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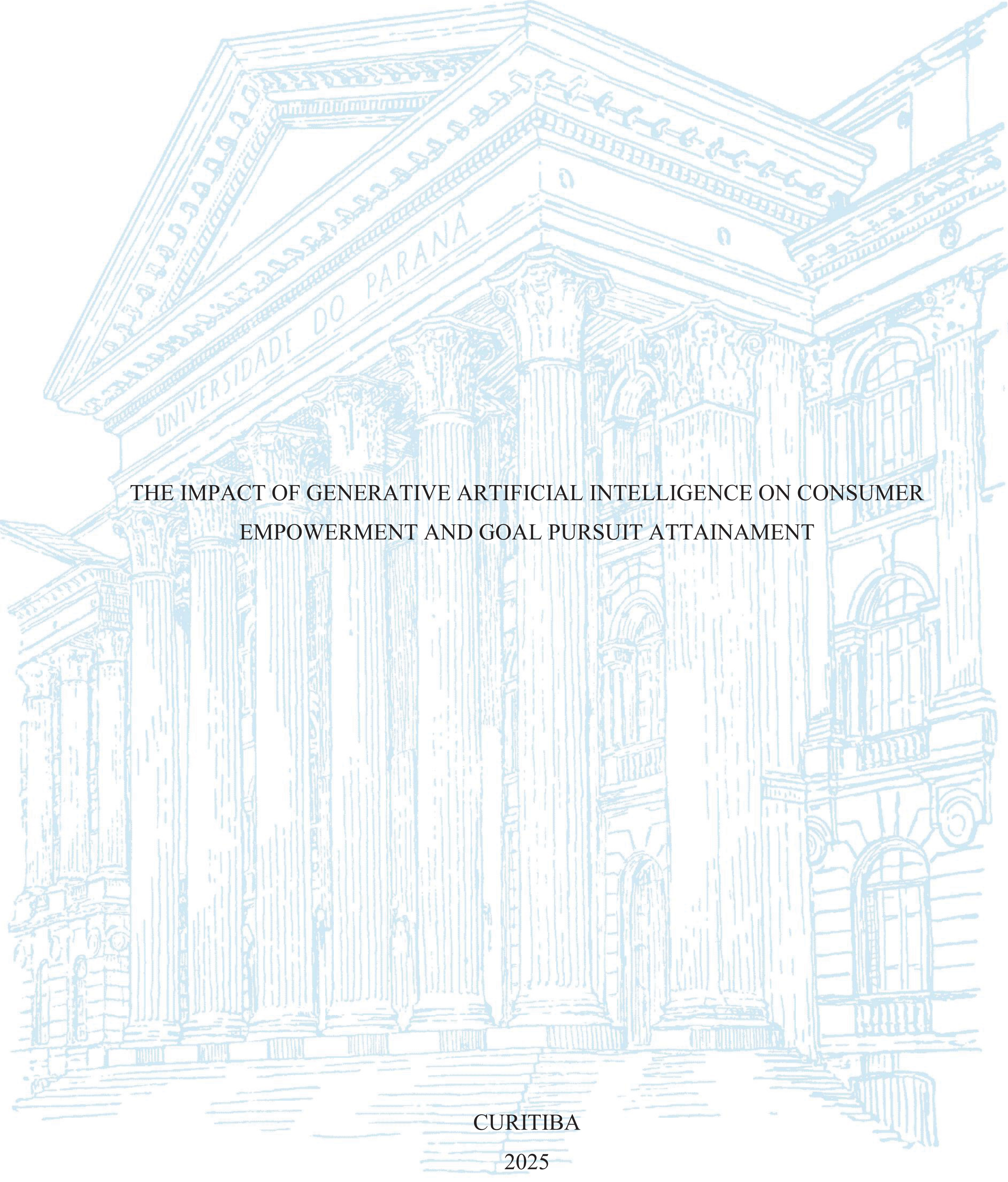

THE IMPACT OF GENERATIVE ARTIFICIAL INTELLIGENCE ON CONSUMER EMPOWERMENT AND GOAL PURSUIT ATTAINAMENT

CURITIBA

2025

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THE IMPACT OF GENERATIVE ARTIFICIAL INTELLIGENCE ON CONSUMER EMPOWERMENT AND GOAL PURSUIT ATTAINMENT

Tese apresentada ao Programa de Pós-Graduação em Administração, área de concentração Estratégia e Organizações – Linha de pesquisa em Estratégia de Marketing e Comportamento do Consumidor, do Setor de Ciências Sociais Aplicadas da Universidade Federal do Paraná, como requisito parcial à obtenção do título de Doutora em Administração.

Orientador: Prof. Dr. Paulo Henrique Muller Prado

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação ADMINISTRAÇÃO da Universidade Federal do Paraná foram convocados para realizar a arguição da tese de Doutorado de **ANA PAULA MERENDA RICHARDE**, intitulada: **The Impact Of Generative Artificial Intelligence On Consumer Empowerment And Goal Pursuit Attainment"**, sob orientação do Prof. Dr. PAULO HENRIQUE MULLER PRADO, que após terem inquirido a aluna e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.

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RESUMO

A Inteligência Artificial Generativa (GenAI) está a transformando as interações com os consumidores, oferecendo soluções personalizadas e criativas que vão desde ideias genéricas até recomendações específicas. No entanto, pouco se sabe sobre os impactos das interações dos consumidores com a GenAI na tomada de decisões. Esta pesquisa investiga de que forma as sugestões da GenAI (específicas vs. genéricas) afetam o empoderamento do consumidor e a realização de metas na sua decisão de consumo, enfatizando o papel mediador da desejabilidade da meta. Baseando-nos na *Construal Level Theory* (CLT), na Teoria do Alcance de Metas e na Teoria de *Nudging*, examinamos se os *nudges* GenAI específicos (vs. amplos) impulsionam a percepção de empoderamento dos consumidores e a sua capacidade de atingir suas metas em contextos de tomada de decisão mediados por IA. Cinco estudos usando métodos mistos (três estudos qualitativos e dois estudos experimentais) revelam que os *nudges* GenAI específicos (vs. genéricos) aumentam significativamente a desejabilidade da meta, levando a um maior empoderamento do consumidor e alcance de metas. As nossas descobertas contribuem para a compreensão teórica do papel crescente da GenAI no alcance de metas de consumo, detalhando a forma como o ajuste das respostas da IA pode levar os consumidores a atingir os seus objetivos, aumentando a desejabilidade da meta na tomada de decisões. Estes conhecimentos oferecem implicações práticas para a concepção de sistemas de IA que capacitem eficazmente os consumidores, estimulando as suas respostas no âmbito de melhores arquiteturas de escolha.

Palavras-chave: Inteligência Artificial Generativa; Alcance de Metas; Empoderamento do Consumidor; Construal Level Theory; Nudging Theory; Desejo da meta; Arquitetura de Escolhas.

ABSTRACT

Generative Artificial Intelligence (GenAI) is transforming consumer interactions by offering personalized and creative solutions that range from broad ideas to narrow recommendations. However, little is known about the impacts of consumer interactions with GenAI on decision-making. This research investigates how GenAI nudges (narrow vs. broad) affect consumer empowerment and goal pursuit attainment in their consumption decision, emphasizing the mediating role of goal desirability. Drawing upon Construal Level Theory (CLT), Goal Pursuit Theory, and Nudging Theory, we examine whether narrow (vs. broad) GenAI nudges drives consumers' perception of empowerment and their ability to achieve their goals within AI-mediated decision-making contexts. Five studies using mixed-methods (three qualitative study and two experimental studies) reveal that narrow (vs. broad) GenAI nudges significantly increase goal desirability, leading to higher consumer empowerment and goal pursuit attainment. Our findings contribute to the theoretical understanding of GenAI's growing role in consumption goal pursuit by detailing how adjusting AI responses can nudge consumers toward their goals by enhancing goal desirability on decision-making. These insights offer practical implications for designing AI systems that effectively empower consumers by nudging their responses within choice architectures.

Keywords: Generative Artificial Intelligence; Goal Pursuit; Consumers Empowerment; Construal Level Theory; Nudging Theory; Goal Desirability; Choice Architecture.

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LISTA DE SIGLAS E ABREVIAÇÕES

AI	Artificial Intelligence
ANOVA	Analysis of Variance
CLT	Construal Level Theory
CMB	Common Method Bias
DV	Dependent Variable
GenAI	Generative Artificial Intelligence
IV	Independent Variable
UFPR	Federal University of Parana

Summary

1 Introduction

According to global data from McKinsey & Company (2024) on Artificial Intelligence (AI) adoption in companies, 65% of companies are already regularly using Generative Artificial Intelligence (GenAI) to support manager decision-making. The adoption of GenAI as a service has been growing rapidly, reaching \$14 billion in investments in 2024, with impressive projections to reach \$72.1 billion until 2029 (Markets and Markets, 2024). The growing adoption of GenAI is not only impacting the corporate landscape and the way as consumers interact with companies mediated by AI, but also the way as consumers search information for their consumption decisions. For instance, recent studies identify the role of GenAI influencing how consumers formulate and pursue their consumption goals, particularly by affecting the desirability of those goals (Hermann & Puntoni, 2024; Mogaji & Jain, 2024).

Generative Artificial Intelligence (GenAI) is further transforming the way we work and carry out everyday tasks (Amankwah-Amoah et al., 2024), improving performance (Howatson, 2024). Consumer behavior is no different and changes in consumption are taking place as the development of GenAI progresses (Hermann & Puntoni, 2024; Mogaji & Jain, 2024).

The pursuit of goals and making decisions is a central aspect of consumer behavior. Previous studies have extensively explored how consumers use technology-based tools to reach their objectives and enhance their sense of empowerment (Clegg et al., 2024; Dwivedi et al., 2023; Flavián et al., 2024; Kirshner, 2024; Mele et al., 2021; Mele & Russo-Spena, 2024). However, the introduction of new technologies such as GenAI is significantly transforming consumption paradigms (Dwivedi et al., 2023; Kshetri et al., 2024). GenAI is transforming the way consumers interact with technology, offering unprecedented levels of personalization and creativity in everyday tasks (Amankwah-Amoah et al., 2024). Unlike traditional AI systems that provide standardized recommendations, GenAI leverages natural language processing and machine learning to generate unique, context-specific responses, effectively mimicking human creativity and thought processes (Hirschberg & Manning, 2015).

There are many definitions of artificial intelligence (Belk et al., 2023; Manning, 2020). In this study, we define it as "the use of computational machinery to emulate capabilities inherent to humans" (Huang & Rust, 2021, pp. 31). GenAI offers personalized responses and recommendations, altering the traditional decision-making architecture by providing real-time data and continuously adapting to consumer preferences. This shift not only influences how consumers interpret their goals (Fishbach & Ferguson, 2007) but also reconfigures their perception of progress toward achieving these goals, especially in terms of efficiency and control in the decision-making process (Trope & Liberman, 2010).

Although much is already known about the theories under analysis and the literature on this topic is extensive, the growing adoption of GenAI tools by companies in their interactions with consumers has redefined the decision-making landscape and challenged traditional consumer paradigms. These tools are reshaping the way consumers relate to brands, introducing new layers of personalization and decision architecture that did not previously exist. Thus, the research question that guides this study is: how GenAI interaction nudges consumers to achieve their goals or feel empowered in decision-making?

To address this gap, we aim to investigate how the type of response generated by GenAI (GenAI nudges) (ranging from narrow to broad responses) influences consumer goal pursuit attainment. Specifically, it aims to understand how these varying levels of information impact consumers' perception of empowerment and their ability to achieve their goals within AI-mediated decision-making contexts.

By nudging consumers into narrow (vs. broad) outcomes, GenAI may be altering consumers' perception of empowerment and goal achievement. Thus, this study integrates three theoretical bodies: Construal Level Theory (CLT) (Liberman & Trope, 1998), Goal Pursuit Theory (Fishbach & Ferguson, 2007) and the Nudge Theory (Thaler & Sunstein, 2008). Construal Level Theory (CLT) explains how psychological distance (temporal, spatial, social, or hypothetical) influences people's mental representations of events. Greater distance leads to abstract thinking focused on desirability, while proximity emphasizes concrete details like feasibility, shaping decision-making processes (Liberman & Trope, 1998). This framework interacts with Goal Pursuit Theory, which explores how individuals set, prioritize, and strive toward goals, emphasizing that perceived progress and motivation influence their behavior. By highlighting the dynamic balance between goal commitment and adjustments in response to progress, Goal Pursuit Theory drives goal-directed actions and choices (Fishbach & Ferguson, 2007). Complementing these theories, Nudge Theory (Thaler & Sunstein, 2008) proposes that subtle interventions, or "nudges", can guide individuals toward better decisions without restricting their freedom of choice. By structuring choices to leverage cognitive biases, nudges shape behavior in areas such as health, finance, and consumer decisions (Thaler & Sunstein, 2008). Together, these theoretical bodies illustrate how psychological framing, motivation, and strategic interventions shape consumer behavior and goal attainment.

Using a mixed methods approach, five studies (2 pilots and 3 studies) reveal the emerging role of GenAI on consumer choice architecture, working as nudges (narrow vs. broad) that potentially lead customers to higher goal attainment motivation and empowerment perception. The two pilots' studies were carried out to understand the phenomenon being studied from the consumers' point of view and were intended to help us outline the research model. Study 1 applies a qualitative methodological lens to examine consumer incorporation of GenAI on the consumption process and its role in goals pursuit and empowerment perception in consumers decision-making. Study 1 offers empirical evidence for the theoretical assumption proposed in our research model (Figure 1) and better illustrates the phenomenon under investigation in the following studies. In Study 2, we tested whether the type of response generated by GenAI (narrower vs. broader) in a travel tips search scenario influences consumers' ability to achieve their goals (H1). Finally, Study 3 replicated the travel tips search scenario to test the proposed hypotheses (H2a and H2b), further reinforcing the findings from the previous study and investigating the desirability mechanisms that explain why narrow GenAI suggestions result in higher levels of goal empowerment.

This research provides important theoretical implications for the literature on GenAI interactions (Belk et al., 2023; Clegg et al., 2024; Mele et al., 2021; Mele & Russo-Spena, 2024), goal empowerment, and the integration of Goal Pursuit Theory with Construal Level Theory (CLT). First, our research extends the understanding of the psychological effects of AI interactions (Hermann & Puntoni, 2024) by empirically demonstrating that narrow (vs. broad) GenAI nudges enhance consumers' perception of empowerment and facilitate the desire to pursue a consumption goal. Specifically, we explore various types of goals, including social and professional contexts, contributing to Mogaji and Jain (2024) by showing that goal desirability mediates the effects on consumers empowerment perception to achieve the goal.

Second, we advance Goal Pursuit Theory and Construal Level Theory (CLT) by offering new insights into how goal attainment is shaped by GenAI interactions that range from narrow to broad responses. Building on the work of Trope and Liberman (2010) and Fishbach and Ferguson (2007), we challenge the traditional CLT perspective by demonstrating that GenAI shapes goal desirability. Specifically, narrower responses make goals feel more achievable, fostering goal empowerment and increasing success in goal attainment. This integration expands the practical application of goal theory to AI-mediated consumer environments, where the structure of interaction directly influences motivation and perceived efficacy.

Third, our research expands the application of construal level in digital, technology-mediated environments. We examine how GenAI can adjust its responses to offer narrower or broader interactions based on the context of the decision, addressing the call by Liberman et al. (2007) to explore new contexts where construal levels can be manipulated to influence behavior. By investigating the consumer integration of GenAI in the consumption decision-making process, we provide a new perspective on the application of CLT in the era of GenAI. This approach allows us to test CLT and Nudge Theory in a practical, technology-assisted setting, which has become increasingly relevant with the growing use of GenAI in business due its capacity to act as nudges in in consumption choice architecture.

Finally, our findings reveal significant practical implications for information systems developers involved in AI-driven consumer interactions. The study demonstrates that narrower GenAI nudges (vs. broad) increase consumers' desirability for their goals, which, in turn, boosts empowerment and facilitates the implementation of objectives. In practical terms, this leads to better outcomes for consumers, who feel more motivated and confident in achieving their goals, while companies adopting GenAI see improved engagement and satisfaction. By integrating adaptive mechanisms into AI systems that adjust the broadness or narrowness of responses based on the consumer's psychological state and goal context, businesses can enhance GenAI applications in order to support and facilitate consumption decision-making.

2 Background Theory

In this background theory section, we will explore the theoretical foundations that underpin this study, focusing on Nudge Theory, Construction Level Theory (CLT) and Goal Pursuit Theory. It looks at how these frameworks contribute to understanding consumers' decision-making and goal achievement processes.

2.1 Nudge Theory

Nudge Theory, popularized by Thaler and Sunstein (2008), explores how subtle interventions can guide individuals toward better decision-making without restricting their freedom of choice. The essence of this theory is the concept of "choice architecture", which refers to the design of decision environments that influence the choices people make. A nudge is a way of structuring choices in such a manner that it gently encourages certain behaviors without forcing them, leveraging cognitive biases to produce favorable outcomes (Thaler & Sunstein, 2008). Nudges can take the form of default options, reminders, or framing effects that subtly shift how choices are perceived and acted upon. The central idea of nudge theory is paternalism libertarian, where interventions steer people in certain directions while still preserving their autonomy and freedom to choose (Laran et al., 2018; Thaler & Sunstein, 2008).

In the realm of consumer behavior, nudges have been used extensively to promote healthier lifestyle choices, financial savings, and even environmentally conscious behavior (Laran et al., 2018; Romero & Biswas, 2016; Thaler & Sunstein, 2008; Torma et al., 2018). For instance, placing healthier foods at eye level in a cafeteria or setting default options for retirement savings plans have been proven to significantly influence behavior without overtly limiting options (Thaler & Sunstein, 2008). The success of nudges lies in their ability to work within human cognitive limitations, acknowledging that people often make decisions based on heuristics and biases rather than full rationality.

The growing influence of Nudge Theory is deeply intertwined with the idea that small changes in how options are presented can have significant impacts on behavior (Laran et al., 2018). In consumer behavior, nudges have proven effective in guiding people toward more optimal choices, helping them align their decisions with long-term goals. However, with the emergence of advanced technologies, particularly GenAI, the nature of nudges is being reshaped. This shift introduces a new layer of complexity in how decision architectures are designed, as GenAI offers personalized, dynamic interactions that can act as digital nudges tailored to the individual's context.

2.2 Construal Level Theory

The Construal Level Theory (CLT) emerged in the late 1990s with the aim of systematizing how psychological distance impacts the cognitive construction of events and goals. In their seminal study, Liberman & Trope (1998) demonstrated that temporal distance influences the way people interpret future events, favoring abstract aspects, such as the desirability of an outcome, over concrete aspects, such as the feasibility of achieving it. This initial perspective was expanded to include other dimensions of distance, such as spatial (for example, distant versus nearby locations), social (differences between self and others) and hypothetical (reality versus possibility). These developments opened up space for exploring the interactions between different forms of psychological distance and how they affect decision-making processes.

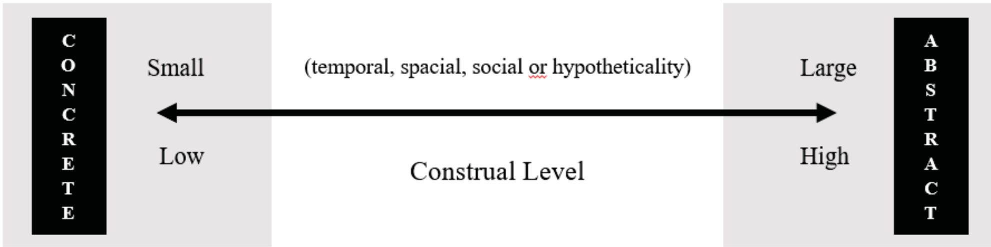
In other words, CLT explores how psychological distance (temporal, spatial, social and hypothetical) influences the way people construct their perceptions of events, goals and behaviors. According to CLT, the greater the psychological distance from an event, the greater the level of abstraction in cognitive construction (Liberman & Trope, 1998). The Psychological Distance can be temporal (time), spatial (space), social (relationships), or hypothetical (likelihood). Each type of distance affects how people perceive and think about events and objects. For instance, events in the distant future are thought of in more abstract terms compared to those in the near future (Trope et al., 2007; Trope & Liberman, 2003).

This theory emphasizes that events that are distant in time or space, or that belong to other people, are processed in a more abstract way, focusing on central and desirable characteristics. On the other hand, nearby events are processed in a more concrete way, emphasizing specific details and the feasibility of actions (Liberman & Trope, 1998).

According Mccrea et al. (2012), Trope et al. (2007) and Trope & Liberman, 2003), the construal level is also understood from its construction level (high-level vs. low-level construal). High-level construals are abstract, generalized, and decontextualized representations that capture the essence of an event or object. In contrast, low-level construals are detailed, specific, and contextualized representations. For example, planning a vacation next year might involve high-level thoughts about relaxation and adventure, while planning a vacation next week might involve low-level thoughts about packing and travel arrangements. Figure 1 illustrates the Construal Level Theory in an integrated way.

Figure 1. Construal level and psychological distance

Psychological Distance



Source: Based on Liberman et al. (2007).

CLT has significant implications for consumer behavior (Liberman et al., 2007). It helps explain how consumers make decisions based on the psychological distance of their choices. For example, consumers might focus on the desirability of a product when thinking about a distant purchase but consider feasibility and practical details for an imminent purchase (Dhar & Kim, 2007; Fiedler, 2007; Liberman et al., 2007). In addition, the CLT suggests that the level of construal influences various aspects of behavior and decision-making. High-level construals are associated with broader, goal-oriented thinking and can affect long-term planning and moral judgments. Low-level construals, on the other hand, are linked to immediate, practical considerations and feasibility (Mccrea et al., 2012; Trope et al., 2007).

2.3 Goal Pursuit Theory

Goal Pursuit Theory focuses on the role of goals as cognitive structures that guide human behavior. Goals function as mental representations that influence not only how individuals evaluate alternatives but also how they set priorities and regulate subsequent behaviors (Fishbach & Ferguson, 2008). The theory highlights that motivation in goal pursuit is dynamically influenced by intrinsic and extrinsic factors, allowing individuals to navigate trade-offs between immediate rewards and long-term aspirations. Over time, the theory has evolved to explore complexities such as perceived progress in goal attainment. Fishbach & Dhar (2005) reveal that perceived progress can paradoxically lead to inconsistent behaviors, where consumers feel "licensed" to pursue conflicting objectives, illustrating the delicate balance between goal commitment and competing priorities.

Zhang et al. (2010) expand this understanding by introducing the concept of counteractive construal, wherein consumers amplify the perceived negative consequences of temptations to prioritize long-term goals. This cognitive adjustment underscores how mental representations of rewards and costs actively shape goal-oriented decision-making. Such strategies are especially relevant in contexts where consumers face distractions or competing incentives, emphasizing the adaptive nature of goal regulation.

Woolley & Fishbach (2016) further refine Goal Pursuit Theory by demonstrating the critical role of immediate rewards in sustaining motivation for long-term objectives. Their findings indicate that individuals are more likely to persist in goal-directed activities when these activities also offer intrinsic enjoyment or other immediate benefits. This dual focus on immediate and delayed rewards shifts the traditional perspective of Goal Pursuit Theory, highlighting that immediate gratification can complement, rather than compete with, long-term aspirations. For example, enjoying the process of working toward a fitness goal (e.g., a fun workout) can bolster persistence.

From a consumer behavior perspective, this framework provides valuable insights into how individuals negotiate the temporal dynamics of goal pursuit. Perceived progress, cognitive reframing of temptations, and the interplay of immediate and delayed rewards all influence how consumers prioritize, evaluate, and sustain their goals. Zhang et al. (2010) illustrate how consumers reframe temptations to align their choices with desired outcomes, while Woolley and Fishbach (2016) highlight the motivational interplay between short-term and long-term rewards. These dynamics are critical for marketers aiming to design interventions and strategies that not only align with consumer goals but also sustain engagement and motivation over time. By leveraging the principles of Goal Pursuit Theory, businesses can create more effective tools and messages to support consumer decision-making, balancing immediate satisfaction with enduring goal achievement.

2.4 Rethinking Traditional Theories: Nudge, CLT, and the Goal Pursuit in the Context of Generative Artificial Intelligence

The rise of GenAI has introduced a transformative and challenging context in consumer decision-making. As digital tools capable of generating highly personalized and context-sensitive responses, GenAI reshapes the architecture of choices available to consumers, offering an unprecedented level of interaction and guidance (Hermann & Puntoni, 2024; Kshetri et al., 2024). This advancement raises fundamental questions about how traditional theories of consumer behavior, such as Nudge Theory, Construal Level Theory (CLT), and Goal Pursuit Theory, apply in this new technological landscape. These theories, when integrated, provide a comprehensive framework to explore how GenAI may influence consumer perceptions of empowerment and goal attainment.

Nudge Theory, as proposed by Thaler and Sunstein (2008), emphasizes how subtle interventions, or nudges, can guide individuals toward better decisions without restricting their freedom of choice. Nudges work by simplifying decision-making or framing options to highlight certain desirable outcomes. In the context of GenAI, this theory finds new relevance as digital nudges delivered through AI interactions can be tailored to the consumer's context. By structuring responses to offer either broad, exploratory possibilities or narrow, actionable recommendations, GenAI acts as a sophisticated choice architect. Unlike traditional nudges, GenAI's capacity to personalize its guidance dynamically adapts to the evolving needs and goals of the user (Amankwah-Amoah et al., 2024).

This interaction aligns closely with Construal Level Theory (CLT), which explains how psychological distance (whether temporal, spatial, social, or hypothetical) affects how people mentally represent events or goals (Liberman & Trope, 1998; Trope & Liberman, 2010). Events perceived as distant are represented abstractly, with a focus on their desirability and overarching purpose. Conversely, events perceived as closer are represented concretely, emphasizing feasibility and immediate action. CLT provides a lens to understand how GenAI can tailor its nudges based on the psychological distance of the consumer's goals. For instance, broad, abstract responses might encourage consumers to focus on long-term aspirations, while narrow, concrete responses highlight short-term feasibility and practical steps.

The integration of CLT with Goal Pursuit Theory further enriches this understanding. Goal Pursuit Theory, as described by Fishbach and Ferguson (2007), explores how individuals set, prioritize, and strive toward their objectives. It highlights the dynamic interplay between intrinsic and extrinsic motivations, as well as the importance of perceived progress in sustaining goal-directed behavior. The theory underscores that the desirability of a goal significantly influences the effort and commitment individuals are willing to invest (Fishbach & Tu, 2016; Zhang et al., 2007). This study builds on these insights by examining how GenAI nudges (whether broad or narrow) interact with goal desirability to shape consumer empowerment and goal attainment. For example, abstract responses emphasizing the desirability of long-term goals may inspire motivation but leave consumers uncertain about actionable steps. In contrast, concrete responses may provide clarity and a sense of control, particularly for short-term objectives.

By integrating Nudge Theory, CLT, and Goal Pursuit Theory, this research explores how GenAI can act as a bridge between these theoretical frameworks. The digital nudges delivered by GenAI adjust the breadth and specificity of responses to align with the consumer's psychological distance and goal desirability, thereby influencing perceptions of empowerment. For instance, in an e-commerce setting, broad recommendations might focus on aspirational attributes like style or innovation, aligning with hedonic and highly desirable goals. Narrow recommendations, on the other hand, might emphasize practical aspects like cost-effectiveness or functionality, catering to utilitarian and short-term goals.

This integration also addresses gaps in the existing literature by extending these theories to technology-mediated contexts. While Nudge Theory and CLT have traditionally been applied in more static decision-making environments, the dynamic and adaptive nature of GenAI introduces new complexities. As Mele et al. (2021) suggest, digital nudges have the potential to enhance consumer decision-making by dynamically adjusting their level of abstraction or specificity based on real-time data. This flexibility ensures that consumers remain engaged and feel empowered in their decision-making process, with GenAI functioning as a form of "paternalistic libertarianism" in line with Thaler and Sunstein's original framework.

Moreover, the mediating role of goal desirability is central to understanding how GenAI influences consumer behavior. By connecting Goal Pursuit Theory with CLT, this research investigates how the attractiveness and importance of a goal determine the effectiveness of GenAI's nudges. Whether guiding consumers toward abstract, long-term aspirations or concrete, immediate actions, the desirability of the goal mediates the relationship between the type of GenAI response and the consumer's perception of empowerment and success.

From the perspectives of Construal Level Theory (CLT) and Goal Pursuit Theory, we can deepen our understanding of how goal desirability influences interactions with GenAI, shaping consumer empowerment and goal pursuit. Traditionally, CLT posits that concrete, low-level construal’s focus on feasibility and the "how" of actions, while abstract, high-level construals emphasize desirability and the "why" (Liberman & Trope, 1998). However, we propose that, in the context of highly personalized GenAI interactions, narrow, concrete responses not only help consumers visualize goal implementation but also intensify their desire to achieve those goals. This challenges traditional CLT assumptions by suggesting that the specificity of GenAI responses can enhance emotional and motivational engagement, increasing goal desirability regardless of psychological distance.

For instance, narrow and focused responses from GenAI provide consumers with clear and actionable plans, making goals appear more accessible and attainable. This specificity boosts consumers' sense of empowerment and motivation by increasing their confidence in the feasibility of the goal. On the other hand, broad and abstract responses may make it harder for consumers to visualize the necessary steps, which could paradoxically reduce their desire to pursue the goal. This dynamic suggests an inversion of CLT’s expectations, where broad and abstract interactions might not reinforce desirability but instead create a sense of uncertainty and detachment.

These dynamics position personalized GenAI interactions as a form of digital nudge, facilitating not only empowerment but also shaping consumers’ perceptions of desirability and success in goal pursuit. For example, when consumers receive abstract, high-level responses focusing on long-term benefits or emotional aspects, they may feel more empowered if the goal is highly desirable. Conversely, concrete, low-level responses that highlight immediate feasibility and efficiency may increase perceptions of control but fail to enhance empowerment if the goal lacks sufficient desirability.

Empirical evidence supports this nuanced understanding. For instance, in a platform like Stitch Fix (Kim et al., 2022), consumers with utilitarian goals, such as saving money or improving practicality, prefer concrete recommendations emphasizing price and functionality. However, for hedonic goals, such as pleasure or comfort, abstract recommendations focusing on aesthetic or emotional aspects generate greater empowerment and a stronger sense of goal achievement. We propose that this process is mediated by goal desirability, with more desirable goals amplifying emotional engagement and perceptions of control.

By integrating these insights, this research builds on Nudge Theory, CLT, and Goal Pursuit Theory, examining how GenAI's nudges—broad or narrow—interact with goal desirability to influence consumer empowerment. Digital nudges delivered through GenAI dynamically adapt to consumer contexts, either reinforcing the long-term desirability of goals through abstract responses or emphasizing short-term feasibility through concrete interactions. These mechanisms suggest that goal desirability plays a pivotal mediating role in determining the effectiveness of GenAI interactions, shaping both motivation and perceived success in goal attainment.

In conclusion, the integration of these theoretical frameworks provides a robust foundation for understanding the role of GenAI in shaping consumer behavior. By exploring how GenAI's nudges interact with psychological distance and goal desirability, this study contributes to a deeper understanding of consumer empowerment and goal pursuit attainment in a rapidly evolving technological landscape. As companies increasingly adopt GenAI tools, the ability to leverage these interactions effectively will be critical for creating decision architectures that align with consumer needs and motivations. This research not only extends the application of traditional theories but also highlights the transformative potential of GenAI in redefining how consumers pursue and achieve their goals. Table 1 summarizes the main studies that connect the theories in focus.

Table 1. Summary of studies on central theories (CLT, goals and nudge) applied to empowerment and goal pursuit attainment.

Study	**Findings**	**Central Theories**	**Dependent Variable**
Mele & Russo-Spena (2024)	Cognitive technologies, including AI, serve as smart nudges by influencing decision-making, encouraging value co-creation. Smart nudges extend human agency through enhanced engagement.	Nudge Theory, Service-Dominant Logic	Value co-creation
Stillman & Woolley (2023)	Emphasizing short-term costs of unhealthy behaviors is more effective at reducing these behaviors than focusing on long-term consequences of ignoring costs altogether.	Self-regulation, Goal Pursuit Theory	Unhealthy behaviors
Kim et al. (2022)	Explores the impact of AI-driven recommendation agents on consumer behavior, showing that AI enhances the perceived value of personalized recommendations, influenced by consumption goals.	AI recommendation agents, Goal-derived theory	Intention to use AI-driven recommendation agents
Torma et al. (2018)	Investigates self-nudging strategies used by consumers to drive sustainable consumption. Found that self-nudging simplifies decision-making and promotes consistent pro-environmental choices.	Nudge Theory, Self-nudging	Sustainable consumption behavior
Romero & Biswas (2016)	Focused on the use of nudges to promote healthier eating choices, showing that minor environmental modifications can guide consumer behavior toward healthier decisions.	Nudge Theory	Health-related decision-making
Park & Hedgcock (2016)	Examines the relationship between goal progress and construal level and its influence on subsequent goal pursuit.	Construal level theory Goal Pursuit Theory	Goal pursuit
Woolley & Fishbach (2016)	The study demonstrates that immediate rewards are stronger predictors of persistence, suggesting that both marketers and consumers can leverage these rewards to enhance commitment to long-term goals.	Goal Pursuit Theory Self-Control	Goal Persistence
Laran & Janiszewski (2011)	Studied how nonconscious goal activation can sustain goal-consistent behavior, demonstrating that nonconscious nudges can support long-term goal pursuit in consumers.	Nonconscious goal pursuit, Nudge Theory	Goal-consistent behavior across multiple choices
Capa et al. (2008)	Examined the role of achievement motivation, task and goal difficulty on effort mobilization, finding that higher motivation and task difficulty lead to greater effort and better performance.	Achievement Motivation Theory, Goal Difficulty	Effort expenditure
Fishbach & Ferguson (2007)	Explored how consumers set and pursue goals, highlighting the role of progress perception in motivation and goal achievement.	Goal Pursuit Theory	Goal Commitment and Progress
Bagozzi &	Provided a framework for	Goal Pursuit Theory	Goal-directed

Dholakia (1999)	understanding goal setting and goal striving in consumer behavior, focusing on how goals influence decision-making processes.		behavior
Liberman & Trope (1998)	Explores how psychological distance influences whether individuals focus on abstract goals (desirability) or concrete steps (feasibility).	Construal Level Theory (CLT)	Goal Pursuit

Source: Elaborated by the author (2025).

To integrate insights from previous literature with empirical observations, the next section will present testable hypotheses to explain how the nudges of GenAI responses shape consumer perceptions and behaviors, laying the groundwork for targeted interventions in AI-mediated decision-making contexts.

3 Relationships Between Variables: A Hypothetical-deductive Model

To develop a deeper understanding of how generative AI (GenAI) influences consumer behavior, this section focuses on the deductive reasoning that forms the basis of our hypotheses. Grounded in theoretical frameworks such as Construal Level Theory (Liberman & Trope, 1998), Goal Pursuit Theory (Fishbach & Ferguson, 2007), and Nudge Theory (Thaler & Sunstein, 2008), we examine the causal relationships between the type of GenAI nudge (narrow vs. broad) and key consumer outcomes, including goal desirability, consumer empowerment, and goal pursuit attainment. By integrating insights from preview literature with empirical observations, this section articulates testable hypotheses to explain how the nudges of GenAI responses shape consumer perceptions and behaviors, paving the way for targeted interventions in AI-mediated decision-making contexts.

3.1 Nudge Theory: How GenAI Shapes Consumer Decision-Making

The Nudge Theory by Thaler and Sunstein (2008) explores how subtle interventions can guide individuals towards better decision-making without restricting their freedom of choice. The essence of this theory is the concept of *choice architecture*, which refers to the design of decision environments that influence the choices people make (Mertens et al., 2022). A nudge is a way of structuring choices in such a manner that it gently encourages certain behaviors without forcing them, leveraging cognitive biases to produce favorable outcomes (Thaler & Sunstein, 2008). Nudges can take the form of default options, reminders, or framing effects that subtly shift how choices are perceived and acted upon. The central idea of nudge theory is paternalism libertarian, where interventions steer people in certain directions while still preserving their autonomy and freedom to choose (Thaler & Sunstein, 2008).

In the context of consumer behavior, nudges have been used extensively to promote value co-creation (Mele et al., 2021; Mele & Russo-Spena, 2024), healthier lifestyle choices (Romero & Biswas, 2016), financial decisions, and even environmentally conscious behavior (Laran et al., 2018; Torma et al., 2018). The success of nudges lies in their ability to work within human cognitive limitations, acknowledging that people often make decisions based on heuristics and biases rather than full rationality (Thaler & Sunstein, 2008).

The growing influence of Nudge Theory is deeply intertwined with the idea that small changes in how options are presented can have significant impacts on behavior (Thaler & Sunstein, 2008). In consumer behavior, nudges have proven effective in guiding people toward more optimal choices, helping them align their decisions with long-term goals. However, with the emergence of advanced technologies, particularly GenAI, the nature of nudges is being reshaped (Mele et al., 2021). This shift introduces a new layer of complexity in how choice architectures are designed, as GenAI offers personalized, dynamic interactions that can act as digital nudges tailored to the individual's context.

The rise of GenAI presents opportunities for integrating nudges within the consumer's choice architecture. As digital tools capable of producing highly personalized responses (Wedel & Kannan, 2016), GenAI acts as an effective choice architect, subtly guiding users through their decision-making journey (Malloy & Gonzalez, 2024). By adjusting the breadth of interactions — either presenting a wide array of possibilities that promote exploration or offering specific, actionable suggestions — we propose that GenAI can influence not only the consumer's immediate choices but also how they conceptualize and pursue their long-term goals.

Following previous studies on Construal Level Theory (CLT), psychological distance in a mechanism (Stillman & Woolley, 2023; Park & Hedgcock, 2016; Woolley & Fishbach (2016) operating the decision-making processes (Trope & Liberman, 2010). Thus, by bringing the CLT theoretical lenses, we add an additional comprehensive layer to explain the relationship between GenAI and choice architecture. CLT posits that the psychological distance (whether temporal, spatial, social, or hypothetical) between an individual and an event determines the level of abstractness or concreteness with which that event is represented mentally. Originally, Construal Level Theory (CLT) indicated that when a goal is perceived as distant, people tend to represent it in an abstract way, focusing on the "why" of achieving it, which generates greater attractiveness. On the other hand, when the goal is perceived as close, the focus shifts to the concrete details, or the "how" of achieving it, and this generates a greater perception of feasibility (Liberman & Trope, 1998).

In the context of consumer behavior, this means that when consumers are faced with abstract, long-term goals, they may be more motivated by the desirability of the goal, while in more immediate decisions, feasibility becomes more salient (Trope & Liberman, 2010). However, we propose that with the unprecedented changes that GenAI has brought to consumer relationships (especially in how consumers search for information to support decision-making) the effects outlined by Construal Level Theory (CLT) are reversed in this new context. According to CLT, concrete information typically enhances the perception of feasibility, while abstract information heightens the desirability of a goal (Liberman & Trope, 1998). Yet, in the context of GenAI, this dynamic is altered: narrower, more concrete responses provided by AI not only make the goal seem achievable but also intensify the consumer's desire to pursue it. Conversely, broader, more abstract responses may fail to ignite desirability, as they create uncertainty about the steps required to achieve the goal, leading to a reduced motivation to pursue it. We believe this happens because, unlike traditional choice architectures, GenAI offers precise, actionable pathways toward goal attainment, which can heighten motivation and empowerment from the outset. By delivering concrete nudges, GenAI reduces psychological distance, enabling consumers to better visualize and connect with their goals, thereby altering their emotional and motivational states. This unique capacity to reshape goal desirability and attainability represents a significant departure from traditional theories like CLT and Goal Pursuit Theory, highlighting the direct and adaptive influence of digital interactions on consumer behavior and decision-making.

Additionally, this shift suggests that the nature of AI-generated responses reshapes the psychological distance that consumers feel toward their goals. In a world dominated by personalized and precise AI interactions, the traditional assumption CLT (that abstraction fuels long-term motivation) is being challenged. Rather than abstract responses enhancing desirability, it is now the concrete, narrow responses that not only break down the steps toward goal attainment but also generate desire in the consumer. These concrete responses foster both feasibility and desirability in consumers' minds, effectively inverting the classical logic of CLT in the context of digital, AI-driven decision-making. By making the steps to achieve a goal more tangible, GenAI influences the consumer to feel both empowered and motivated, showing that concreteness can simultaneously increase both the practicality and attractiveness of a goal.

The rise of GenAI introduces new opportunities for integrating nudges within consumption decision-making. As digital tools capable of generating highly personalized and context-sensitive responses, GenAI can function as an effective nudge in choice architect, subtly guiding users toward specific decisions. This digital nudging operates by adjusting the breadth of interactions, whether providing a wide range of potential options or focusing on more specific, actionable recommendations. By doing so, GenAI can influence not only the immediate decision-making but also how they perceive and pursue their long-term goals.

The use of GenAI in this capacity mirrors many of the principles of Nudge Theory. In traditional contexts, nudges work by simplifying the decision-making process or framing options in a way that highlights certain desirable outcomes (Thaler & Sunstein, 2008). In the case of GenAI, the nudge comes from the way the AI structures its responses, either by presenting a broad array of possibilities that encourages exploration of different pathways or by focusing on narrow, concrete steps that guide immediate action. In both cases, the architecture of choice remains intact, but the AI's ability to customize the interaction adds a layer of personalization that traditional nudges lack.

For Mele et al. (2021), the interaction between digital tools and consumer empowerment can be complex. Thus, GenAI nudges offer an opportunity to enhance consumer decision-making by tailoring the level of abstraction in responses to match the consumer's needs at any given time. Broad interactions might nudge consumers to think more deeply about the desirability of their long-term goals, while narrow, concrete responses can act as a nudge toward immediate action, emphasizing feasibility. This creates a dynamic decision-making environment where consumers can feel both empowered and guided, with the AI functioning as a paternalistic libertarian nudge in line with the ideas of Thaler and Sunstein (2008).

Moreover, the customization capabilities of GenAI mean that nudges can be fine-tuned not only based on consumer preferences but also on real-time data. This allows for adaptive nudging, where the AI can shift between broad and narrow responses depending on the consumer's progress toward their goal or changing circumstances. This flexibility ensures that consumers remain engaged in the decision-making process, with the AI facilitating goal pursuit by dynamically adjusting its level of intervention (Mele et al., 2024).

3.2 GenAI Nudges in Consumption: A Construal-Level Perspective (CLT)

According to Construal Level Theory (CLT), psychological distance influences whether thinking will be more focused on specific details of the present (low level of construction) or on general and long-term aspects (high level of construction). For example, purchasing decisions that will take place in the distant future tend to be represented abstractly, while immediate purchasing decisions tend to be processed concretely (Trope & Liberman, 2010). This has direct implications for consumer behavior, especially when the decision-making process takes place through technologies such as GenAI.

Previous research shows that the level of construction affects how consumers evaluate different product features (Liberman et al., 2007). For example, consumers who are planning a purchase for the future (high temporal distance) may prioritize abstract attributes such as status and quality. Consumers who need to make an immediate decision, on the other hand, focus more on concrete attributes such as price and functionality. In the context of interactions with AI, these construction characteristics become even more relevant, as the technology allows different levels of abstraction to be presented according to the consumer profile and the moment of interaction.

More recently, Stillman & Woolley (2023) demonstrate, within the context of unhealthy behaviors, that emphasizing short-term costs (such as irritability or indigestion) curbs such behaviors more effectively than focusing on long-term consequences. This finding aligns with the premise that narrow GenAI nudges, which emphasize concrete and immediate aspects, can drive goal pursuit more effectively by focusing on actionable, near-term outcomes (Stillman & Woolley, 2023). Woolley & Fishbach (2016) show that immediate rewards increase persistence in long-term goals

We propose that broader GenAI responses, which highlight the long-term benefits of a product or service, make it easier to visualize and commit to long-term goals. For example, messages that emphasize how buying and taking a course today can open up new career opportunities in the future, or how investing in a dream trip can provide life-changing experiences, help consumers connect emotionally with more distant goals.

In this way, we propose that by personalizing the interaction to be broader or narrow with its consumer, GenAI can shape the individual's perception of empowerment, making the consumer experience more aligned with their needs and preferences. For example, broad interactions that demonstrate how a product will contribute to the consumer's future well-being can increase the feeling of control and satisfaction, especially when the consumer is pursuing goals related to personal development or life improvement. On the other hand, narrow interactions that provide specific details, such as functionalities and price, facilitate the immediate decision, increasing the perception of effectiveness and viability of the choice. We therefore propose the following research hypothesis:

H1: Narrow (vs. broad) nudges in GenAI responses leads to greater attainment of short-term (vs. long-term) consumer goals.

In other words, while broad interactions reinforce the consumer's connection to distant goals and core values, narrow answers offer practical support for the fulfillment of immediate goals, promoting desirability and greater empowerment in the context of consumer decisions (Fishbach & Ferguson, 2007; Liberman et al., 2007; Stillman & Woolley, 2023).

3.3 Goal Pursuit Attainment and Consumer Empowerment Using GenAI

The way we organize our behavior, thoughts, feelings and objectives is directly related to the goals we set, pursue or abandon throughout our lives (Fishbach & Ferguson, 2007). In light of the current context, in which technology and GenAI are increasingly present in our daily lives, it becomes evident that the attainment of individual goals is undergoing transformation, as GenAI interferes with consumer relations, the workplace, and various aspects of everyday life.

Previous studies show that recommendation agents based on artificial intelligence help improve the quality of decisions made by consumers (Kim et al., 2022). And that consumers tend to prefer products that use highly adaptive algorithms in smart products, as these algorithms are perceived as more creative (Clegg et al., 2024). These technologies help empower consumers (Tajurahim et al., 2020).

Consumer empowerment is a multifaceted construct that integrates individual abilities, access to information, and participation in decision-making processes (Perkins & Zimmerman, 1995; Tajurahim et al., 2020). Theoretically, empowerment connects psychological well-being with broader social and political contexts, emphasizing individuals' ability to gain control over their lives and make informed decisions (Perkins & Zimmerman, 1995). This construct goes beyond traditional concepts like self-efficacy or locus of control, encompassing critical reflection, community participation, and equitable access to resources. The European Consumer Empowerment Index identifies key dimensions of empowerment, including consumer skills, awareness of rights, and active engagement in decision-making (Nardo et al., 2011). Empowerment is thus seen as both a process and an outcome: it is shaped by the structures enabling informed choices and realized in the ability to act on these choices to achieve desired outcomes. As markets and technologies evolve, empowerment becomes a crucial framework for assessing how innovations, such as artificial intelligence (AI), shape consumer behavior and agency.

With the development of technologies that help consumers make decisions, such as GenAI, the concept is gaining more strength. The integration of GenAI tools into consumer decision-making redefines traditional notions of empowerment by providing tailored, actionable insights. GenAI has the capacity to enhance consumer empowerment by offering personalized information, reducing decision-making complexity, and aligning recommendations with individual goals. In view of this, the concept of consumer empowerment that we are going to use in this study is a mix of Perkins & Zimmerman (1995) and Nardo et al. (2011) concepts applied in the context of GenAI. Thus, consumer empowerment can be understood as the individual's capacity to act toward achieving a goal, enhanced by GenAI's ability to provide tailored, actionable insights that make decision-making more informed and efficient. Therefore, this technology mirrors the empowerment framework by bridging information gaps and increasing consumer agency through interactive choice architectures. However, unlike traditional sources of empowerment, GenAI introduces dynamic interactions that can adapt to consumer prompts, fostering a sense of control and facilitating informed choices in real time. These features underscore GenAI's potential to act as both an informational and motivational agent, reshaping how consumers perceive and achieve their goals while engaging with digital environments. By operationalizing empowerment through AI-mediated interfaces, businesses can enhance consumer engagement and satisfaction, ensuring alignment with their preferences and fostering long-term trust.

Building on the findings of Liberman & Trope (1998), we aim to explain why narrow GenAI answers result in higher levels of consumer empowerment (Fuchs et al., 2010), leveraging the framework of Construal Level Theory (CLT) (Trope & Liberman, 2010). According to CLT, the way individuals construct their goals (either abstractly or concretely) can significantly influence their decision-making process. Traditionally, desirability considerations, which reflect the value or end state of a goal, are associated with high-level, abstract construal, while feasibility considerations, which pertain to the ease or difficulty of achieving a goal, are linked to low-level, concrete construal (Liberman & Trope, 1998).

However, in the context of GenAI interactions, we propose that this dynamic is reversed. Rather than abstract suggestions leading to greater empowerment through desirability, it is the concrete, narrow suggestions from GenAI that both highlight the feasibility of achieving the goal and simultaneously enhance the consumer's desire to pursue it. The specific, actionable nature of these responses based on AI not only makes the goal seem more achievable but also generates stronger motivation and emotional engagement. Additionally, concrete GenAI suggestions enhance both feasibility and desirability, leading to a greater sense of empowerment.

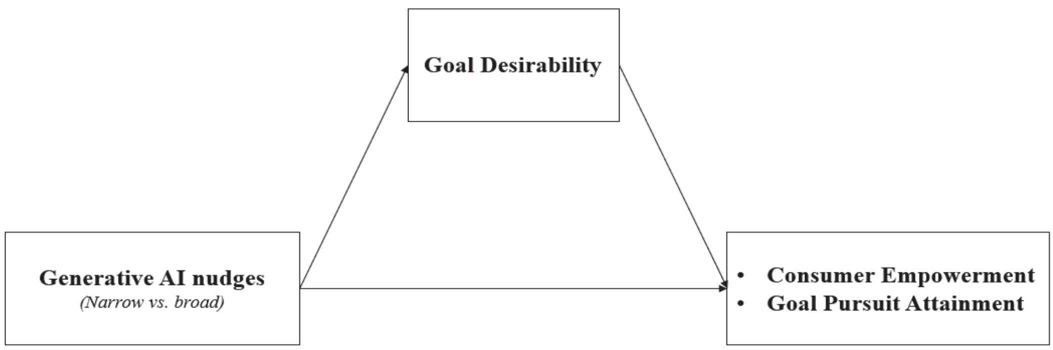
In contrast, we suggest that abstract suggestions, which traditionally emphasize the desirability of a goal, may not foster the same level of empowerment in this digital context. Broader, more abstract responses might leave the consumer uncertain about how to implement the goal, reducing their overall motivation and sense of control. Therefore, we propose that concrete responses, by clearly outlining the steps toward goal pursuit attainment, foster both a practical understanding and a greater emotional drive to achieve the goal. Thus, we propose the following hypotheses:

H2a: Consumers exposed to narrow (vs. broad) nudges in GenAI responses will experience higher levels of consumer empowerment in their decision-making process.

H2b: This effect will be mediated by increased goal desirability, with narrow cues enhancing both the perceived feasibility and desirability of the goal, thereby increasing consumer empowerment.

These hypotheses challenge the traditional predictions of CLT (Liberman & Trope, 1998), where desirability typically becomes more influential over time and in more abstract contexts, while feasibility is more salient in immediate, concrete situations. Instead, we propose that in the context of GenAI, it is the concrete and narrow GenAI suggestions (by making the steps toward goal pursuit more tangible) that both foster a sense of feasibility and enhance desirability, thereby leading to greater consumer empowerment. These proposed relationships are illustrated in Figure 2.

Figure 2. Research model



Note: Elaborated by author (2025).

4 Research Design: Mixed-method Approach

This study adopted a mixed-method approach (Creswell, 2014). Initially, semi-structured and structured interviews were carried out to better understand the theoretical model of the research and check whether the proposed relationships between the variables reflected the reality of consumers. In addition to the interviews, the study also used an experimental design to collect primary data from users of generative artificial intelligence tools, with the aim of testing the hypothesis formulated.

According to Hayes (2009), the experiment design context involves systematically manipulating independent variables to observe their direct and indirect effects on dependent variables, with an emphasis on mediation analysis to understand the underlying causal mechanisms.

Finally, this research was approved by the Ethics Committee of NOVA University Lisbon in April 2024. See Appendix 1 for the approval report.

4.1 Overview of studies

Through five studies, three of which were qualitative and two experimental, we tested our research hypotheses. First, a qualitative pilot study was conducted with Portuguese students to understand how they interacted with generative artificial intelligence tools in their daily lives, in order to align the theoretical-empirical propositions. The second qualitative pilot study was conducted at Prolific and sought to understand the participants' perception of the use of GenAI.

Study 1 then explored consumer perceptions of generative AI through structured online interviews. Study 2 tested, through an experiment in a travel tips search scenario using a generative artificial intelligence tool, whether the type of GenAI response (more concrete or more abstract) affects consumers' ability to achieve their goals (H1) and promotes a sense of empowerment (H2a). Finally, Study 3 also used the scenario of the previous study and tested the proposed hypotheses (H2a and H2b), reinforcing the findings of the previous study and exploring the desirability mechanisms that explain why concrete GenAI suggestions lead to higher levels of consumer empowerment.

The experimental study data were collected using the Qualtrics software (https://www.qualtrics.com/pt-br/). The sample sizes for the experiments were calculated with the G-Power software, version 3.1 (https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower). All studies, except for the pilot, were pre-registered on the AsPredicted platform (https://aspredicted.org/). Additionally, all experiments included attention check questions to ensure data quality. All the scales used in quantitative studies can be accessed in Appendix 4. The statistical analyses were conducted using IBM SPSS Statistics software, employing the PROCESS macro (Hayes, 2018) for modeling the proposed relationships.

5 Pilot Study 1 - Qualitative interviews

We conducted an exploratory qualitative study with Portuguese students with the aim of understanding how they interacted with generative artificial intelligence tools in their daily lives. The interview questionnaire was semi-structured and the participants were volunteers.

5.1 Method

Although preliminary, this section describes the collection of samples, the characteristics of these samples, the structure of the interviews and the analysis.

5.1.1 Data collection and sample

The study included 19 participants, comprising both male and female students, aged between 19 and 30 years. The participants were a mix of undergraduate, master's, and doctoral students from various disciplines. The diverse academic backgrounds of the participants provided a comprehensive understanding of how generative AI tools are utilized across different fields of study.

Participants were randomly approached in the corridors of a university and were given the option to voluntarily participate in the study. The interviews were conducted using a semi-structured questionnaire, which allowed for in-depth responses while maintaining a consistent framework for each interview.

5.1.2 Interview Structure and analysis

The semi-structured questionnaire used in the interviews comprised a series of open-ended questions designed to explore various aspects of the participants' interactions with generative AI tools. The questions were divided into two main categories: general usage and ethical considerations. The average duration of the interviews was between 5 to 15 minutes.

5.2 Results Piloty Study 1

This exploratory qualitative study provided valuable insights into how participants interact with generative AI tools in their daily lives.

Table 2. Classification of GenAI use

Themes	Labels	Number of mentions
Purpose of using GenAI	Writing	3
	Code creation	1
	General research	6
	Work	1
	Finance	1
	Study/research	2

Note: Three participants said they don't use any kind of generative artificial intelligence. As participants can mention different use cases from the same theme, the aggregated numbers of mentions are not expressed in number in relation to the sample size.

In line with Wolf & Maier (2024), the results of this preliminary study indicate that the most common application of generative AI (GenAI) among participants is for general research purposes, followed by writing and academic study/research. This suggests that GenAI is primarily perceived as a tool for information gathering and academic support.

With only a few mentions of code creation, work, and finance, it is evident that these areas are not the primary focus for most users in this sample. This finding aligns with broader trends indicating that while GenAI has diverse potential applications, its adoption varies significantly across different domains. The fact that some participants do not use GenAI tools at all points to potential barriers such as lack of awareness, perceived complexity, or other factors that warrant further investigation.

Overall, these findings contribute to a better understanding of the practical applications and perceived value of generative AI among students, highlighting areas of both prevalent use and underutilization.

6 Pilot Study 2– Online Qualitative Interviews

This qualitative study aims to explore consumers' perceptions of GenAI. As GenAI technologies such as ChatGPT, Bard, and others become increasingly integrated into various aspects of daily life, understanding how people perceive and interact with these tools is essential. Specifically, we seek to address the following question: What is people's perception of generative artificial intelligence? In addition, we want to analyze how GenAI helps consumers achieve their goals, be they professional, social, financial, etc.

By investigating the attitudes, beliefs, and experiences of consumers regarding GenAI, this study intends to provide insights into the perceived benefits, challenges, and ethical considerations associated with these technologies. Through 20 semi-structured interviews in Prolific.

6.1 Method

As in the previous study, the interviews were conducted in an exploratory manner. We structured a questionnaire focused on understanding how people perceived the issues directly linked to the variables we listed in the literature studied, in order to understand people's perceptions of GenAI as a tool for empowerment in consumer relations.

Therefore, this section describes the data collection, the characteristics of these samples, the structure of the interviews and the analysis.

6.1.1 Data collection and sample

Interviews were conducted with 20 participants. This study was carried out at Prolific with respondents from Portugal and included a sample of GenAI tool users who had been filtered at Prolific. The participants were mostly men (65%) with an average age of 27. This study was preregistered. The full roadmap for this study can be accessed at Appendix 2 and https://aspredicted.org/RKP_8RR.

6.1.2 Interview Structure and analysis

The structured questionnaire used in the interviews included seven open-ended questions designed to explore various specific aspects of the participants' interaction with generative AI tools. The questions were divided into categories related to the general use of GenAI, type of response, perceived empowerment, goal achievement, desirability and decision making through GenAI. The average duration of the interviews was 10 to 15 minutes.

6.2 Results Pilot Study 2

The analysis of the responses indicates a diverse perception of the concreteness (narrow) and abstractness (broad) of GenAI responses among participants. While some view these responses as predominantly narrow due to their reliance on internet-based information and factual data, others perceive them as abstract, particularly when the questions are complex or the responses are generated based on predictions. Additionally, a significant portion of the participants acknowledge that the nature of the GenAI model and the specificity of the questions play crucial roles in determining the concreteness or abstractness of the responses. This nuanced understanding reflects the multifaceted nature of GenAI technology and its varying applications in different contexts.

Regarding the belief that GenAI will or won't help them achieve their goals in the second question, the responses indicate a mixed perception of the effectiveness of GenAI in helping users achieve their goals. While many respondents appreciate its time-saving benefits and usefulness in educational and professional contexts, others are more skeptical, noting limited utility or lack of use for important tasks. The effectiveness of GenAI appears to be context-dependent, varying with the nature of the task and the way the tool is utilized. This diverse range of opinions highlights the complex and multifaceted impact of GenAI on users' ability to achieve their goals.

About the perceived desirability of GenAI for achieving goals in the third question, the analysis of the responses indicates diverse perspectives on the desirability of GenAI for achieving professional goals. While many respondents appreciate its ability to save time, facilitate processes, and optimize tasks, others highlight its limitations in linguistic knowledge, reliability, and applicability to certain jobs. The desirability of GenAI appears to be context-dependent, varying with the nature of the professional tasks and the manner in which the tool is utilized. This range of opinions underscores the complex and multifaceted impact of GenAI in professional environments.

About the perception of goal pursuit, the responses indicate a generally positive perception of GenAI's ability to improve goal attainment, particularly in educational and professional contexts. Many respondents appreciate its speed, efficiency, and support in research and learning. However, there are concerns about its comparative advantage over traditional methods and its reliability in sensitive areas like financial management. The effectiveness of GenAI appears to be context-dependent, varying with proper usage and the specific goals of the users. This range of opinions highlights the nuanced impact of GenAI on personal and professional goal achievement.

When asked about delegating important decisions to artificial intelligence, the responses indicate a strong reluctance among many respondents to delegate important decisions to GenAI, primarily due to concerns about the need for critical thinking and human judgment. However, there is also a recognition of the potential for GenAI to assist in the decision-making process, provided there are appropriate safeguards such as human supervision and empirical validation of the tool's effectiveness. This range of opinions highlights the cautious approach many people take towards integrating GenAI into critical decision-making processes.

When asked if they believe AI will surpass human intelligence, the responses indicate a mix of opinions on whether GenAI can surpass human intelligence. While many respondents acknowledge GenAI's superiority in specific areas such as data storage, mathematical calculations, and rapid information retrieval, others emphasize the importance of human critical thinking, originality, and the inherent limitations of GenAI's dependency on human knowledge. The potential for future development and the risks associated with GenAI surpassing human intelligence are also significant themes in the responses. The complete table with the study participants' answers can be found in Appendix 3.

6.3 Discussion of Pilot Study 2

The qualitative findings underscore the multifaceted nature of interactions between users and generative AI (GenAI), revealing diverse perceptions regarding the concreteness and abstractness of GenAI responses. These perceptions align with the theoretical frameworks provided by Construal Level Theory (CLT), which suggests that psychological distance influences how information is construed—either concretely or abstractly (Liberman & Trope, 1998). The participants' varying experiences highlight how specific questions and tasks influence the level of abstraction in GenAI outputs, with narrow prompts leading to more actionable, concrete responses and broad prompts eliciting generalized, predictive information. These insights resonate with prior research suggesting that digital tools like GenAI act as adaptive choice architects, shaping decision-making by framing responses according to user input (Thaler & Sunstein, 2008). This variability in response type suggests that GenAI can play a dual role in both short-term, task-oriented goals and long-term, exploratory objectives, depending on how users engage with the tool.

Participants' mixed perceptions of GenAI's effectiveness and desirability in achieving goals further emphasize the context-dependent nature of these tools. While many respondents highlighted its efficiency and time-saving potential, particularly in educational and professional contexts, others expressed skepticism about its utility for complex or critical tasks. These findings align with Goal Pursuit Theory (Fishbach & Ferguson, 2007), which posits that perceived progress and motivation are key drivers of goal attainment. GenAI's ability to enhance goal pursuit may depend on its perceived reliability and alignment with user objectives, as suggested by Stillman and Woolley (2023), who emphasize the role of immediate, actionable feedback in sustaining motivation. Moreover, concerns about delegating decision-making to GenAI highlight the importance of human judgment and critical thinking, echoing calls for transparency and ethical safeguards in AI-mediated environments (Mele et al., 2024). These results suggest that while GenAI holds promise for enhancing goal achievement, its effectiveness is contingent on the alignment between tool capabilities and user needs, reinforcing the importance of trust, adaptability, and appropriate context in its design and application.

7 Study 1 – Qualitative interviews

7.1 Method

Our empirical plan starts with exploratory research to fully investigate how consumers incorporate GenAI tools in their daily decision-making process when pursuing goals. Exploratory study allows us to map some signs to navigate the opacity of the phenomenon under investigation without being restricted to a particular type of GenAI – e.g., Netflix (Gonçalves et al., 2024) or a specific type of consumption interaction – e.g., Chatbot (Kirshner, 2024).

For that, we apply qualitative methodological resources through 25 semi-structured interviews (16 male and nine female, average age: 26 years old). Participants were recruited in Portugal and Brazil. The participant selection was guided by convenience sampling. Participants' inclusion-exclusion criteria were: (a) being a regular GenAI user, (b) demonstrating the capacity to reflect on their choice architecture in their regular life, and (c) contemplating gender and age variations. To enhance the trustworthiness and validity of the qualitative study (Morse et al., 2002), we adopted three verification steps: (1) we conducted data collection and analysis simultaneously to create an iterative process to ensure all themes were covered, (2) during the last interview, we discussed the main interpretations with the participant to ensure the outcomes were coherent, and (3) we apply the data code and meaning saturation (Hennink et al., 2016) to define the number of interviews. We consider the data collection saturation point when new interviews showed no new information.

To conduct the interviews, we follow an interview guide with 15 questions inspired by the research model and literature review. The average time for each interview was 20 minutes.

Interviews were conducted face-to-face or mediated by videoconferencing technology (Zoom) in Portuguese by the last authors, who transcribed, anonymized, and translated into English. The authors' team coded the dataset following Saldaña's (2013) coding manual and inspired by theoretical constructs previously identified in the literature. Data analysis results in three main categories: (a) GenAI's role in consumption decision-making; (b) goal enhancement by GenAI; and (c) GenAI in choice architecture. Finally, to ensure the results' reliability, we triangulate interview quotes with theoretical explanations to offer a full explanation for each category, as detailed next.

7.2 Findings

Previous literature is prominent in describing how GenAI aids companies in exploring options that align with consumers goals (Huang & Rust, 2021), enhances consumers' emotions (Huang & Rust, 2023), and getting insights about customer needs and sentiments (Sterne & Davenport, 2024). However, our exploratory study identifies a growing role of GenAI in consumer tasks not directly associated with a particular company or service, like getting inspiration to decorate the house or mapping travel destinations for the next vacation. Thus, interpreting the qualitative data, we observe that GenAI is revolutionizing not only service interactions but also the way consumers perform regular life choices.

7.2.1 GenAI's growing role in consumption decision-making

The growing adoption of GenAI contributes in transforming consumers into creators (Osmëni & Ali, 2023). Our interviewed manifested diverse situations in which the GenAI works as a resource helping in obtaining more creative consumption ideas. For example, Milena reports that at least once a day she goes "to ChatGPT to see something", while detailing her most recent research about the car model that fit better in her consumers' necessity. Like Milena, informants are unanimous in recognizing that GenAI serves as a versatile instrument for assisting operational tasks. Thus, the second point that emerges in the interviews is the consumers' recognition of the potential of GenAI in supporting operational tasks which do not imply major risks when associated with decision-making. As interviewee Jhonny explains, GenAI is not reliable enough to replace consumers in their regular life decisions: “GenAI is a tool, and as such it can help consumers. However, I wouldn't trust ChatGPT to make decisions about my finances, for example. GenAI can help offer choice options to decision making, but critical thinking is something (at least for now) exclusive to humans” (Jhonny).

The interviews allow us to understand that, at consumption choices level, GenAI does not replace human decision-making, but contributes at two central instances. The first instance is informational. GenAI becomes an instrument to obtain information to support decision-making, even replacing or complementing other traditional information-obtaining mechanisms, as explained by Milena: “I will never ask ChatGPT to make a decision for me or just follow it recommendation. No! I always consider the information obtained on ChatGPT and if I feel I need more informations, I search on Google” (Milena). In a similar way, Peter recognizes GenAI as an easy-to-use source of information that can offer a ‘full picture’ of a specific subject for decision-making, complementing that: “they facilitate the search for online information on specific topics. If GenAI's knowledge base is everything that has been written/studied/created by humans, so they would tend to support us to develop new paradigms about what is going on” (Peter).

Thus, the GenAI is recognized by consumers as a facilitator of the decision-making process due its capacity to offer useful information. Empirically, our interviewees draw attention to the emergence of GenAI that operates as search engines – e.g., GenAI embedded in Google and Perplexity. For the Lily interview, GenAI facilitates the search for information "because waste less time in searching once it encompasses in a single answer what is normally found in multiple searches" (Lily).

The second central instance of GenAI in the decision-making process is its inspirational role. Fabrício explains the role of GenAI as an inspirational element for decision-making: "I use artificial intelligence a lot to provide tips that can inspire me. For example, I need to write a text, I ask some ideas. Or, I'm writing a text and I need to revise it. Then I ask GenAI to make suggestions for improvements to the text. Or even some more complex things, such as decoration ideas."

In line with Wolf & Maier (2024), the results of this exploratory study indicate that GenAI has a growing role as an inspirational and informational source for decision-making. However, we observe that the scope of answers (e.g., quality of the information) can offer some limitations in the GenAI support consumption decision-making. Milena explains that narrow answers tend to be less assertive, while broad answers tend to be less useful, complementing arguing the users' role in making prompts that offer useful answers: "depending on the question you ask, very generic answers come" (Milena). In line with these findings, the growing informational and inspirational role of GenAI is also associated with the consumer perceptions about the answers' contribution in supporting consumers' decision-making. Next, we detail the relationship between GenAI and consumer empowerment.

7.2.2 GenAI on Consumer Empowerment

Even though consumers recognize an inspirational and informational role to the GenAI, it is clear that it produces outputs that are far more contextually responsive to open-ended interactions with users, becoming a meaningful agent in choice architecture

(Satyanarayan & Jones, 2024). Our interviews offer some explanation for that by describing the GenAI empowering potential residing in raising questions that impact human agency. The perception of empowerment can be related to the confidence that people make decisions. For example, interviewees reinforce GenAI's ability to "shorten paths and simplify tasks that carry out multiple perspectives that usually are not considered" (Arthur).

Thus, interviewees highlight the GenAI capacity to indicate paths to define or achieve a consumption objective, not in defining the objectives themselves or even replacing the consumer in decision-making. To this end, it is observed that GenAI operates in two ways. The first is stimulating desirability. It offers alternatives for consumers to define how much they want something. In the case of consumer goals, the desire can empower consumers by increasing motivation and perceived agency to pursue those goals (Fishbach & Ferguson, 2007). One of the interviews illustrates GenAI's ability to help you achieve a personal goal: "If you have a defined goal, for example, to lose 10 kilos by the end of the year, GenAI can show you some ways to make you feel capable of reaching it. But of course, it all depends on the person's capacity to achieve them" (Maria).

Second, GenAI can offer concrete suggestions that make the goal feasibility. It involves offering informational and inspirational support about how consumers can achieve the goal. Interviewees illustrate the GenAI feasibility in different ways, mentioning examples about putting together a travel itinerary and detailing places that must be visited. In this case, consumers already feel able to make the decision to travel and GenAI helps to make concrete what will be accomplished on the trip.

However, interviewees also notice situations in which GenAI answer variation can contribute to increasing desirability - such as providing more abstract possibilities - or feasibility by describing situations that make a given objective concrete. Isabella illustrates: "I don't know anything about saving money. I asked GPT to draw up some suggestions about how to save money over the next three months. It will bring things that can really encourage saving money. But then I can ask him to create an investment portfolio with this savings." Thus, considering Isabella's reflection, the type of answer can reinforce a goal desirability or a goal feasibility. In line with Liberman & Trope (1998), the explanation for this effect resides in the fact that when GenAI brings concrete paths in its answers, it enhances the perception of the feasibility of this goal.

These findings contribute in explaining why more abstract AI responses can enhance perceived empowerment, allowing consumers to interpret and apply suggestions flexibly, while concrete responses are often linked to higher levels of goal attainment and practical satisfaction. Important to note that, while improving the desirability and feasibility, GenAI does not directly reach the goal, but offers paths for consumers to better define and empower themselves seeking the goal. Next, we detail how this relationship between GenAI and consumer empowerment is introduced in choice architecture.

7.2.3 GenAI acting in Choice Architecture

By exploring the nuances of GenAi incorporation in consumer daily decision-making, we can observe that GenAI does substitute, even that partially, other stages in decision-making process. Rather, GenAI contributes in adding a new informational/inspirational level to inspire decision-making. We observe a strong reluctance among the informants to delegate important decisions to GenAI, primarily due to concerns about the need for critical thinking and human judgment. However, there is also a recognition by the informants about the potential for GenAI to assist choices when they have appropriate safeguards such as human supervision.

Thus, we identify a perceptual effect of GenAI subtly influencing decision making even that consumers feel to control the final decision, as Fabrício illustrates: “I think it depends on the level of delegation. I always delegate the matter to help me think about something that I might not have thought of or that in a little while I won't have. Now, the decision-making still rests with me. I never let the AI fully make the decision.” However, despite the perception of control over the tool, consumers admit the growing incorporation of GenAI as part of the decision-making processes. For example, Gustavo perceives the interaction as a collaborative process, in which he defines the objectives and directs the search for information, but he admits that consider the answers as part of the decision process.

The ability to ignore or even reinterpret the responses provided by GenAI demonstrates the consumer's ability to lead with nudges, as Fabrício and Gustavo reports. Nudge works as an orientation trigger in consumer decisions but does not necessarily restrict individual freedom of choice (Thaler & Sunstein, 2008). In this type of choice architecture, the decisions are under the consumer control, but affected by the information presented by the GenAI. GenAI works as nudges that inform and/or inspire the decision-making, directing consumer attention to some point that potentially reinforce some consumer perception and, implicitly, can influence behavior (Thaler, Sunstein, & Balz, 2013). As described before, GenAI impact on choice architecture resides in the type of answer, being able to offer more relevant, reliable informational or useful inspiration. In this regard, what makes GenAI unique in the decision-making is exactly the contextually responsive to open-ended interactions (Satyanarayan & Jones, 2024) that make each interaction tailored specifically to the user's context, preferences, and query nuances, thereby creating a highly personalized experience that adapts the choice architecture dynamically to individual needs.

7.3 Discussion

Our first study explores how GenAI has been affecting consumers decision-making. Firstly, we identify the growing practice of incorporating GenAI as an informational and inspirational resource in consumption decision-making. It reinforces previous studies that identify the incorporation of technology-based tools are significantly transforming the company-consumers relationships (Gonçalves et al., 2024; Huang & Rust, 2023) by the transformations in consumption paradigms (Dwivedi et al., 2023; Kshetri et al., 2024), Particularly, we describe the growing incorporation of GenAI as a resource to support psychological efforts involved in consumption decision-making.

GenAI does not substitute the consumers in making decisions, but its agentic role is not null, once it can increase the consumers motivation toward the decision. Our qualitative data particularly illustrate the capacity of GenAI increasing desirability or feasibility in accordance with the type of answer. This feature allows us to understand GenAI as a nudge in consumption decision-making processes (Thaler, Sunstein, & Balz, 2013). As the interviews illustrate, the way as the information is presented, it can offer different motivations to consumers pursuing its goals. In addition, by offering nuances to the goal pursuit literature (Fishbach & Ferguson, 2007), we identify that the consumer does not reach the goal with AI, but receives help to build paths in defining it or seeking to achieve the goals. We particularly call attention to the fact that, when consumers do not trust in the answer, they tend to ignore the GenAI recommendation. Moreover, it is important to associate that GenAI is a tool offering answers for prompts. These answers are the key element in GenAI-consumers relationship and, as evidenced in the interviews, the answers variation can provoke distinct reactions. The type of answer (e.g., narrow vs. broad) emerges as a central issue to test this relationship and its consequences, as we explore in the next studies.

8 Study 2 – Experiment: GenAI influence in goal pursuit and empowerment

8.1. Overview and purpose

The integration of generative artificial intelligence (GenAI) tools into consumer decision-making processes is becoming increasingly prevalent (Hermann & Puntoni, 2024). Whether selecting travel options or seeking information on various products, GenAI responses often vary in their level of specificity, ranging from broad, abstract guidance to narrow, concrete recommendations. This variability raises important questions about whether the type of GenAI response impacts consumers' ability to achieve their short-term versus long-term goals and fosters their sense of consumer empowerment. To explore this, the present study tests Hypotheses H1 and H2a within a framework that draws on CLT, Nudge Theory, and Goal Pursuit Theory to better understand how different GenAI nudges influence decision-making.

In the context of decision-making related to travel goals, this study examines how narrow GenAI nudges (offering concrete and specific responses) can lead to greater attainment of short-term consumer goals by enhancing perceptions of effectiveness and viability through detailed, actionable information. Conversely, broad GenAI nudges, which provide more abstract responses, are associated with long-term goals, emphasizing how a product or service contributes to future well-being. By tailoring interactions to be either narrow or broad, GenAI has the potential to shape an individual's perception of empowerment, aligning consumer experiences with their needs and preferences. Specifically, broad interactions may enhance feelings of control and satisfaction when consumers pursue long-term goals tied to personal development, while narrow interactions facilitate immediate decisions, reinforcing perceptions of effectiveness and immediate goal attainment.

8.2 Research method

8.2.1 Participants

Using a single factor with two conditions for manipulating GenAI responses: concrete and abstract, this study was conducted online with 144 GenAI users 55,3% female and 44,7% male (average age 33,4 years, SD= 10,7). Three participants failed the manipulation check and were removed from the study (N=141). The Concrete GenAI condition (N=68) and the Abstract GenAI condition (N=73).

8.2.2 Procedure and stimuli

The Prolific platform (https://www.prolific.co) was used for the recruitment of participants residing in the United Kingdom and Portugal and we used Qualtrics software to build the online experiment. Within Prolific we filtered the participants by "Technology and online behavior that use AI chatbots" characteristics, as the aim was to target the survey with people who already had some contact with GenAI, in order to understand their perception. The participants were compensated 0.6£ for four minutes.

Participants were exposed to an online search scenario using a generative artificial intelligence tool to obtain tips for a one-week trip. We created an image that simulated interaction with an artificial intelligence tool and in both conditions (Figure 3), the input was identical (*Please, suggest ideas for one-week tips*), but the AI's responses varied: in the narrow condition, the responses were specific, prescriptive, and emphatic, while in the broad condition, they were more generic and descriptive, as shown in Figure 4.

The sample size was calculated using the G-Power software. This study was preregistered, details of this study can be accessed at https://aspredicted.org/7X4_MJB.

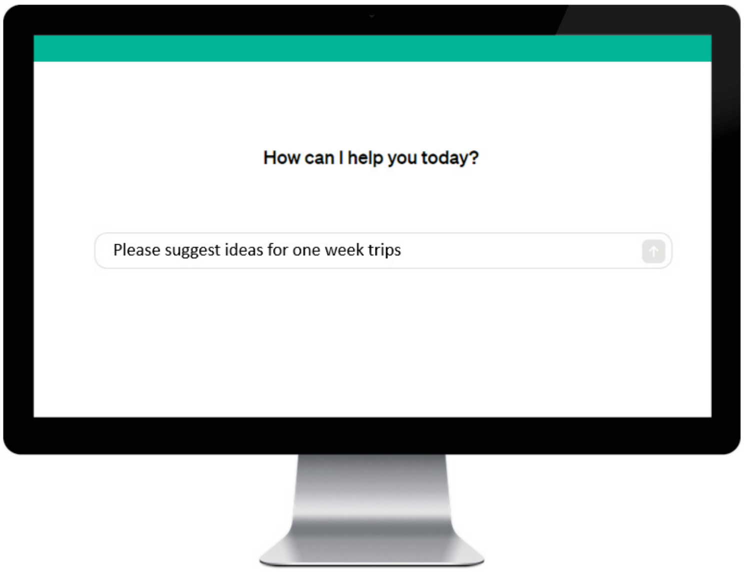


Figure 3: Initial stimulus used in the different manipulation scenarios in study 2.

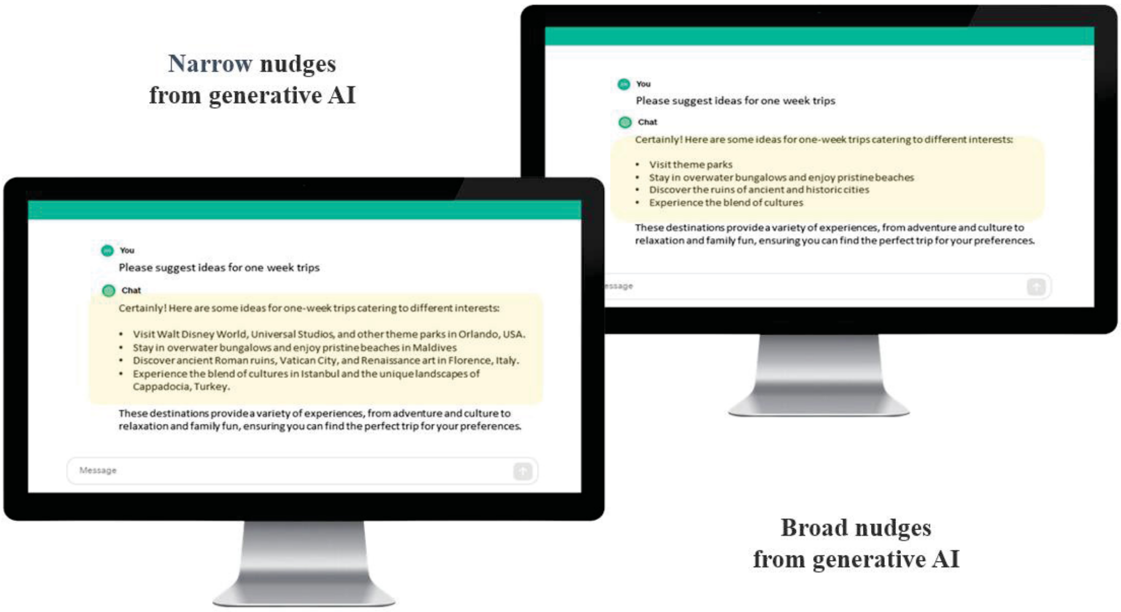


Figure 4: Stimuli used in the different manipulation scenarios in study 2.

8.2.3 Common method bias

To minimize common method bias (CMB) in this study, several procedural controls were employed, consistent with established recommendations in the literature (Podsakoff et al., 2003; Viswanathan & Kayande, 2012). First, psychological separation techniques were used to mask the causal link between the independent variable (IV) and the dependent variable (DV), thereby reducing participants' likelihood of guessing the study's purpose or hypothesized relationships (Podsakoff et al., 2003). This procedural measure helps to mitigate biases stemming from participants' assumptions about the study's objectives.

Additionally, survey design controls were applied to ensure data quality and minimize bias. This included providing clear instructions, guaranteeing anonymity of responses, and avoiding complex or ambiguous items. Surveys were also kept concise to reduce participant fatigue and improve response accuracy (Podsakoff et al., 2003).

Randomization was used throughout the study to reduce potential systematic biases by randomly assigning participants to experimental conditions, thereby ensuring any observed effects could be attributed to the manipulation of the IV and not extraneous factors (Hair et al., 2009). To further minimize bias, the DV was measured immediately following the scenario presented to participants, limiting the opportunity for speculation or memory decay that could influence responses.

Besides, all measurement scales were translated and validated by two native-speaking peers to ensure cultural and linguistic accuracy (e.g., Portuguese of Portugal). This step was critical to maintaining the validity and reliability of the measures in the local context. Taken together, these procedural controls represent a comprehensive approach to mitigating common method bias, enhancing the robustness and internal validity of the study's findings.

All quantitative studies conducted in this research were pre-registered to enhance transparency, credibility, and the robustness of the findings according to Logg & Dorison (2021). Pre-registration involved specifying the study design, hypotheses, data collection methods, and analysis plans in advance of data collection. This approach minimizes the risk of researcher bias, including practices such as p-hacking or selective reporting, and ensures that the analyses reflect pre-determined plans without retrospective alterations (Logg & Dorison, 2021).

8.2.4 Instrument and manipulation check

To measure consumer empowerment, we used the scale adapted from (Nardo et al., 2011), measured using a 9-point Likert Scale. The manipulation check was measured by means of a binary item recognizing the type of response that GenAI presented in the visualized scenario.

An independent sample t-test was conducted to compare the effectiveness of the GenAI scenarios (Concrete vs. Abstract) on participants' perceptions. The analysis revealed a significant difference in the scores for the GenAI Concrete group ($M = 1.85$, $SD = 0.996$) and the GenAI Abstract group ($M = 2.97$, $SD = 0.234$); $t(73.883) = -9.036$, $p < 0.001$.

8.3 Results on Consumer Empowerment

An analysis of variance (ANOVA) was conducted to examine the effect of GenAI nudges type (narrow vs. broad) on consumer empowerment (α=0,803). The results showed that participants who received narrow GenAI nudges reported significantly higher levels of consumer empowerment ($M_{narrow} = 5.17$, $SD = 1.54$, 95% CI [4.80, 5.55]) than those who received broad GenAI nudges ($M_{broad} = 4.54$, $SD = 1.42$, 95% CI [4.21, 4.87]), as shown in Figure 5. The ANOVA revealed a significant effect of GenAI type on consumer empowerment, $F(1, 141) = 6.477$, $p = 0.012$. This indicates that the type of GenAI suggestion (narrow vs. broad) had a statistically significant impact on how empowered consumers felt in their decision-making processes, and supported hypothesis H2a. Specifically, narrow GenAI nudges led to greater consumer empowerment than broad ones.

These findings support the hypothesis that narrow GenAI nudges are more effective in helping consumers achieve their goals and feel empowered, emphasizing the importance of specificity and clarity in GenAI response types.

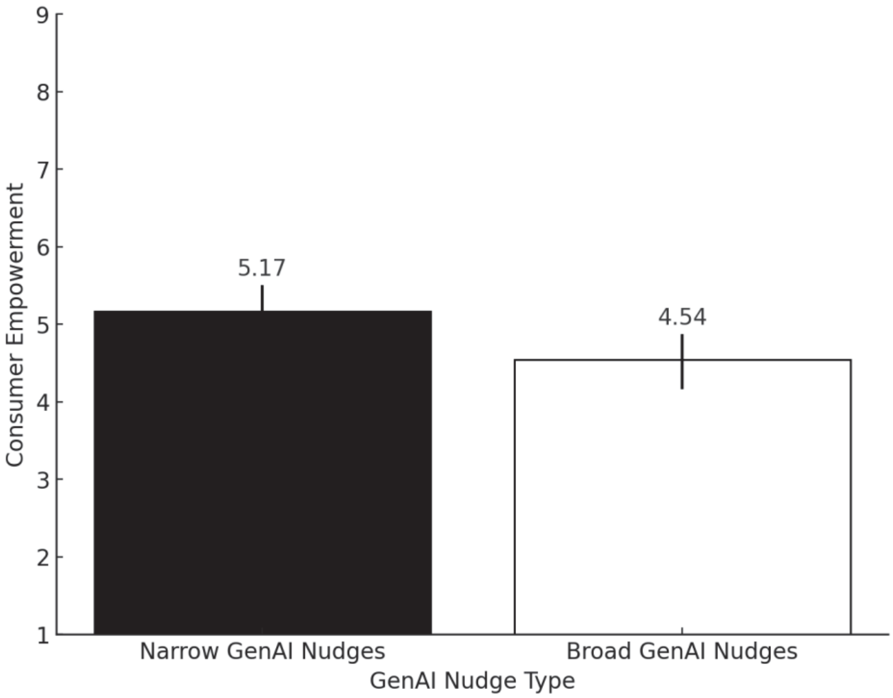


Figure 5. Consumer Empowerment by GenAI Nudge type.

8.4 Results in the Goal pursuit attainment using GenAI.

An analysis of variance (ANOVA) was conducted to examine the effect of GenAI nudge types (narrow vs. broad) on the goal pursuit attainment using GenAI (α=0,872). The results showed that participants who received narrow GenAI nudges reported significantly higher levels of goal pursuit attainment (M_{narrow} = 6.40, SD = 1.99, 95% CI [5.92, 6.88]) than those who received broad GenAI nudges (M_{broad} = 5.04, SD = 2.34, 95% CI [4.49, 5.59]), as shown in Figure 6. The ANOVA revealed a significant effect of GenAI type on consumer empowerment, $F(1, 141) = 13.650$, $p = 0.000$. This indicates that the type of GenAI suggestion (narrow vs. broad) had a statistically significant impact on how empowered consumers felt in their decision-making processes. Specifically, narrow GenAI nudges led to greater consumer empowerment than broad ones. The Post-hoc tests of study 2 can be found in Appendix 5.

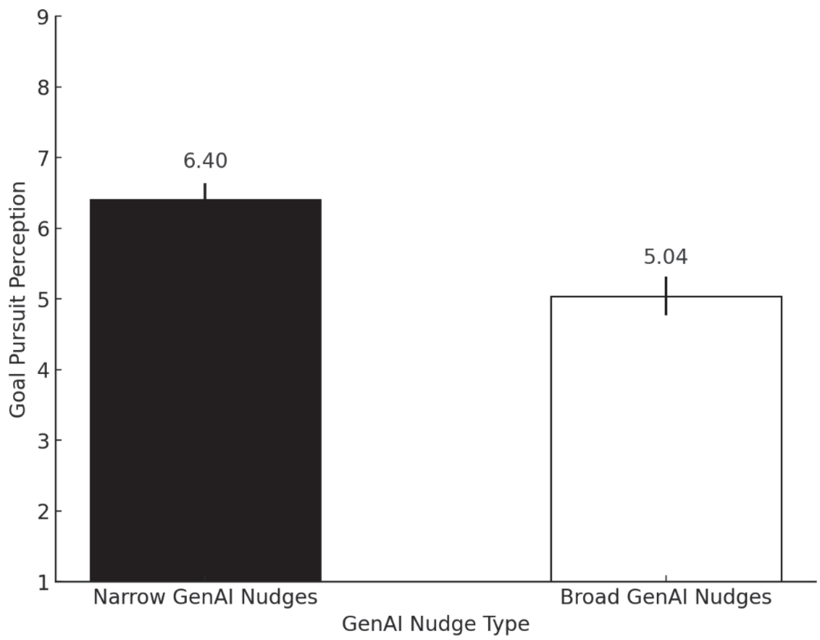


Figure 6. Perception of Goal pursuit perception using GenAI by nudge type.

The results indicated that abstract (broad) GenAI nudges were associated with a perception of goals as more distant and long-term, whereas concrete (narrow) nudges led to a perception of goals as more immediate and short-term. This suggests that the level of specificity in GenAI responses can significantly influence how consumers perceive the temporal distance of their goals.

8.5 Discussion of Study 2

The results of Study 2 support H1 and H2a, which seeks to understand how different types of nudges in GenAI responses (ranging from narrow to broad) influence consumer perceptions of empowerment in pursuing their goals in a GenAI-mediated decision-making context. The ANOVA results reveal that participants exposed to narrow GenAI nudges reported significantly higher levels of consumer empowerment compared to those who received broad nudges (M = 5.17 vs. M = 4.54, respectively). This finding underscores the critical role of response specificity in enhancing consumer perceptions of empowerment.

Additionally, the results indicated that broad (abstract) GenAI nudges were associated with perceiving goals as more distant and long-term, whereas narrow (concrete) nudges led to perceiving goals as more immediate and short-term. This suggests that the level of specificity in GenAI responses can significantly influence how consumers perceive the temporal distance of their goals. By shaping temporal perception, more specific nudges can prompt immediate, concrete actions, while broader nudges may encourage long-term planning, depending on user needs and context. The results align with Stillman & Woolley (2023), who found that emphasizing short-term costs is more effective at influencing behavior due to their immediacy and strong association with action. Similarly, narrow (concrete) GenAI nudges make goals feel more immediate and actionable, enhancing motivation and goal pursuit. In contrast, broad (abstract) nudges position goals as distant, prompting reflection but lacking the immediate motivational impact. This demonstrates that specificity in GenAI responses effectively drives consumer action by shaping temporal perceptions and aligning motivation with goal attainability.

Thus, these results suggest that narrow GenAI responses, which provide precise, actionable, and context-specific information, effectively empower consumers by making the steps toward goal attainment clearer and more tangible. This clarity likely enhances consumers' perception of feasibility, boosting their confidence and motivation to pursue and achieve their goals. In contrast, broad GenAI responses, which emphasize more generalized or long-term benefits, appear to dilute the sense of control and immediate practicality, thereby reducing the overall feeling of empowerment.

From a theoretical standpoint, these findings present an interesting contrast to the predictions made by Construal Level Theory (CLT) (Liberman & Trope, 1998). According to CLT, abstract, high-level construal (akin to broad responses) should enhance goal desirability by focusing on the "why" of the goal, thus motivating long-term engagement and commitment. Conversely, concrete, low-level construals (similar to narrow responses) are traditionally associated with feasibility, focusing on the "how" of goal attainment. However, the results of this study challenge these assumptions, revealing that narrow GenAI responses not only facilitate feasibility but also enhance goal desirability, thereby leading to greater consumer empowerment.

This apparent reversal may be attributed to the unique context of Generative AI (GenAI) interactions. Unlike traditional goal-setting contexts where psychological distance and abstract construal's drive motivation, AI-mediated decision-making offers a personalized, immediate, and adaptive interaction that allows consumers to better visualize the steps needed to achieve their goals. Thus, narrow, concrete responses from GenAI provide a sense of immediate practicality while simultaneously reinforcing the desirability of achieving the goal through enhanced clarity and direction.

The findings underscore the importance of designing GenAI systems that prioritize narrower, more specific responses to optimize consumer empowerment and goal attainment. By offering tailored, precise nudges, businesses can improve consumer engagement, satisfaction, and decision-making outcomes. This stands in contrast to the traditional emphasis on broad, abstract interactions, suggesting a need for rethinking how CLT principles apply within the rapidly evolving AI-driven decision-making landscape.

Overall, these findings highlight that specificity and clarity in GenAI interactions are not merely tools for enhancing consumer understanding but are fundamental drivers of empowerment and goal pursuit attainment. The reversal of CLT's expected effects within this context suggests a paradigm shift in how psychological distance and construal levels function when mediated by adaptive, responsive technologies.

9 Study 3 – Experiment: GenAI nudges and the desirability of consumption goals

9.1 Overview and purpose

In this study, we aim to reinforce the findings of hypothesis 1 and H2a, and to test H2b within the context of decision-making related to travel goals. This experiment aims to reinforce the findings of previous studies and explore the mechanisms that explain why narrow GenAI nudges lead to higher levels of consumer empowerment. Specifically, the study leverages Goal Pursuit Theory to understand how the desirability of a goal mediates this effect.

The theory CLT (Trope & Liberman, 2010) suggests that abstract suggestions (broad nudges), which emphasize the desirability of a goal, enhance consumer empowerment by increasing motivation and perceived agency, while concrete suggestions (narrow nudges) focus more on feasibility. However, this study proposes and tests that narrower GenAI nudges generate greater goal desirability by helping individuals clearly visualize concrete steps for implementation, thereby increasing their motivation to pursue the goal. In contrast, broader GenAI nudges, which highlight the long-term benefits of a goal (such as social goals), may aid in visualizing and committing to the goal over the long term but tend to reduce immediate desirability.

9.2 Research method

9.2.1 Participants

The study was conducted with an initial sample of 140 participants; however, two participants failed the attention check and were subsequently excluded from the analysis, resulting in a final sample size of 138 (N = 138). The study was conducted online, targeting GenAI users, with a demographic composition of 60.9% male and 38.4% female (mean age = 28 years, SD = 7.45). Participants were divided into two conditions: The Narrow GenAI Nudges condition (N = 68) and the Broad GenAI Nudges condition (N = 70).

9.2.2 Procedure and stimuli

Following in the footsteps of the previous study, the Prolific platform was used for the recruitment of participants residing in Portugal and we used Qualtrics software to build the online experiment. Within Prolific we filtered the participants by "Technology and online behavior that use AI chatbots" characteristics.

We kept the same manipulation because it worked in the previous study and the aim was to replicate the results. Participants were exposed to an online search scenario using a generative artificial intelligence tool to obtain tips for a one-week trip. We kept the image created that to simulate interaction with an artificial intelligence tool and in both conditions, the input was identical (*Please, suggest ideas for one-week tips*), but the AI's responses varied: in the concrete condition, the responses were specific, prescriptive, and emphatic, while in the abstract condition, they were more generic and descriptive, as shown in the Figure 4.

The sample size was calculated using the G-Power software and this study was preregistered. The full roadmap for this study can be accessed at https://aspredicted.org/G9F_DJF

9.2.3 Common method bias

We employed the same approach as in study 2 to mitigate potential methodological bias. This ensured that study 3 did not face any risks of bias stemming from the shared methodology.

9.2.4 Instrument and manipulation check

Again, to measure consumer empowerment, we used the scale adapted from (Nardo et al., 2011), measured using a 9-point Likert Scale. Goal perception abstraction using the GenAI, we used a 9-point Linkert scale of extremes, with 1 being the most abstract and 9 the most concrete. Feasibility and desirability were measured based on Liberman & Trope (1998) using a 9-point Likert scale.

For the manipulation check, an independent sample t-test was conducted to compare the effectiveness of the GenAI scenarios (Narrow vs. Broad) on participants' perceptions. The analysis revealed a significant difference in the scores for the GenAI narrow nudge group (M_{narrow} = 1.65, SD = 0.979) and the GenAI broad nudge group ((M_{broad} = 3.00, SD = 0.00); $t(67.00) = -10.403$, $p < 0.000$).

9.3 Results

Consumer Empowerment. An analysis of variance (ANOVA) was conducted to examine the effect of GenAI nudge (narrow vs. broad) on consumer empowerment (α=0,805). Results showed that participants who received narrow GenAI nudge reported significantly higher levels of consumer empowerment (M_{narrow} = 6.04, SD = 1.99, 95% CI [5.56, 6.53]) than those who received broad GenAI nudge (M_{broad} = 5.20, SD = 1.86, 95% CI [4.76, 5.64]), as shown in Figure 7. The ANOVA shows a significant effect of GenAI type on consumer empowerment, $F(1, 138) = 6.605$, $p = 0.011$. This result reinforces the findings of the previous study and supports hypothesis 1, demonstrating that the type answer of GenAI nudge narrow (vs. broad) had a statistically significant impact on consumers' perceived empowerment in their decision-making processes. Specifically, narrow GenAI nudge led to a greater sense of consumer empowerment compared to broad ones.

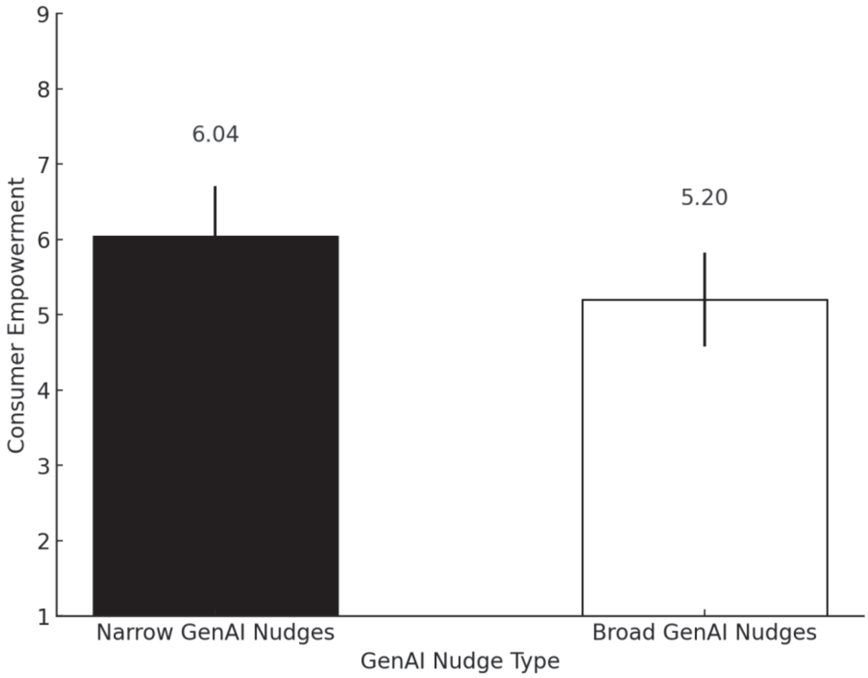


Figure 7. Consumer Empowerment by GenAI Nudge type.

Goal pursuit attainment using GenAI. An analysis of variance (ANOVA) was conducted to examine the effect of GenAI nudges type (narrow vs. broad) on consumer perception of goal pursuit attainment. The results showed that participants who received narrow GenAI nudges reported higher levels of goal pursuit attainment (M_{narrow} = 4.88, SD = 2.10, 95% CI [4.37, 5.39]) compared to those who received broad GenAI nudges (M_{broad} = 4.00, SD = 2.23, 95% CI [3.47, 4.53]), as shown in Figure 8. The ANOVA revealed a significant effect of GenAI nudge type on goal pursuit attainment, $F(1, 136) = 5.733$, $p = 0.018$, reinforcing the findings of study 2 and proving H1. This suggests that the specificity of GenAI responses significantly impacts how consumers perceive their pursuit of goals, with narrow GenAI nudges leading to stronger perceptions of immediate goal engagement compared to broader nudges.

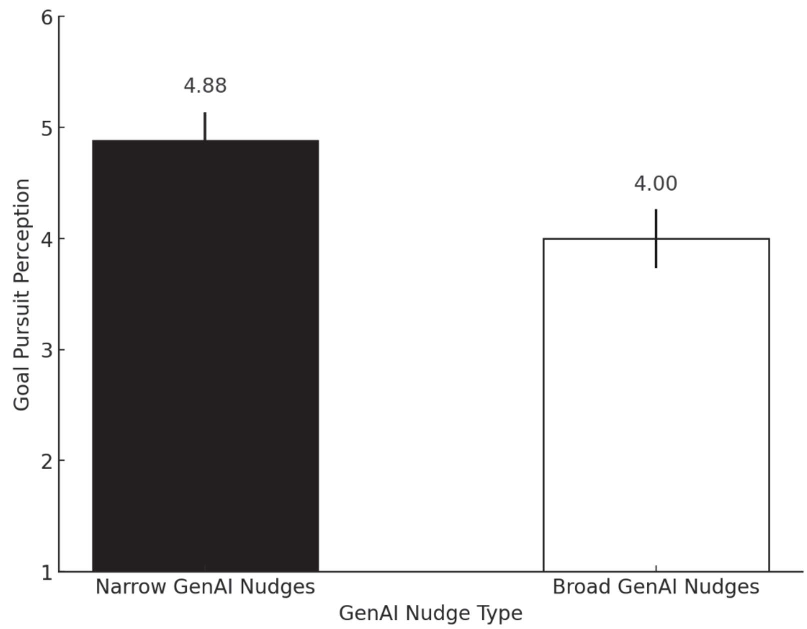


Figure 8. Perception of Goal pursuit attainment using GenAI by nudge type.

For the mediation analysis of goal desirability and testing of hypothesis H2b, was conducted using the Macro of PROCESS (Model 4) for simple mediation analysis (Hayes, 2018). The results show that the type of GenAI nudge significantly influenced the desire to perform the task (β = -0.8185, p = 0.0107; CI [-1.444; -0.192]), with participants in the broad GenAI nudge condition reporting lower levels of goal desire compared to those in the narrow condition. Furthermore, the desire to perform the task was a significant predictor of consumer empowerment (β = 0.5548, p < 0.0001; CI [0.405, 0.704]).

Although the direct effect of the GenAI nudge condition on consumer empowerment was not statistically significant (β = -0.3900, p = 0.1741; CI [-0.954, 0.174]), the analysis revealed a significant indirect effect through desire (β = -0.4541, BootSE = 0.1769, 95% CI [−0.7964, −0.1102]), indicating that the reduced desire to perform the task in the broad condition led to lower levels of consumer empowerment, as shown in Figure 9.

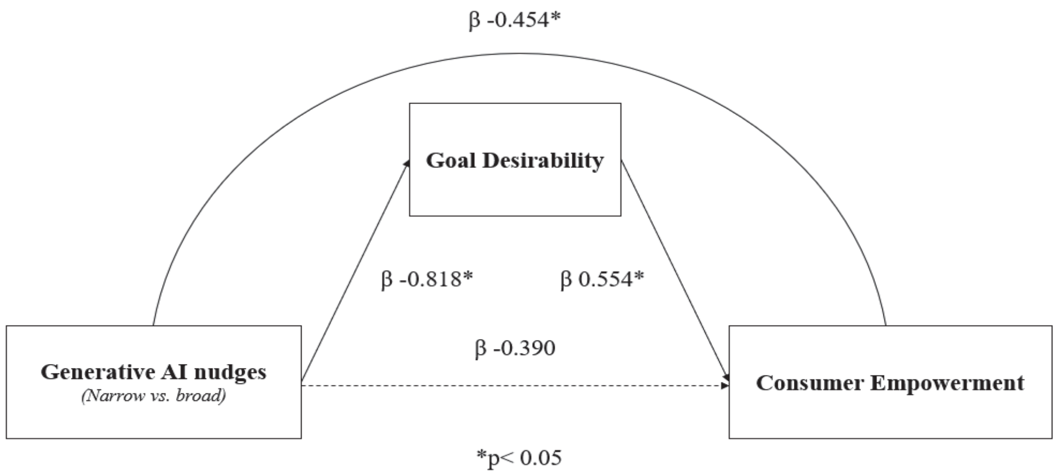


Figure 9. Mediation analysis of goal desirability on empowerment.

In summary, these findings support the hypothesis that narrow GenAI nudges (vs. broad) increase (vs. decrease) consumers' perceived levels of empowerment. The mediation analysis further underscores goal desirability as a key factor, illustrating how different types of GenAI suggestions impact consumer empowerment. This suggests that the specificity of

AI-driven responses plays a crucial role in fostering motivation and facilitating goal pursuit attainment. The Post-hoc tests of study 3 can be found in Appendix 6.

9.4 Discussion of Study 3

This result means that the type of answer generated by the GenAI can directly influence how consumers feel about their decision-making power. Specifically, when GenAI provides broad nudges (more general and less direct), it tends to decrease consumers' desire to follow or act on those suggestions. This reduced desire, in turn, leads to a diminished sense of empowerment or confidence in making decisions independently.

Therefore, the study suggests that broader GenAI nudge may be less effective in making consumers feel confident and empowered in their decision-making. Instead, more narrow nudges, which are more specific and direct, tend to increase consumers' desire to act and, consequently, their sense of empowerment. This finding is important for understanding how the form of GenAI answers can impact consumer behavior and perceptions.

This result is significant as it demonstrates to managers aiming to implement GenAI-based tools in their companies that training GenAI algorithms to provide narrower, more specific nudges is essential. Such tailored nudges not only assist customers in making informed decisions but also enhance their ability to visualize the steps needed to achieve their desired goals, fostering a greater sense of empowerment. By focusing on concrete, actionable guidance, companies can improve customer engagement and satisfaction, positioning GenAI as a strategic tool that both simplifies decision-making and strengthens the customer’s connection to the brand.

10 General Discussion

Three studies using mixed-methods provide converging evidence on the impact of GenAI nudging on decision-making. Firstly, following an exploratory approach, we empirically analyze the growing role of GenAI as an informational and inspirational resource in consumer decision-making. However, more than a supportive source, users recognize that the capacity of GenAI in adjusting the answer in accordance with situations can increase the perceived feasibility and desirability of the goal associated with the decision. Thus, the type of answer provided by GenAI operates as nudges in choice architecture. Second, supported by the theoretical model and study 1 interpretations, study 2 and 3 contributes in detailing the impact of GenAI choice architectures (narrow vs. broad) in reshaping consumers' perceptions of the psychological distance to their goals, as well as enhancing their sense of empowerment when making decisions. Next, we present a summary of the main results of studies 2 and 3 in Table 3.

Table 3. Summary of the main results.

Hypotheses	Proposed relationships	Hypothesis testing	Studies
H1	GenAI nudges (broad vs. narrow) → short-term (vs. long-term) consumer goals	Supported	Studies 2 and 3 (experiments)
H2a	GenAI nudges (broad vs. narrow) → consumer empowerment	Supported	Studies 2 and 3 (experiments)
H2b	GenAI nudges (broad vs. narrow) → goal desirability → consumer empowerment	Supported	Study 3

Note. Elaborated by the author (2025).

The findings regarding GenAI nudges and their impact on consumer perception of goal pursuit align with the literature from Stillman and Woolley (2023) and Laran and

Janiszewski (2011). The results demonstrated that narrow, concrete GenAI nudges significantly heightened consumers' perceptions of immediate goal engagement, whereas broader, abstract nudges were associated with perceiving goals as more distant and long-term. Stillman and Woolley (2023) highlighted how focusing on short-term costs can better curb unhealthy behaviors than emphasizing long-term consequences, reflecting a similar theme where immediacy influences behavior effectively. This shows that narrowing focus on more concrete elements aligns immediate perception and motivation.

In parallel, Laran and Janiszewski (2011) discussed the role of task construal (whether perceived as work (extrinsic) or fun (intrinsic)) in influencing regulatory behavior. Concrete, narrow nudges can foster a more actionable and engaging pathway, potentially vitalizing the consumer's motivation akin to intrinsic enjoyment in tasks, which enhances goal pursuit attainment. Conversely, broad responses may resemble a less defined construal, impacting long-term engagement but lacking immediate motivational vitality. Together, these insights reinforce how the level of specificity and immediacy in nudges can shape consumer perceptions and behaviors, offering a pathway to more effective engagement strategies through GenAI-driven interactions.

With the emergence of GenAI, new paradigms for searching for and consuming information were disrupted, as well as the ways individuals worked and related to one another (Huang et al., 2019; Rust & Huang, 2020). GenAI amplified these changes and presented new challenges (Kshetri et al., 2024). This was particularly evident in the context of consumer behavior (Mogaji & Jain, 2024). Generative tools like ChatGPT allowed users to search for virtually anything and receive personalized answers almost instantly. Prior studies demonstrated that artificial intelligence reduced the time and cognitive effort required for decision-making (Hollebeek et al., 2024; Lim et al., 2022; Li et al., 2023). Moreover, we experienced a shift in the nature of human cognition (Smith et al., 2020), wherein consumers increasingly transferred decision-making responsibilities to intelligent digital systems capable of enhancing human capabilities (Frischmann & Selinger, 2018).

To address this evolving and complex landscape, we relied on the theoretical frameworks of Construal Level Theory (CLT) (Liberman et al., 2007; Liberman & Trope, 1998; Trope & Liberman, 2010), Goal Pursuit Theory (Fishbach & Ferguson, 2007; Fishbach & Tu, 2016), and Nudge Theory (Thaler & Sunstein, 2008). CLT provided a robust foundation for analyzing how varying levels of abstraction in GenAI responses influenced consumer decision-making processes, while Goal Pursuit Theory illuminated how goal desirability mediated these interactions. Additionally, Nudge Theory framed the role of GenAI as an active architect in shaping consumer choices. Following this, we explored the theoretical implications, identifying knowledge gaps and outlining how this research addressed them. Table 4 summarizes key studies and highlights how our findings contribute to advancing these theoretical perspectives.

Table 4: Theoretical contributions of this research.

Reference	What do we know	What we didn't know	Our contribution
Hermann & Puntoni, 2024	The study examines the impact of AI on consumer behavior, focusing on predictive and generative AI. It differentiates between Convergent Thinking (task-specific) and Divergent Thinking (innovative) AI.	It is not yet clear which strategies based on generative artificial intelligence might be suitable to help the consumer face challenges, goals, etc. As well as showing how GenAI can increase consumer safety and empowerment.	We contribute to filling this gap by empirically showing that broad (vs. narrow) GenAI nudges increase the perception of empowerment and facilitate goal achievement. This is directly in line with Hermann & Puntoni (2024) suggestions to study the psychological effects of interactions with AI.
Mogaji & Jain, 2024	The article underscores the transformative potential of GenAI in shaping consumer behavior through personalized recommendations and interactive shopping experiences.	What are the boundary conditions for generative AI effectiveness in consumer behavior? What factors mediate or moderate the impact of GenAI on consumer behavior?	We contribute to this study by exploring other types of goals and showing the mediating effect of goal desirability as a conditioning factor for GenAI to lead to consumer

			empowerment.
Kim et al., 2022	The study shows the relationship between personal hedonic goals and the attitude towards and value of driven interactive recommendation agents (IRAs), as well as the effects of these goals, which ultimately influence the intention to use IRAs. The results provide practical implications for IRAs that can be used to help consumers research and choose products.	It does not extensively explore other consumer contexts (apart from the Stitch Fix case), or other categories. It also limits itself to investigating just one type of recommendation agent, which makes it difficult to replicate in other consumer contexts.	We contribute by expanding mixed empirical evidence to enhance the replicability of findings. Additionally, we explore theoretical understanding in other goal contexts (travel tips), broadening the comprehension of how consumer goals affect interactions. This helps to determine whether broader vs. narrow GenAI nudges lead to changes in attitudes and influence the choice of architecture.
Trope & Liberman, 2010	This seminal study on Construction Level Theory (CLT) explains how psychological distance affects the abstractness or concreteness with which individuals represent events and objects. Distant events are processed abstractly (high level), while nearby events are processed concretely (low level).	With increasing technological change, future studies need to investigate how CLT interacts in generative artificial intelligence contexts. The study does not investigate how the difference between abstract and concrete responses affects consumers' perception of empowerment or goal achievement. Nor does it explore the mediating role of goal desirability.	Our contribution is to investigate how GenAI changes its responses (broad or narrow) depending on the psychological closeness perceived by consumers and how this affects the perception of empowerment. In addition, we showed an opposite effect to CLT, as narrower nudges generate more desire to achieve the goal and more ability to implement.
Fishbach & Ferguson, 2007	This is one of the seminal studies on Goal Pursuit Theory. It addresses goal pursuit and focuses on how people define, pursue and adjust their goals, depending on intrinsic and extrinsic motivational factors. The desirability of the goal is crucial for goal-directed behavior.	Given the increasing changes in technology and consumer behavior, the study does not address the impact of generative AI responses (abstract vs. concrete) on the perception of goal achievement. The study also does not explore how these responses directly affect the perception of empowerment in consumers.	insights into how motivation for goal attainment is shaped in interactions with GenAI, depending on the use of broad versus narrow responses. This integration examines how goal desirability mediates the relationship between the type of GenAI nudge and consumers' perceptions of empowerment and success in achieving their goals.

Liberman et al. (2007)	The study examines Construal Level Theory (CLT), demonstrating that greater psychological distance leads to abstract representations, while smaller distances result in concrete representations. These insights are applied to consumer behavior, highlighting how temporal, spatial, social, and hypothetical distances influence purchasing decisions. decisions, consumers tend to focus on abstract aspects such as value and quality, while more immediate decisions tend to focus on cost and practicality.	While this study is seminal for Construal Level Theory (CLT), it focuses solely on how the dimensions of psychological distance (temporal, spatial, social, and hypothetical) interact to influence behavior. It highlights the need for future research to examine how abstract and concrete representations affect various decision types, including consumer, social, and professional contexts. Additionally, it emphasizes the importance of testing CLT in new settings, such as digital environments or technology-mediated scenarios, to understand its applicability in more complex consumer situations.	Our central contribution lies in applying this theory to a GenAI consumer context, where decision-making is influenced by the type of response nudges. We expanded on previous findings by exploring how GenAI can adjust the level of construal in consumer interactions, providing broader or narrower responses depending on the context of each decision. This addresses the original study's recommendation to investigate new contexts, such as digital environments, where construal levels can be manipulated to influence purchasing behavior.

Note. Elaborated by the author (2025).

11 Conclusions

This study provides insights into the impact of narrow versus broad GenAI nudges on consumer empowerment and goal attainment, but certain limitations should be noted. First, while the qualitative study offered detailed perspectives on consumer interactions with GenAI, emphasizing variability in trust and engagement based on response specificity, the context-specific does not contemplate all nuances of the phenomenon. Future research would explore the particular role of trust in the answer as a key driver in GenAI adoption as an informational and inspirational source on decision-making and its influence on sustained goal pursuit. In addition, further studies could detail - using both quantitative or qualitative approaches - the consumer capacity to create prompts and its impact on GenAI adoption in decision-making.

Second, although findings of quantitative studies were robust, the controlled experimental setting may not fully reflect real-world GenAI interactions (to be multiple other forms of interaction with Gen AI). Additionally, in Study 3, the mediator was measured rather than manipulated. Future studies should examine these effects in more dynamic, real-world settings through field studies to better understand how tailoring GenAI responses impacts consumers. Exploring other potential mediating variables such as perceived control, emotional engagement, or cognitive load during decision-making would offer valuable insights. Moreover, testing the effectiveness of narrow versus broad responses across different goal types, such as health or financial goals, or among consumer segments with varying digital literacy levels, could add depth to the findings.

11.1 Theoretical Contributions

The findings presented here carry significant theoretical and empirical implications for understanding consumer behavior and decision-making in the context of GenAI. From a theoretical standpoint, this research contributes to the body of literature on Construal Level Theory (CLT) and Goal Pursuit Theory by challenging the traditional assumptions of CLT in the GenAI landscape. CLT has long posited that abstract representations of goals enhance desirability, while concrete representations focus on feasibility (Liberman & Trope, 1998). However, our findings suggest that in interactions with GenAI, this dynamic is reversed. Narrow (Concrete) GenAI nudges foster both feasibility and desirability, indicating that the very nature of personalized, detailed GenAI nudges answers can alter how consumers process and pursue their goals. This is our main theoretical contribution because it reshapes the understanding of how psychological distance operates in the context of digital technologies, where specificity and actionable information can boost both motivation and empowerment.

This shift in how GenAI influences goal desirability suggests that GenAI-driven choice architectures function differently from traditional human-based architectures. The Goal Pursuit Theory (Fishbach & Ferguson, 2007) traditionally emphasizes the role of progress perception in goal attainability, but our study reveals that GenAI can intervene even before goal initiation, shaping the desire to pursue a goal from its inception. The ability of GenAI to provide concrete, feasible paths toward goal attainability immediately impacts the emotional and motivational state of the consumer, increasing their sense of empowerment and making the goal seem more desirable, contrary to traditional CLT predictions.

Additionally, we contribute by integrating Goal Pursuit Theory (Fishbach & Ferguson, 2007) and Nudge Theory (Thaler and Sunstein, 2008), providing new explanations of how goal attainment motivations are influenced in interactions with GenAI, adjusted between more narrow and broad nudges. Through this integration, we explore how goal desirability acts as a mediator between the form of the interaction (narrow vs. broad) and the perception of empowerment and success in pursuing a goal. This extends the practical application of goal pursuit theory by testing it in GenAI-mediated consumer contexts, where the type of response (nudge) can directly influence consumers' motivation and perceived effectiveness in the process of attaining their goals.

Furthermore, our findings respond to the call by Hermann & Puntoni (2024) and Mogaji & Jain (2024) to examine the psychological effects of interactions with artificial intelligence on individuals. We demonstrate that the type of GenAI nudge plays a crucial role in fostering consumer empowerment and identify goal desirability as the key psychological factor underlying these interactions. This highlights how specific AI-driven responses can shape consumer motivation, providing evidence that the design of AI interactions has significant implications for enhancing consumer engagement and perceived agency.

Additionally, this research advances the field by demonstrating how GenAI-driven nudges serve as a dynamic tool within digital choice architectures, directly shaping consumer behavior and psychological outcomes. By examining the interplay between nudge specificity (narrow vs. broad) and consumer empowerment, the study provides empirical evidence for how the design of AI interactions can influence decision-making processes. Unlike traditional nudges, which rely on static interventions, GenAI nudges adapt dynamically to consumer prompts, enabling a personalized decision-making experience. This adaptive capacity not only enhances the immediacy and relevance of responses but also establishes a foundation for further exploration of real-time nudge customization in GenAI-mediated environments, opening avenues for future innovation in GenAI applications.

The subsequent sections will delve deeper and discuss the contributions in each area of study.

11.1.1 Contributions of the Construal Level Theory to Consumer Behavior

In the context of consumer behavior, Construal Level Theory has direct implications for how individuals make purchasing decisions. For long-term goals, consumers are more likely to prioritize abstract and desirable product attributes, such as status and technological innovation (Liberman et al., 2007). On the other hand, when dealing with immediate purchases tied to short-term goals, concrete aspects like price and functionality take precedence in decision implementation (Costa Pinto et al., 2013; Liberman et al., 2007).

Despite the theoretical robustness of CLT, it does not address technology-mediated contexts, such as those involving GenAI, nor how the type of GenAI response nudge (narrow vs. broad) might influence consumer perceptions of empowerment and their ability to achieve goals. While the theory establishes that different levels of construal affect how consumers perceive product attributes (Liberman et al., 2007), it remains unclear how changes in choice architecture impact self-efficacy or perceptions of control over decisions (factors critical to consumer empowerment) (Nardo et al., 2011; Rogers et al., 1997).

Additionally, our research expands the application of construal level in digital, technology-mediated environments. We examine how GenAI can adjust its responses to offer narrower or broader interactions based on the context of the decision, addressing the call by Liberman et al. (2007) to explore new contexts where construal levels can be manipulated to influence behavior. By investigating the consumer integration of GenAI in the consumption decision-making process, we provide a new perspective on the application of CLT in the era of GenAI. This approach allows us to test CLT and Nudge Theory in a practical, technology-assisted setting, which has become increasingly relevant with the growing use of GenAI in business due its capacity to act as nudges in in consumption choice architecture.

We also contribute to CLT by connecting the mediating role of goal desirability, integrating Goal Pursuit Theory with CLT (a connection that is not commonly explored in the literature). Goal desirability, which reflects how important or attractive a goal is to the consumer, serves as a critical variable mediating the relationship between GenAI nudges at different construal levels and consumer empowerment and goal attainment. For instance, it remains unclear how goal desirability interacts with GenAI-generated responses that are either broad or narrow and whether this interaction directly influences consumer decision-making processes.

11.1.2 Contributions of Goal Pursuit Theory to Consumer Behavior

Goal Pursuit Theory, as discussed by Fishbach and Ferguson (2007), focuses on the dynamics of goal pursuit, emphasizing the interaction between intrinsic and extrinsic factors in goal setting and attainment. The theory suggests that individuals define goals based on internal motivations (such as personal satisfaction) or external drivers (such as external rewards or social pressure). Moreover, goal desirability is a critical factor in determining the intensity of effort and commitment toward achieving these goals (Fishbach & Tu, 2016; Zhang et al., 2007).

While Goal Pursuit Theory provides a valuable framework for understanding how consumers pursue their goals, it does not directly address how GenAI tools might influence this dynamic. Specifically, there is limited knowledge on how GenAI responses interact with goal desirability and the goal pursuit process, particularly when these responses vary between narrow and broad formats. Furthermore, there is little clarity on how GenAI might impact consumers' perceptions of empowerment regarding their ability to achieve goals. It is known that consumers with clear goals tend to exhibit greater persistence (Fishbach & Ferguson, 2007). However, how GenAI can tailor its recommendations based on construal level (Trope & Liberman, 2010) or goal desirability (Liberman & Trope, 1998), and how this tailoring affects empowerment perception, remains an open question. This study aims to contribute to the intersection of these theoretical domains.

Thus, this research contributes to the literature by examining how goal desirability mediates the relationship between construal level, employed as a nudge in GenAI responses, and perceptions of empowerment and goal pursuit attainment. Specifically, we aim to understand whether more abstract (broad) responses, emphasizing long-term or emotional aspects, enhance consumers' perception of empowerment when the goal is highly desirable. Similarly, we seek to explore whether more concrete (narrow) responses, focusing on feasibility and practical aspects, are more effective for short-term, less desirable goals.

For instance, in a GenAI-mediated shopping scenario, such as selecting clothing on an e-commerce platform, a broad recommendation emphasizing aesthetic appeal might be more effective for consumers with hedonic and highly desirable goals. Conversely, consumers pursuing utilitarian goals, such as cost-saving or practicality, might prefer more concrete responses addressing functionality or cost-benefit considerations. In these cases, goal desirability would mediate the relationship, shaping the degree of consumer engagement and their perception of empowerment.

Construal Level Theory (CLT) and Goal Pursuit Theory provide robust frameworks for understanding consumer information processing and decision-making. However, significant gaps remain, particularly concerning the role of Generative AI (GenAI) in shaping perceptions of empowerment and goal attainment. This research aims to investigate how goal desirability mediates the relationship between the construal level in AI-generated responses and consumer empowerment. By doing so, it contributes to the emerging and highly relevant field at the intersection of technology and consumer behavior in marketing (Amankwah-Amoah et al., 2024; Hermann & Puntoni, 2024; Kshetri et al., 2024).

11.2 Practical implications

Our results also contribute in guiding managers to understand the role of GenAI at the consumption level and provide suggestions for actions in three main topics: marketing, information management and public policy. Companies that adopt GenAI can use the insights from this study to fine-tune GenAI incorporation in its platforms, defining when more concrete or abstract responses best meet users' needs. In this way, we offer four relevant contributions, helping companies and policymakers to improve their practices based on the results of this research.

Firstly, we contribute to marketing managers by empirically showing that GenAI has the potential to personalize interactions with consumers based on their psychological distance from the product or service offered, generating messages that can be more concrete or abstract, depending on the profile of the consumer and the situation. For marketing managers, this ability to adapt has several practical implications; a) personalization of marketing: by adjusting the level of response construction, managers can offer more effective campaigns. More abstract responses, which focus on long-term benefits or emotional aspects of a product, can be effective for consumers focused on status or hedonic goals, as demonstrated in studies on AI and consumer behavior (Kim et al., 2022). More concrete answers, on the other hand, may be more appropriate for consumers who prioritize practical and immediate goals, such as price and convenience. B) customer segmentation: GenAI also makes it easier to segment customers based on their preferences and goals. By analyzing consumer behavior, marketing managers can adjust AI messages to emphasize aspects that resonate more with each segment. For example, if a consumer is looking for quality or status, a more abstract approach can be used, while consumers looking for functionality or value for money respond better to concrete messages (Liberman et al., 2007). C) Increased efficiency of recommendations: AI-based recommendations can increase the efficiency of marketing strategies by offering precise and personalized recommendations. The combination of abstract and concrete goals enables a more personalized and efficient experience, which can increase the perception of brand value and, ultimately, customer loyalty. When AI manages different levels of mental construction, it can be compared to a salesperson adapting their message according to the customer's profile, which generates more agility and effectiveness in marketing.

For marketing managers, it is essential to have a deep understanding of their product and the type of consumer goal (whether short-term or long-term). This understanding is crucial when implementing GenAI tools, as it allows for the alignment of the most suitable nudge in choice architecting to enhance consumer engagement and goal attainment. For example, if the consumption goal is linked to short-term objectives, such as immediate promotions or rapid behavior change, narrow, concrete nudges can be more effective by providing specific and actionable information that enhances consumers' perception of feasibility and motivation. Conversely, when the product relates to long-term goals, such as investments or health improvements, broad, abstract nudges emphasizing future benefits may be more appropriate for engaging consumers at a more reflective and aspirational level.

Moreover, the findings provide practical insights for allocating resources toward GenAI algorithm development. Companies can prioritize investments in training algorithms to deliver context-specific, narrower nudges, which align better with the goal-pursuit preferences of consumers. This approach not only saves development costs but also ensures that GenAI's impact is maximized by focusing on features that directly contribute to consumer empowerment.

Secondly, this study has contributions for information managers. Information managers play a key role in managing the data that feeds GenAI. The collection and proper use of data is essential to ensure that AI responses are accurate and useful for consumers (Dwivedi et al., 2023). GenAI can thus significantly reduce the time and effort invested in repetitive informational processes. We contribute by showing that concrete answers can optimize quick and pragmatic interactions, such as customer service, while abstract answers can be applied to obtain more strategic or branding-related queries.

Empirically, this research shows that businesses can leverage GenAI as an effective decision-support tool. By using GenAI to generate narrow, precise responses, companies can enhance both the feasibility and desirability of products or services, thus driving consumer motivation and goal pursuit attainment. This is particularly relevant in consumer contexts where decision fatigue is prevalent, as GenAI can simplify complex decisions by presenting tangible, actionable options. Moreover, the dynamic nature of AI allows for real-time adjustments to consumer interactions, further boosting the relevance and impact of each interaction.

Additionally, companies that adopt GenAI are not merely automating customer service but are actively redefining the architecture of decision-making. By providing consumers with specific, step-by-step guidance, businesses can foster a deeper connection between the consumer and their goals. This has implications for marketing strategies, where companies can use AI-driven nudges to guide consumer behavior toward desired outcomes. For example, an AI system that offers personalized product recommendations based on past behavior and stated preferences can increase both the perceived feasibility of purchasing a product and the desirability of doing so, leading to higher conversion rates.

The integration of GenAI into the consumer decision-making process challenges and extends existing theories of psychological distance and goal pursuit. The empirical findings suggest that AI can serve as a powerful tool for businesses to empower consumers, ultimately enhancing both their decision-making process and their likelihood of achieving desired outcomes. This research opens new avenues for future studies on how AI-driven choice architectures can further evolve and influence consumer behavior across various domains.

From the point of view of public policy, this study offers contributions for public managers, politicians and other interested parties because, as generative artificial intelligence is still a very recent technology, there is a need to create public policies that guarantee transparency, responsibility and ethics in the use of this technology by companies and individuals. The interactions between AI and consumers also have implications for public policy, especially with regard to transparency, privacy and the protection of consumer rights (Kshetri et al., 2024; Mogaji & Jain, 2024).

The results of this research show that, despite the benefits provided to consumers by the use of GenAI (such as empowerment and achieving goals), they are still very susceptible to this technology. This is reflected in the qualitative analyses of this study, which indicate that consumers have little knowledge of how AI works. As such, public policies must ensure that there is transparency in AI-mediated interactions, especially in relation to the origin of the data used to generate responses. It is essential that consumers understand that they are interacting with a GenAI and know how the responses are generated. The study Dwivedi et al.

(2023) suggests that transparency in the use of AI is fundamental to guaranteeing consumer confidence.

Protecting consumers from AI-generated misinformation is a priority. As GenAI responses work as an informational and inspirational source to make important decisions, it is necessary to implement policies that ensure consumers have access to channels to correct information. In line with Mogaji and Jain (2024), we highlight the need to create regulations that require companies to take responsibility for the content generated by their GenAI, or at least ensure clarity about the presence of GenAI in the process of interacting with a brand or company. In addition, policies that promote education and awareness about the use of GenAI can further empower consumers, allowing them to use these technologies in a critical and informed manner (Flavián et al., 2024).

11.3 Limitations and Future Researches

While this study provides valuable insights into the impact of narrow versus broad GenAI nudges on consumer empowerment and goal pursuit, several limitations should be acknowledged. First, the qualitative study offered rich and nuanced perspectives on consumer interactions with GenAI, highlighting variations in trust and engagement based on response specificity. However, the inherently context-specific and small sample size of qualitative research limits generalizability. Future studies could expand on these findings by employing larger and more diverse qualitative samples, including cross-cultural comparisons, to explore how consumer perceptions differ across various demographic and market contexts.

Second, the quantitative studies employed controlled experimental designs to validate the proposed relationships. While robust, these controlled settings may not fully capture the complexity of real-world GenAI interactions. Additionally, in the third study, the mediator (goal desirability) was measured but not experimentally manipulated, which limits causal inferences. Future research should test these effects in dynamic, real-world contexts, such as field studies, to better understand how tailored GenAI responses operate in practical decision-making environments. Exploring additional mediating variables, such as perceived control, emotional engagement, or cognitive load, would also enrich the understanding of these mechanisms.

Another promising avenue is investigating the boundaries of consumer acceptance regarding GenAI's role in decision-making. Studies could explore when GenAI nudges are perceived as helpful versus intrusive, as well as the impact of transparency and consent on trust and autonomy. Longitudinal research could examine how familiarity with GenAI systems influences consumer attitudes over time. Moreover, understanding cultural and demographic differences in expectations and acceptance of GenAI would provide valuable insights for companies seeking to deploy AI tools responsibly and effectively.

Finally, while this study focused on consumer empowerment, it did not address potential unintended consequences of GenAI, such as over-reliance on AI-generated suggestions, erosion of consumer autonomy, or ethical concerns related to algorithmic bias. Future research should explore the long-term implications of AI-driven nudges, assessing their effects on decision quality, consumer independence, and potential biases introduced by personalization algorithms. By addressing these limitations, future studies can deepen the understanding of how GenAI can optimally support consumer goal achievement while respecting ethical and practical considerations in increasingly complex AI-mediated environments.

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Appendix 1 - Ethics Committee approval of the research

NOVA IMS
Information Management School

This is to certify that

Project No.: **OTHER2024-4-99912**

Project Title: **The Impact of Generative Artificial Intelligence on goal pursuit**

Principal Researcher: **Diego da Costa Pinto**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 4/9/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 4/9/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

Appendix 2 - Structured Questionnaire - Pilot study 2

1) Do you think the answers provided by generative artificial intelligence (GenAI) are abstract or concrete? Please comment based on your opinion.

2) In your experience, do you believe that GenAI helps you achieve your goals? Be they professional, social, personal, financial, etc. goals. Please comment on this question.

3) Why do you consider GenAI a desirable or undesirable tool for achieving your professional goals?

4) Do you think GenAI can empower people? Please comment.

5) Do you think that GenAI improves your ability to achieve goals (e.g. good results at work, in your studies, in your finances, etc.)?

6) Would you be willing to delegate important decision-making to a generative artificial intelligence tool?

7) Do you believe that GenAI can surpass human intelligence in certain areas? If so, in which areas? Please comment on your opinion.

Appendix 3 - Table of responses from participants in pilot study 2

Table 5. Content analysis of the interviews

Question	Theme	Label	Number of Mentions
1) Do you think the answers provided by generative artificial intelligence (GenAI) are abstract or concrete? Please comment based on your opinion.	Concreteness of GenAI Responses	Based on Internet Information	- Concrete, as they are based on information found on the internet. - Concrete, based on the penetrative information of AI. - I think the responses are concrete, based on concrete information previously provided as training.
		Fact-Based responses	- Concrete, as they are based on research that attempts to verify facts. - Concrete, because they are based on documentation and real facts available on the internet. - They are concrete, made based on pre-existing information.
		Pre-Existing Information	- Concrete, made based on pre-existing information.
	Abstractness of GenAI Responses	Keyword and Concept-Based	- Abstract. They are generated according to keywords and basic concepts that have a programmed response.
		Context Dependency	- Based on existing data, they can be abstract due to the context. - Abstract due to the context.
		Prediction-Based	- Abstract. GenAI creates content based on a prediction, not on logic.
	Mixed or Context-Dependent Views	Nature of the Question	- Concrete most of the time, but the more specific the topic, the more abstract it becomes. - It depends on the questions, some may generate factual answers, others predictions/projections. - Generally, direct questions tend to be concrete, while more elaborate questions tend to be more abstract.
		Model Used	- As I understand, it depends on the model used, there are more concrete models and others more abstract.
		Combination of Both	- Sometimes abstract, sometimes concrete. - A bit of both, I don't think AI responses are always completely true, I think it depends on the information available on the internet. - They are concrete in the sense that they tend to answer what we ask, however, they are not always very precise.
Question	**Theme**	**Label**	**Number of Mentions**
2) In your experience, do you believe that GenAI helps you achieve your goals? Be	Positive responses	Time-Saving	- Yes, they save me a lot of time. - In some cases, yes, speeding up the acquisition time of specific information.

they professional, social, personal, financial, etc. Please comment on this question.		Facilitating Tasks and Organization	- Yes, they significantly facilitate the process of task execution and help with work organization.
		Educational and Work-Related Benefits	- Yes, mainly in educational and work contexts, as they facilitate online information search on specific topics. - Yes, educational objectives.
		Enhanced Information Access	- In some cases yes, speeding up the acquisition time of specific information or response.
		Improving Traditional Search	- Yes, it is better than traditional search engines because it saves time by consolidating multiple search results into one response.
		Broad Applicability	- It can help achieve professional, social, and personal goals by providing information, ideas, and support.
	Negative Responses	Lack of Use	- 2x not
		Limited Utility	- No. The most GenAI has helped me with is quicker information provision, which could have been obtained through more extensive research.
		Occasional Usefulness	- I don't use GenAI much for important things, but for quick and simple tasks, yes.
	Mixed or Context-Dependent Views	Task-Dependent	- Yes, with proper use it can help us perform tasks, obtain information, or even create some products.
		Model and Usage	- Yes, GenAI can be a tool that can assist in achieving a wide variety of goals, considering it is a virtual assistant capable of providing useful information through previously trained information.
3) Why do you consider GenAI a desirable or undesirable tool for achieving your professional goals?	Desirable Views	Organizing Ideas and Saving Work	- Helps me immensely to organize ideas and saves work.
		Facilitating Processes	- I consider it desirable because it facilitates processes and assists in correcting them.
		Accelerating Processes	- It will tend to accelerate generally slower processes.
		Information Analysis and Retrieval	- It can analyze and find immense information in a short amount of time, summarizing it into a single response.
		Different Perspectives and Solutions	- Because it can offer different perspectives and solutions to a problem.
		Routine Task Optimization	- It is desirable because it helps with the optimization of routine tasks that do not create much value.
		Automation and Insight Creation	- It is desirable due to its capacity for automation and creation of insights.
		Saving Time	- It saves time, making it desirable, though the potential for mental laziness is a negative aspect.

		Valuable Resource for Basic Tasks	- It is a valuable resource that can perform many of the most basic tasks.
		Speed in Information Creation	- GenAI is a desirable tool as it can help obtain and create information quickly to achieve professional goals.
	Undesirable Views	Linguistic Knowledge Limitation	- AI can never replace the linguistic knowledge of a native speaker, so it should not/cannot replace human editors and proofreaders.
		Misunderstanding and Job Elimination	- Undesirable because many people do not understand what GenAI is. Jobs are already being eliminated by something that only copies what already exists.
		Unreliability	- It is not 100% reliable.
		Inapplicability in Certain Jobs	- In my job, it doesn't apply. The work is all manual, and not even machines could do what I do.
		Lack of Crucial Help	- I sometimes use AI in my work, but it is not a crucial help.
	Mixed or Context-Dependent Views	Controlled Use	- It is desirable if used in a controlled way to accelerate professional goals, but undesirable if used to infringe rules, laws, or other ethical impositions.
4) Do you think GenAI can empower people? Please comment.	Positive Views	Tool for Learning and Problem Solving	- Yes. GenAI can help empower as it is a tool, a resource, that can be used to learn, for example.
		Enhancing Knowledge and Skills	- Can empower people by providing accessible knowledge and personalized assistance.
		Career Advancement	- Proper use of this tool can help a person in career advancement, for example.
		Integration and Balance	- Maybe, if well managed, it can accelerate work capacity and reduce human strain, allowing better integration of information and experience of the day with a better balance between personal and professional life.
		Societal Advancement	- GenAI can empower people who know how to manipulate it and use it to its full potential, leaving behind those who do not in a future where AI will be an integral part of society.
	Negative Views	Over-Reliance and Lack of Critical Thinking	- No, I think it can 'facilitate' too much, and does not foster critical or creative thinking.
		Inherent Limitations	- No. I think it can facilitate learning and help with certain problems, but not in terms of empowerment.
		Negative Empowerment	- Yes, but in a negative way.
		Specific Job Applicability	- In my job, it doesn't apply. The work is all manual, and not even machines could do what I do.

	Mixed or Context-Dependent Views	Proper Usage	- In a way yes, if well used.
		Learning from AI	- Maybe, if the person learns from AI.
		Assisting in Specific Contexts	- Maybe, it can help solve various day-to-day problems and make people think they are better than they actually are.
Question	**Theme**	**Label**	**Number of Mentions**
5) Do you think that GenAI improves your ability to achieve goals (e.g. good results at work, in your studies, in your finances, etc.)?	Positive Views	General Agreement	- Yes. - Yes, for sure. - Yes.
		Educational Support	- In studies, it is possible as an auxiliary tool, as it is usually based on existing information.
		Faster Research and Content Creation	- Improves in terms of helping to conduct faster research, create content, or accelerate certain processes.
		Knowledge and Learning	- Yes. More knowledge necessarily brings more value, and GenAI allows us to learn various things quickly.
		Utility in Specific Functions	- In certain functions, it is quite useful. Speed of results.
		Support and Insights	- Improves the ability to achieve goals by offering support and insights.
		Comprehensive Use	- Yes, GenAI, when used to its full potential and understanding its limitations, can improve the ability to achieve goals.
	Negative Views	No Improvement Over Traditional Methods	- Not more than a search on search engines or Wikipedia.
		Lack of Trust in Financial Management	- GenAI is a tool and can help achieve goals. However, I would not trust my finances to ChatGPT, for example.
	Mixed or Context-Dependent Views	Proper Usage	- Well used, yes.
		Work Area Dependency	- It depends on the area of work, but it can help facilitate various tasks and, due to this, help in career advancement.
6) Would you be willing to delegate important decision-making to a generative artificial intelligence tool?	Negative Views	Complete Rejection	- 6x No
		Critical Thinking and Human Judgment	- AI can help in decision-making, for example in statistical or mathematical questions, but critical thinking is something (at least for now) exclusive to humans.
		Opinion Seeking Rather than Delegation	- No. I could seek the opinion, but never delegate that decision.
		Dependence on Human Confirmation	- No, information can be given this way, even analyzed, but I would have to confirm it personally for the decision to be consciously mine.
	Conditional or Mixed Views	Partial Delegation	- Not totally. - Not in its entirety.

		Testing and Proof	- It depends on how important and how tested it is, but I think not yet.
		Human Supervision	- Yes, as long as there is human supervision.
		Empirical Proof of Effectiveness	- I would be willing after repeatedly and empirically proving that decision-making fits the best way of what is intended.
	Positive Views	General Acceptance	- 3x yes.
Questions	**Theme**	**Label**	**Number of Mentions**
7) Do you believe that GenAI can surpass human intelligence in certain areas? If so, in which areas? Please comment on your opinion.	Affirmative Views	General Agreement with Concern	- Yes, and it is scary.
		Specific Domains	- Art, calculation, and many others. - Yes, in the speed of research/access to information and especially quick response capacity. - Yes, in terms of memory and data storage, or in mathematical terms. But it's like saying a computer or a calculator is superior to a human.
		Superlative Data Storage	- Yes, it has a superlative data storage capacity compared to a human. So, it has a superior response capability.
		Scientific and Mathematical Domains	- Yes, in areas of sciences like programming and mathematics. - Can surpass human intelligence in areas like big data analysis, pattern recognition, and automation of repetitive tasks.
		Potential for Future Development	- Not now as it is still developing, but maybe in the future.
		Error Reduction	- Believes it can add capacity in certain areas and eventually eliminate some percentage of human error.
		Comprehensive Superiority with Risks	- Can, in fact, in all areas. That's why I think it's a great technological advance, but also a weapon if used incorrectly. It's necessary to regulate its use to prevent this from becoming a reality.
	Negative Views	Complete Rejection	- 2x no
		Dependence on Human Knowledge	- No. If the knowledge base of GenAI is everything written/studied/created by humans, then they would always tend to keep up with us as we develop new paradigms.
		Inability to Define Intelligence	- No. Also, because it is not easy to define intelligence, but as far as I know, the GenAI we have so far is based on probabilities and not precision.

Appendix 4 - Scales used in quantitative studies

Consumer Empowerment
Nardo et al. (2011, adapted) measured on a 9-point Likert scale.

- I feel confident with this travel tips.
- I feel I have enough information to plan a trip.
- I feel safe with these travel tips.
- I feel that I have autonomy of choice with these travel tips.
- I feel that these travel tips empower me.
- I find these travel tips feasible (easy to implement)
- I find these travel tips desirable (highly appealing)

Goal Attainment Motivation
(Cheema and Bagchi, 2011, adapted) measured on a 9-point Likert scale.

- Generative artificial intelligence helps me achieve my travel goals.
- I am committed to achieving my goals using generative artificial intelligence.

Attainability
Liberman & Trope, (1998, adapted) measured on a 9-point Likert scale.

- The trip suggestions given by generative AI are very easy
- The trip suggestions given by generative AI are challenging
- The travel suggestions provided by generative AI are attainable

Self-efficacy
Fuchs, Prandelli, and Schreier (2010, adapted) measured on a 9-point Likert scale.

- These travel tips can make a difference for me.
- These travel tips help me to implement my travel plans.
- These travel tips provide clear steps to implement my travel plans.

Knowledge of GenAI
Huisman et al. (2021, adapted) measured on a 9-point Likert scale.

- I've never heard of generative AI.
- I've heard of generative artificial intelligence.

- I have basic knowledge of generative artificial intelligence.
- I have intermediate knowledge of generative artificial intelligence.
- I have advanced knowledge of generative artificial intelligence.
- Active research/development of generative artificial intelligence.

Goal pursuit perception abstraction

Still considering the solution suggested by the generative artificial intelligence tool, evaluate the extremes below:

Abstract	o	o	o	o	o	o	o	o	o	Concrete

Control Questions

- I would use generative AI for travel suggestions.
- I trust generative AI travel suggestions.
- I usually rely on generative AI tools for travel suggestions.
- Generative AI tools help me make travel decisions.

Appendix 5 – Post-hoc tests of study 2

Table 6. Descriptive statistics table of Study 2

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	GenAI Narrow	68	48,2	48,2	48,2
	GenAI Broad	73	51,8	51,8	100,0
	Total	141	100,0	100,0	

Table 7. Descriptive Statistics Table for Gender in Study 2

Gender

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	Female	78	55,3	55,3	55,3
	Male	63	44,7	44,7	100,0
	Total	141	100,0	100,0	

Table 8. Descriptive Statistics Table for age in Study 2

Estatísticas

Age		
N	Válido	141
	Ausente	0
Média		33,43
Desvio Padrão		10,776
Variância		116,132
Mínimo		19
Máximo		65

Table 9. Manipulation Check of Study 2

Estatísticas de grupo

	Conditions	N	Média	Desvio Padrão	Erro padrão da média
The scenario you saw was relative to	GenAI Narrow	68	1,85	,996	,121
	GenAI Broad	73	2,97	,234	,027

Table 10. Independent samples test of study 2

Teste de amostras independentes

		Teste de Levene para igualdade de variâncias		teste-t para Igualdade de Médias						
		Z	Sig.	t	df	Sig. (2 extremidades)	Diferença média	Erro padrão de diferença	95% Intervalo de Confiança da Diferença	
									Inferior	Superior
The scenario you saw was relative to	Variâncias iguais assumidas	808,585	,000	-9,330	139	,000	-1,120	,120	-1,357	-,882
	Variâncias iguais não assumidas			-9,036	73,883	,000	-1,120	,124	-1,367	-,873

Table 11: Factor analysis: Rotated component matrix of the Consumer Empowerment scale

Items	Component
Empw_1: I feel confident with this travel tips	0.891
Empw_2: I feel I have enough information to plan a trip	0.773
Empw_3: I feel safe with these travel tips	0.807
Empw_4: I feel that I have autonomy of choice with these travel tips	0.558
Empw_5: I feel that these travel tips empower me	0.710
Variance extracted (%)	57.17 %
Cronbach's Alpha	0.803
Bartlett's test of sphericity	p<0,05
KMO	0.779

Table 12. ANOVA GenAI → Consumer Empowerment: Descriptive Statistics table

Descriptive								
Média dos itens de consumer empowerment								
	N	Média	Desvio Padrão	Erro Padrão	Intervalo de confiança de 95% para média		Mínimo	Máximo
					Limite inferior	Limite superior		
GenAI Narrow	68	5,1735	1,53949	,18669	4,8009	5,5462	1,20	8,60
GenAI Broad	73	4,5397	1,41762	,16592	4,2090	4,8705	1,00	8,00

Total	14 1	4,8454	1,50625	,12685	4,5946	5,0962	1,00	8,60

Table 13. ANOVA GenAI → Consumer Empowerment

ANOVA					
Média dos itens de consumer empowerment					
	Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Entre Grupos	14,142	1	14,142	6,477	,012
Nos grupos	303,487	139	2,183		
Total	317,630	140			

Table 14. ANOVA GenAI → Goal: Descriptive Statistics table

Descritivos								
	N	Média	Desvio Padrão	Erro Padrão	Intervalo de confiança de 95% para média		Mínimo	Máximo
					Limite inferior	Limite superior		
GenAI Narrow	68	6,40	1,986	,241	5,92	6,88	2	9
GenAI Broad	73	5,04	2,342	,274	4,49	5,59	1	9
Total	141	5,70	2,274	,191	5,32	6,07	1	9

Table 15. ANOVA GenAI → Goal

ANOVA: GenAI →Goal					
Broad; Narrow					
	Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Between groups	64,730	1	64,730	13,650	,000
In the groups	659,156	139	4,742		
Total	723,887	140			

Appendix 6 – Post-hoc tests of study 3

Table 16. Descriptive Statistics of study 3

Descriptive Statistics				
		Conditions: Narrow 0 Broad 1	Age	Gnder
N	Valid	138	138	138
	Absentee	0	0	0
Media		,51	28,20	1,63
Standard Deviation		,502	7,451	,528
Minimum		0	19	1
Maxime		1	54	4

Conditions:

		Frequency	Percentage	Percentage valid	Percentage accumulative
Valid	Narrow	68	49,3	49,3	49,3
	Broad	70	50,7	50,7	100,0
	Total	138	100,0	100,0	

Gender

		Frequency	Percentage	Percentage valid	Percentage accumulative
Valid	female	53	38,4	38,4	38,4
	male	84	60,9	60,9	99,3
	don't want to answer	1	,7	,7	100,0
	Total	138	100,0	100,0	

Table 17. Manipulation Check: T-Test Descriptive Statistics

Statistics of group					
	Conditions:	N	Media	Standard Deviation	Standard error of the mean
Check	Narrow	68	1,76	,979	,119
	Broad	70	3,00	,000	,000

Figure 10. Manipulation Check: T-Test

Teste de amostras independentes

		Teste de Levene para igualdade de variâncias		teste-t para Igualdade de Médias						
									95% Intervalo de Confiança da Diferença	
		Z	Sig.	t	df	Sig. (2 extremidades)	Diferença média	Erro padrão de diferença	Inferior	Superior
Check	Variâncias iguais assumidas	1177,065	,000	-10,556	136	,000	-1,235	,117	-1,467	-1,004
	Variâncias iguais não assumidas			-10,403	67,000	,000	-1,235	,119	-1,472	-,998

Table 18. ANOVA: Gen AI → Empowerment: Descriptive Statistics table

Descriptions							
	N	Media	SD		Intervalo de confiança de 95% para média		

					Standard error	Lower limit	Upper limit	Minimum	Maxime
I feel confident with this travel tips	Narrow	68	6,04	1,996	,242	5,56	6,53	1	9
	Broad	70	5,20	1,862	,223	4,76	5,64	1	9
	Total	138	5,62	1,968	,168	5,28	5,95	1	9
I feel I have enough information to plan a trip	Narrow	68	3,22	1,752	,212	2,80	3,64	1	8
	Broad	70	3,27	2,078	,248	2,78	3,77	1	9
	Total	138	3,25	1,917	,163	2,92	3,57	1	9
I feel safe with these travel tips	Narrow	68	5,62	1,893	,230	5,16	6,08	1	9
	Broad	70	5,27	2,050	,245	4,78	5,76	1	9
	Total	138	5,44	1,974	,168	5,11	5,77	1	9
I feel that I have autonomy of choice with these travel tips	Narrow	68	6,51	2,011	,244	6,03	7,00	1	9
	Broad	70	7,04	1,748	,209	6,63	7,46	1	9
	Total	138	6,78	1,894	,161	6,46	7,10	1	9
I feel that these travel tips empower me	Narrow	68	4,54	2,275	,276	3,99	5,09	1	9
	Broad	70	4,57	1,900	,227	4,12	5,02	1	9
	Total	138	4,56	2,086	,178	4,21	4,91	1	9

Table 19: Factor analysis: Rotated component matrix of the Consumer Empowerment scale

Items	**Component**
Empw_1: I feel confident with this travel tips	0.836
Empw_2: I feel I have enough information to plan a trip	0.718
Empw_3: I feel safe with these travel tips	0.807
Empw_4: I feel that I have autonomy of choice with these travel tips	0.664
Empw_5: I feel that these travel tips empower me	0.772
Variance extracted (%)	56.55%
Cronbach's Alpha	0.805
Bartlett's test of sphericity	p<0,05
KMO	0.793

Table 20. Analysis of Variance Table for GenAI Nudges on Empowerment

ANOVA						
		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
I feel confident with this travel tips	Between Groups	24,577	1	24,577	6,605	,011
	In the groups	506,068	136	3,721		
	Total	530,645	137			
I feel I have enough information to plan a trip	Between Groups	,089	1	,089	,024	,877
	In the groups	503,534	136	3,702		
	Total	503,623	137			
I feel safe with these travel tips	Between Groups	4,135	1	4,135	1,061	,305
	In the groups	529,902	136	3,896		
	Total	534,036	137			
I feel that I have autonomy of choice with these travel tips	Between Groups	9,622	1	9,622	2,716	,102
	In the groups	481,857	136	3,543		
	Total	491,478	137			
I feel that these travel tips empower me	Between Groups	,026	1	,026	,006	,939
	In the groups	596,011	136	4,382		
	Total	596,036	137			

Table 21. Hypothesis Test - Simple Mediation Analysis - Hayes Model 4: GenAI nudges → Desirable of Goal → Consumer Empowerment

```
Run MATRIX procedure:
***************** PROCESS Procedure for SPSS Version 3.4 *****************
        Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
   Documentation available in Hayes (2018). www.guilford.com/p/hayes3
**************************************************************************
Model  : 4
   Y: DVempow1
   X: Conditio
   M: Dvdesire

Sample
Size:  138
**************************************************************************
OUTCOME VARIABLE:
 Dvdesire

Model Summary
       R       R-sq        MSE          F        df1        df2          p
     ,2166      ,0469     3,4520     6,6939     1,0000   136,0000      ,0107
```

Model

	coeff	se	t	p	LLCI	ULCI
constant	6,6471	,2253	29,5018	,0000	6,2015	7,0926
Conditio	-,8185	,3164	-2,5873	,0107	-1,4441	-,1929

Covariance matrix of regression parameter estimates:

	constant	Conditio
constant	,0508	-,0508
Conditio	-,0508	,1001

****

OUTCOME VARIABLE:
DVempow1

Model Summary

R	R-sq	MSE	F	df1	df2	p
,5645	,3186	2,6783	31,5646	2,0000	135,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,3564	,5399	4,3648	,0000	1,2887	3,4241
Conditio	-,3900	,2854	-1,3665	,1741	-,9545	,1745
Dvdesire	,5548	,0755	7,3452	,0000	,4054	,7042

Covariance matrix of regression parameter estimates:

	constant	Conditio	Dvdesire
constant	,2914	-,0704	-,0379
Conditio	-,0704	,0815	,0047
Dvdesire	-,0379	,0047	,0057

************************** TOTAL EFFECT MODEL ********************

OUTCOME VARIABLE:
DVempow1

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2152	,0463	3,7211	6,6049	1,0000	136,0000	,0112

Model

	coeff	se	t	p	LLCI	ULCI
constant	6,0441	,2339	25,8376	,0000	5,5815	6,5067
Conditio	-,8441	,3285	-2,5700	,0112	-1,4937	-,1946

Covariance matrix of regression parameter estimates:

	constant	Conditio
constant	,0547	-,0547
Conditio	-,0547	,1079

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *******

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_ps
-,8441	,3285	-2,5700	,0112	-1,4937	-,1946	-,4289

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps
-,3900	,2854	-1,3665	,1741	-,9545	,1745	-,1982

Indirect effect(s) of X on Y:

Effect	BootSE	BootLLCI	BootULCI

Dvdesire	-,4541	,1769	-,7964	-,1102

Partially standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Dvdesire	-,2307	,0903	-,4080	-,0561

********************** ANALYSIS NOTES AND ERRORS ****************
Level of confidence for all confidence intervals in output:
95,0000
Number of bootstrap samples for percentile bootstrap confidence intervals:
5000
------ END MATRIX -----

Appendix 7 - Declaration of use generative AI, AI-assisted technologies and software's

Table 22. Declaration of use generative AI, AI-assisted technologies and software's

Section	Description of AI use	Specific Tools/Technologies Used	Human Oversight/Editing
Abstract	The author prepares an initial draft, which is then refined for clarity and brevity.	Deepl Translator, ChatGPT	Reviewed and edited by author
Literature Review	The author prepares an initial draft and then the tool helps to improve and synthesize the writing.	ChatGPT Perplexity Consensus	Cross-checked with original sources, edited for accuracy
Data Analysis	None	SPSS	Data analyzed manually
Results	Articulation and revision from the text of the report	ChatGPT	Manually verified and corrected for compliance
Discussion	Drafted initial insights based on provided data and articulation and revision of the text	ChatGPT	Extensively edited by author for accuracy
References	Generated initial APA-style citations for some sources	Mendeley	Manually verified and corrected for compliance
Final Proofreading	Identified grammar, spelling, formatting errors, and articulation and revision of the text	ChatGPT, Deepl Translator	Verified and adjusted by author