (2022) ‘Toward customer hyper-personalization experience — A data-driven approach’, *Cogent Business and Management*, *9*(1), pp. 1–16. https://doi.org/10.1080/23311975.2022.2041384

Vakulenko, Y., Shams, P., Hellström, D. and Hjort, K. (2019) ‘Service innovation in e-commerce last mile delivery: Mapping the e-customer journey’, *Journal of Business Research*, *101*, pp.461-468. https://doi.org/10.1016/j.jbusres.2019.01.016

Vallarino, D. (2025) ‘How Do Consumers Really Choose: Exposing Hidden Preferences with the Mixture of Experts Model’, *arXiv preprint arXiv:2503.05800*. https://doi.org/10.48550/arXiv.2503.05800

Van Cranenburgh, S., Wang, S., Vij, A., Pereira, F. and Walker, J. (2022) ‘Choice modelling in the age of machine learning-discussion paper’, *Journal of choice modelling*, *42*, p.100340. https://doi.org/10.1016/j.jocm.2021.100340

Van Osselaer, S.M. and Janiszewski, C. (2012) ‘A goal-based model of product evaluation and choice.’, *Journal of Consumer Research*, 39(2), pp. 260-292.

van Riel, A.C.R. et al. (2021). A customer-centric five actor model for sustainability and service innovation, *Journal of Business Research*, 136, pp. 389–401. doi:10.1016/j.jbusres.2021.07.035.

van Zyl, L. E., and Dik, B. J. (2025) 'Beyond Universal Prescriptions: Toward a Person-Centered, Bottom-Up Science of Wellbeing', *International Journal of Applied Positive Psychology, 10*(42), https://doi.org/10.1007/s41042-025-00232-2

Vandelanotte, C., Trost, S., Hodgetts, D., Imam, T., Rashid, M., To, Q.G. and Maher, C. (2023) 'Increasing physical activity using an just-in-time adaptive digital assistant supported by machine learning: a novel approach for hyper-personalised mHealth interventions', *Journal of Biomedical Informatics*, *144*, p.104435. https://doi.org/10.1016/j.jbi.2023.104435

Vargo, S. L., and Lusch, R. F. (2004) 'Evolving to a new dominant logic for marketing', *Journal of Marketing*, *68*(1), pp. 1–17.

Vargo, S. L., and Lusch, R. F. (2008) 'From goods to service(s): Divergences and convergences of logics', *Industrial Marketing Management, 37*(3), pp. 254–259. https://doi.org/10.1016/j.indmarman.2007.07.004

Vargo, S.L. and Lusch, R.F. (2014) 'Service-dominant logic: What it is, what it is not, what it might be. In *The service-dominant logic of marketing* (pp. 43-56). Routledge.

Vargo S. L., and Lusch R. F. (2016) 'Institutions and axioms: An extension and update of service-dominant logic', *Journal of the Academy of Marketing Science*, 44(1), pp. 5–23. https://doi.org/10.1007/s11747-015-0456-3

Vargo, S. L., and Lusch, R. F. (2017) 'Service-dominant logic 2025', *International* Journal of *Research in Marketing*, *34*(1), pp. 46–67. https://doi.org/10.1016/j.ijresmar.2016.11.001

Varotto, A., and Spagnolli, A. (2017) 'Psychological strategies to promote household recycling A systematic review with meta-analysis of validated field interventions', *Journal of Environmental Psychology*, *51*, pp. 168-188. https://doi.org/10.1016/j.jenvp.2017.03.011

Vieira, R., McDonald, S., Ara.jo-Soares, V., Sniehotta, F. F., and Henderson, R. (2017) ‘Dynamic modelling of n-of-1 data: Powerful and flexible data analytics applied to individualised studies’, *Health Psychology Review*, *11*(3), pp. 222–234. https://doi.org/10.1080/17437199.2017.1343680

Vimalkumar, M., Sharma, S.K., Singh, J.B. and Dwivedi, Y.K. (2021) ‘Okay Google, what about my privacy?’: Users’ privacy perceptions and acceptance of voice-based digital assistants’, *Computers in Human Behavior*, *120*, 106763. https://doi.org/10.1016/j.chb.2021.106763.

Viswanathan, V., Hollebeek, L. D., Malthouse, E. C., Maslowska, E., Jung Kim, S. and Xie, W. (2017) ‘The dynamics of consumer engagement with mobile technologies’, *Service Science*, *9*(1), pp. 36-49. https://doi.org/10.1287/serv.2016.0161

Voima, P., Heinonen, K. and Strandvik, T. (2010) ‘Exploring customer value formation: a customer dominant logic perspective’ https://helda.helsinki.fi/bitstream/handle/10227/630/552-978-952-232-088-9.pdf (2010), Accessed 29 July 2025

Voima, P., Heinonen, K., Strandvik, T., Mickelsson, K-J. and Arantola-Hattab, J., (2011) 'A Customer Ecosystem Perspective on Service’, in *QUIS 12*: *Advances in Service Quality, Innovation and Excellence*, pp. 1015-1024.

Vroom, V.H. (1966) ‘Organizational choice: A study of pre-and postdecision processes’, *Organizational behavior and human performance*, *1*(2), pp.212-225. https://doi.org/10.1016/0030-5073(66)90013-4

Walker, K.L. and Milne, G.R. (2024) ‘AI-driven technology and privacy: the value of social media responsibility’, *Journal of Research in Interactive Marketing*, *18*(5), pp.815-835. https://doi.org/10.1108/JRIM-02-2024-0072

Wallace, S.G. and Etkin, J. (2018) ‘How goal specificity shapes motivation: A reference points perspective’, *Journal of Consumer Research*, *44*(5), pp.1033-1051. https://doi.org/10.1093/jcr/ucx082

Walrave, M., Poels, K., Antheunis, M.L., Van den Broeck, E. and van Noort, G. (2016) ‘Like or dislike? Adolescents’ responses to personalized social network site advertising’, *Journal of marketing communications*, *24*(6), pp.599-616. https://doi.org/10.1080/13527266.2016.1182938

Waks, R. (1989) *Personal information: Privacy and the law*; Oxford, England: Clarendon.

Walther, J.K., Hecht, M., Nagengast, B. and Zitzmann, S. (2024) ‘To be long or to be wide: How data format influences convergence and estimation accuracy in multilevel structural equation modeling’, *Structural Equation Modeling: A Multidisciplinary Journal*, *31*(5), pp.759-774. https://doi.org/10.1080/10705511.2024.2320050

Wang, L. P., and Maxwell, S. E. (2015) ‘On disaggregating between-person and within-person effects with longitudinal data using multilevel models’, *Psychological Methods, 20*(1), pp. 63–83. https://doi.org/10.1037/met0000030

Wang, Y., and Kim, J. (2021) ‘Interconnectedness between online review valence, brand, and restaurant performance’, *Journal of Hospitality and Tourism Management*, *48*, pp. 138-145. https://doi.org/10.1016/j.jhtm.2021.05.016

Wang, L., Guo, Z., Zhang, G., Xu, X. (2022) ‘Effective destination user-generated advertising: Matching effect between goal framing and self-esteem’, *Tourism management*., 92. Available at: https://doi.org/10.1016/j.tourman.2022.104557.

Wang, Y., Ma, W., Zhang, M., Liu, Y. and Ma, S. (2023) ‘A survey on the fairness of recommender systems’, *ACM Transactions on Information Systems*, *41*(3), pp.1-43. https://doi.org/10.1145/3547333

Wang, G., Xu, Z., Cao., Y, Zhai, S., Liu, P. (2024) 'Cooperative vehicle-infrastructure warning (CVIW) applications: people's willingness to pay and perceived importance', *Transportation Letters*, 17(1), pp. 22–35.
doi: 10.1080/19427867.2024.2319998.

Wang, S., Zhang, X., Ma, J., Hwang, A. and Chilton, L.B., (2025a) 'JumpStarter: Getting Started on Personal Goals with AI-Powered Context Curation;, arXiv preprint arXiv:2410.03882.

Wang, T., Zhan, Y., Lian, J., Hu, Z., Yuan, N. J., Zhang, Q., Xiong, H. (2025b) 'Llm-powered multi-agent framework for goal-oriented learning in intelligent tutoring system', In *Companion Proceedings of the ACM on Web Conference 2025* (pp. 510-519).

Wang, P. Q. (2025c) 'Personalizing guest experience with generative AI in the hotel industry: there's more to it than meets a Kiwi's eye', *Current Issues in Tourism*, 28(4), pp. 527-544. https://doi.org/10.1080/13683500.2023.2300030

Ward, V., House, A., Hamer, S. (2009) 'Developing a framework for transferring knowledge into action: A thematic analysis of the literature', *Journal of Health Services Research and Policy*, 14(3), pp. 156-164.
https://doi.org/10.1258/jhsrp.2009.008120

Waschke, L., Kloosterman, N.A., Obleser, J. and Garrett, D.D. (2021) 'Behavior needs neural variability', *Neuron*, *109*(5), pp.751-766.
https://doi.org/10.1016/j.neuron.2021.01.023

Watson, R. (2022). The Virtual Economy of the Metaverse: Computer Vision and Deep Learning Algorithms, Customer Engagement Tools, and Behavioral Predictive Analytics, *Linguistic and Philosophical Investigations*, 21(1), pp. 41–56. doi: 10.22381/lpi2120223.

Weber, F. D., and R. Schütte. (2019) 'State-Of-The-Art and Adoption of Artificial Intelligence in Retailing', *Digital Policy, Regulation & Governance*, *21*(3), pp. 264–279. https://doi.org/10.1108/ DPRG-09-2018-0050

Wedel, M., and Kannan, P.K., 2016. Marketing analytics for data-rich environments. *Journal of marketing*, *80*(6), pp. 97-121. https://doi.org/10.1509/jm.15.0413

Westin, A. F. (1967). Privacy and freedom. Ig Publishing

Wiener, N. (1948) Cybernetics. *Scientific American*, *179*(5), pp.14-19.

Weingarten, E., Chen, Q., McAdams, M., Yi, J., Hepler, J. and Albarracin, D. (2016) 'On priming action: Conclusions from a meta-analysis of the behavioral effects of incidentally-presented words', *Current Opinion in Psychology*, *12*, pp. 53-57. https://doi.org/10.1016/j.copsyc.2016.04.015

Wertenbroch, K., Schrift, R.Y., Alba, J.W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J.R, Puntoni, S., Zheng, Y., Zwebner, Y. (2020). Autonomy in consumer choice, *Marketing Letters*, 31, pp. 429–439. https://doi.org/10.1007/s11002-020-09521-z

Wieland, M., Nordheim, G.V. and Kleinen-von Königslöw, K. (2021) 'One recommender fits all? An exploration of user satisfaction with text-based news recommender systems', *Media and Communication*, *9*(4), pp.208-221. https://doi.org/10.17645/mac.v9i4.4241

Wieringa, J., Kannan, P. K., Ma, X., Reutterer, T., Risselada, H., and Skiera, B. (2019) 'Data analytics in a privacy-concerned world', *Journal of Business Research, 122*, pp. 915–925. https://doi.org/10.1016/j.jbusres.2019.05.005

Willett, J.B., Singer, J.D., and Martin, N.C. (1998) 'The design and analysis of longitudinal studies of development and psychopathology in context: statistical models and methodological recommendations', *Development Psychololgy*, *10*(2), pp. 395–426. https://doi.org/10.1017/S0954579498001667

Windels, K., Heo, J., Jeong, Y., Porter, L., Jung, A.R., Wang, R. (2018) 'My friend likes this brand: Do ads with social context attract more attention on social networking sites?', *Computers in Human Behavior*, *84*, pp. 420–429. https://doi.org/10.1016/j.chb.2018.02.036.

Wirtz, J., Kunz, W. H., Hartley, N., Tarbit, J. (2023) 'Corporate digital responsibility in service firms and their ecosystems', *Journal of Service Research*, 26(2), pp. 173–190. https://doi.org/10.1177/10946705221130467

Wong, G., Greenhalgh, T., Westhorp, G., Buckingham, J., Pawson, R. (2013). 'RAMESES publication standards: Meta-narrative reviews', *BMC Medicine*, 11 (2013), Article 20, https://doi.org/10.1186/1741-7015-11-20

Wong, M., Farooq, B., Bilodeau, G.-A. (2017) 'Discriminative conditional restricted Boltzmann machine for discrete choice and latent variable modelling', *Journal of Choice Modelling*, *19*, pp. 152–168. https://doi.org/10.1016/j.jocm.2017.11.003

Woodruff, R.B. (1997) 'Customer value: the next source for competitive advantage', *Journal of the Academy of Marketing Science*, 25(2), pp. 139-153. https://doi.org/10.1007/BF02894350

Wright, S. A., and Xie G.-X. (2019) 'Perceived privacy violation: Exploring the malleability of privacy expectations', *Journal of Business Ethics*, *156*(1), pp. 123–140. https://doi.org/10.1007/s10551-017-3553-z

Xia, Z., Shannon, R. (2025) 'Navigating the Digital Frontier: Exploring the Dynamics of Customer–Brand Relationships Through AI Chatbots', *Sustainability*, *17*(5), 2173. https://doi.org/10.3390/su17052173.

Xia Y, Liu Z, Wang S, Huang C, and Zhao W. (2024) 'Unlocking the Impact of User Experience on AI-Powered Mobile Advertising Engagement', *Journal of the Knowledge Economy*, *16*(1), pp. 4818-4854. https://doi.org/10.1007/s13132-024-02153-y.

Yang-Wallentin, F., Schmidt, P., Davidov, E., and Bamberg, S. (2004) 'Is there any interaction effect between intention and perceived behavioral control', *Methods of Psychological Research Online*, *8*(2), pp. 127–157. https://doi.org/10.1.1.574.3164

Yaremych, H.E. and Preacher, K.J. (2024) 'Understanding the consequences of collinearity for multilevel models: The importance of disaggregation across levels', *Multivariate Behavioral Research*, *59*(4), pp.693-715. https://doi.org/10.1080/00273171.2024.2315549

Yasmeen, K. and Hashmat, S. (2025) 'The Role of AI-driven Algorithms on User Engagement and Media Consumption Trends in OTT Platforms', *The Research of Medical Science Review*, *3*(6), pp. 9-21. https://doi.org/10.5281/zenodo.15581215

Yeung, K. (2017) 'Hypernudge': Big data as a mode of regulation by design', *Information, Communication & Society*, *20*(1), pp. 118–136.

Yu, C., Liu, J., Nemati, S. and Yin, G. (2021) 'Reinforcement learning in healthcare: A survey', *ACM Computing Surveys (CSUR)*, *55*(1), pp. 1-36.

Yuan, Y. (2024) 'Research and Application of Transformation-based Generative AI Technology', *Applied and Computational Engineering*,*111*, pp. 1-10.

Zarouali, B., Poels, K., Walrave, M. and Ponnet, K. (2018) 'The impact of regulatory focus on adolescents' evaluation of targeted advertising on social networking sites. *International Journal of Advertising*, *38*(2), pp.316-335. https://doi.org/10.1080/02650487.2017.1419416

Zauskova, A., Miklencicova, R., and Popescu, G. H. (2022) 'Visual Imagery and Geospatial Mapping Tools, Virtual Simulation Algorithms, and Deep Learning-based Sensing Technologies in the Metaverse Interactive Environment', *Review of Contemporary Philosophy* 21(1), pp. 122–137. https://doi.org/10.22381/RCP2120228.

Zeithaml V. A. (1988) ‘Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence’, *Journal of Marketing*, 52(3), pp. 2–22. https://doi.org/10.1177/002224298805200302

Zeithaml, V.A., Jaworski, B.J., Kohli, A.K., Tuli, K.R., Ulaga, W. and Zaltman, G. (2020a) ‘A theories-in-use approach to building marketing theory’, *Journal of Marketing*, *84*(1), pp. 32-51. https://doi.org/10.1177/0022242919888477

Zeithaml, V. A., Verleye K., Hatak I., Koller M., and Zauner A. (2020b) ‘Three decades of customer value research: Paradigmatic roots and future research avenues’, *Journal of Service Research*, *23*(4), pp. 409–432.https://doi.org/10.1177/1094670520948134

Zeng, F., Ye, Q., Yang, Z., Li, J., and Song, Y. A. (2022a) ‘Which Privacy Policy Works, Privacy Assurance or Personalization Declaration? An Investigation of Privacy Policies and Privacy Concerns’, *Journal of Business Ethics*, 176(4), pp. 781–798. https://doi.org/10.1007/s10551-020-04626-x

Zeng, J. (2022b) ‘Orchestrating ecosystem resources in a different country: Understanding the integrative capabilities of sharing economy platform multinational corporations’, *Journal of World Business, 57*(6):101347. https://doi.org/10.1016/j.jwb.2022.101347

Zha, D., Yang, G., Wang, W., Wang, Q. and Zhou, D. (2020) ‘Appliance energy labels and consumer heterogeneity: A latent class approach based on a discrete choice experiment in China’, *Energy Economics*, *90*, p.104839. https://doi.org/10.1016/j.eneco.2020.104839

Zhang, M., Zhang, G.Y., Gursoy, D., and Fu, X.R., (2018) ‘Message framing and regulatory focus effects on destination image formation’, *Tourism Management, 69*, pp. 397-407.

Zhang, C.X., Fong, L.H.N. and Li, S. (2019) ‘Co-creation experience and place attachment: Festival evaluation’, *International Journal of Hospitality Management*, *81*, pp. 193-204. https://doi.org/10.1016/j.ijhm.2019.04.013

Zhang, M. and Bockstedt, J. (2020) 'Complements and substitutes in online product recommendations: The differential effects on consumers' willingness to pay', *Information & Management*, *57*(6), 103341. https://doi.org/10.1016/j.im.2020.103341

Zhang, Z., Wang, D. and Gao, J. (2020) 'Learning automata-based multiagent reinforcement learning for optimization of cooperative tasks', *IEEE transactions on neural networks and learning systems*, *32*(10), pp.4639-4652. https://doi.org/10.1109/TNNLS.2020.3025711

Zhang, J. Z., and Chang, C.W. (2021) 'Consumer dynamics: Theories, methods, and emerging directions' *Journal of the Academy of Marketing Science*, *49* (1) (2021), pp. 166-196, https://doi.org/10.1007/s11747-020-00720-8

Zhang, J., Shi, H., and Sheng, J. (2022) 'The effects of message framing on novel food introduction: Evidence from the artificial meat products in China', *Food Policy*, *112*, pp. 102361.

Zhang, Z., Li, F., Di, C., Zhu, H., Wang, H. and Wang, S. (2024) 'PromptLA: Towards Integrity Verification of Black-box Text-to-Image Diffusion Models', *arXiv preprint arXiv:2412.16257*. https://doi.org/10.48550/arXiv.2412.16257

Zhou, S.A., Yang, Y. and Hiver, P. (2023a) 'Individual growth curve modeling for applied linguistics research', *Research Methods in Applied Linguistics*, *2*(1), p.100043. https://doi.org/10.1016/j.rmal.2023.100043

Zhou, S.A., Hiver, P. and Zheng, Y. (2023b) 'Modeling intra- and inter-individual changes in L2 classroom engagement', *Applied linguistics*, *44*(6), pp.1047-1076. https://doi.org/10.1093/applin/amac065

Zhou, J. and Li, H. (2024) 'Review and prospects of green innovation ecosystems from the perspective of value emergence', *Systems*, *12*(6), p.206. https://doi.org/10.3390/systems12060206

Zhou, R. (2024) ‘Understanding the Impact of TikTok’s Recommendation Algorithm on User Engagement’, *International Journal of Computer Science and Information Technology*, 3(2), pp. 201–208. https://doi.org/10.62051/ijcsit.v3n2.24

Zhu, X., Wang, F., Chen, C. and Reed, D.D. (2020) ‘Personalized incentives for promoting sustainable travel behaviors’, *Transportation Research Part C: Emerging Technologies*, *113*, pp. 314-331. https://doi.org/10.1016/j.trc.2019.05.015

Zhu, Y., Bi, X., Adomavicius, G., Curley, S., (2023) ‘Forecasting Goal-Oriented Activities: A Deep Learning Approach Leveraging Cross-Activity Relationships’. *Available at SSRN 4651870*.

Zilio, D. (2019) ‘Mechanisms within contexts: First steps towards an integrative approach’, *Behavior and Philosophy*, *47*, pp.34-66.
https://www.jstor.org/stable/26921922

Zuboff S (2019) ‘The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power’, 1st ed. New York, NY: Public Affairs.