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**How is Artificial Intelligence and service automation influencing
customer experience and customer engagement?**

Lorena Crepaldi Oliveira Zanata

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

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Instituto Superior de Estatística e Gestão de Informação
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How is Artificial Intelligence and service automation influencing customer experience and customer engagement?

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Digital and Analytics

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July, 2025

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ABSTRACT

This study examines the influence of intelligent recommendation systems on Customer Experience within the retail sector by enhancing the conventional Technological Acceptance Model (TAM) to incorporate emotional and dispositional factors, including Optimism and Hedonic Value. As intelligent automation becomes more integrated into digital purchasing environments, it is crucial understand the psychological and experiential responses it provokes to strike a balance between operational efficiency and consumer trust and enjoyment. An organized online survey ($n = 300$) evaluated essential characteristics, including Perceived Usefulness, Perceived Ease of Use, Attitude Toward AI, and Customer Customer Experience. The resulting model was evaluated through Partial Least Squares Structural Equation Modeling, which revealed that Perceived Usefulness and Attitude Toward AI were the strongest predictors of Customer Experience.

Optimism has a substantial impact on perceived usefulness, Perceived Ease of Use, and Attitude Toward AI. In contrast, Personalization and Anxiety associated with intelligent systems did not have a significant effect on Customer Experience in this setting. These findings suggest that both cognitive and emotional aspects are essential for developing AI-driven retail systems that foster engagement and loyalty. This study contributes to the literature by presenting an enhanced TAM framework tailored to intelligent retail technologies, emphasizing practical insights for creating emotionally engaging and user-centric recommendation systems.

KEYWORDS

Customer Experience; Artificial Intelligence; Recommendation Systems; Customer Engagement; Retail

Sustainable Development Goals (SDG):



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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AIA	AI Anxiety
AIP	AI Personalization
ATU	Attitude Toward AI
CMB	Common Method Bias
CX	Customer Experience
HTMT	Heterotrait-Monotrait Ratio
OP	Optimism
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PSA	Professional Services Automation
PU	Perceived Usefulness
R²	Coefficient of Determination
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
VIF	Variance Inflation Factor

1. INTRODUCTION

The digital transformation revolutionizing service industries is also transforming how brands interact with consumers. As customers' journeys become increasingly complex and omnichannel, businesses are challenged to meet rising expectations for seamless, personalized experiences (Lemon & Verhoef, 2016). Automation and artificial intelligence (AI) are two examples of new technologies that are driving this change. They alter how decisions are made and enhance service delivery flexibility (Grewal et al., 2020; Huang & Rust, 2018).

In the retail sector, AI-driven tools such as virtual assistants, recommendation engines, and automated checkout systems are transforming how companies manage operations and interact with customers (Pantano & Viassone, 2014; Pillai et al., 2020). By analyzing how customers behave in real-time, these technologies facilitate personalization and expedite service, ultimately making operations more efficient and responsive (Guzman & Lewis, 2020; Hoyer et al., 2020).

AI-powered recommendation systems are one of these tools that have become very popular because they can influence the consumer decision journey. By giving individualized, context-aware suggestions, they reduce information overload and simplify choice. They also alter how people perceive value and relevance (Chang & Park, 2024). These systems impact psychological factors, such as trust, as well as their practical benefits. The trust transfer effect (Chang & Park, 2024; McKnight et al., 2002) suggests that when people perceive recommender systems as accurate and helpful, they can build trust not only in the platform itself but also in the items that are suggested, especially those with low brand awareness.

Although these advancements, growing reliance on AI in customer-facing services raises important concerns about emotional connection, perceived authenticity, and the diminishing sense of human connection in brand interactions (Singh & Singh, 2024; Valenzuela et al., 2024). These concerns become even more salient in retail environments, where experiential and affective components of customer experience play a critical role.

Despite international companies investing more in AI and automation, the level of implementation remains inconsistent. For example, only 4% of organizations in Portugal claim to have developed AI plans, despite many recognizing the potential power of AI (InCoDe 2030, 2022). At the same time, many remain hopeful, with most Portuguese people expecting AI to play a significant role in the next industrial revolution (The Portugal News, 2023). This contrast between enthusiasm and practical application highlights the need for a deeper understanding of how AI is perceived and experienced in real-world settings.

Previous studies have examined how AI impacts the operational aspects of service delivery; however, there is limited understanding of how these technologies influence the emotional and experiential aspects of the customer experience (CX), particularly in specific industries such as retail (Badet, 2021; Mariani & Borghi, 2024). Studies often overlook the varying reactions of different consumer segments to AI-enabled interactions, particularly in terms of trust, satisfaction, and engagement. Additionally, the potential negative effects of excessive automation, including reduced personalization and a sense of disconnection from humans, have not been thoroughly studied (Valenzuela et al., 2024). When replacing human interaction with machine interfaces, modern recommendation systems must strike a balance between performance and psychological comfort (Liu et al., 2024).

These systems do have observable functional benefits, but most of the research that has come before has focused on technical or operational outcomes (Valenzuela et al., 2024). In real-world retail environments, there is a significant lack of knowledge regarding the emotional experiences of consumers, the establishment or erosion of trust, and the influence of recommendation systems on perceptions.

This study addresses these gaps by focusing specifically on how AI-driven recommendation systems influence customer experience in the retail sector. Rather than evaluating AI broadly, the research concentrates on intelligent systems that personalize product suggestions and automate decision-making processes, and investigates how these affect consumers' sense of engagement, trust, and satisfaction in digital shopping environments.

To guide this analysis, the study poses the following research questions:

- How do intelligent recommendation systems based on AI influence customer satisfaction, engagement, and attitudes in the retail sector?
- What role do psychological and experiential factors—such as optimism, hedonic value, and perceived usefulness—play in shaping customer experience with AI-powered services?
- How do perceptions of ease of use and emotional appeal impact customers' acceptance and evaluation of automated retail technologies?

This study employs a quantitative approach to address these concerns. It achieves this by using a structured survey to examine constructs such as perceived utility, ease of use, personalization, hedonic value, optimism, AI anxiety, and customer experience. The results aim to help us better understand how recommendation systems impact the emotional and cognitive aspects of the customer experience (CX). They also provide retail brands with valuable insights on how to leverage intelligent automation without compromising authenticity or customer trust.

2. LITERATURE REVIEW

2.1. AUTOMATION AND ARTIFICIAL INTELLIGENCE

2.1.1. AUTOMATION

Automation involves leveraging technology to perform tasks with minimal human involvement, thereby improving efficiency, consistency, and scalability in service delivery. In sectors including retail, finance, and healthcare (Kovács & Keresztes, 2024), tools like self-service kiosks and robotic process automation (RPA) have demonstrated their value by reducing operational costs and streamlining workflows (Parasuraman et al., 1985; Syed et al., 2020). The Professional Services Automation (PSA) segment, for example, is projected to grow at an annual rate of 11.42% between 2024 and 2029 (Mordor Intelligence, 2023).

Although automation facilitates uniformity and process optimization, it frequently lacks the adaptability and emotional sensitivity necessary to satisfy changing consumer expectations (Miremedi et al., 2016). As customer experience (CX) evolves to require more personalized and context-sensitive interactions, relying solely on traditional automation proves inadequate. This constraint has spurred the development of more sophisticated, adaptive technologies, such as artificial intelligence, which can augment and enhance automation.

2.1.2. ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) has many definitions and purposes. According to the European Commission, (2018), AI systems are designed to perceive their environment and act autonomously to achieve specific objectives. AI expands the capabilities of automation by introducing adaptability, learning, and real-time decision-making. In customer-facing applications, AI is widely utilized for tasks such as dynamic product recommendations, sentiment analysis, pattern identification, and intelligent customer support, enabling the personalization of interactions and enhancement of engagement (Huang & Rust, 2018; Prentice et al., 2020). Companies such as Amazon and Netflix demonstrate the effectiveness of AI in delivering highly personalized experiences that adapt to individual user preferences. Nonetheless, incorporating AI into Customer Experience presents challenges concerning data privacy, algorithmic bias, and consumer trust (Gonçalves et al., 2023; Kaplan & Haenlein, 2019).

Artificial intelligence can be understood through three interconnected aspects: (1) mechanical AI, which automates everyday physical activities (such as robots for stocking shelves); (2) thinking AI, which improves analytical functions via diagnostic tools and decision-making algorithms; and (3) feeling AI, which replicates emotional and social interactions in applications like chatbots and virtual

assistants (Huang et al., 2025; Rita et al., 2025). These types of AI are becoming increasingly common across the customer journey, from product discovery to post-purchase assistance (Heinonen et al., 2013; Helkkula et al., 2012). Smart mirrors, virtual try-ons, and recommendation algorithms are among the technologies that have proven essential for enhancing customer engagement and satisfaction in both online and in-store shopping (Rangaswamy et al., 2020).

The convergence of automation and artificial intelligence presents considerable potential: automation enhances operational efficiency, while artificial intelligence introduces a dimension of personalization and contextual awareness in the retail industry. The connection between the physical and digital realms is effectively established (Grewal et al., 2020; Pantano & Viassone, 2014). Together, they enable firms to deliver scalable yet emotionally resonant service experiences. As emphasized by Wirtz et al. (2018) and Van Doorn et al. (2017), this synergy creates opportunities for businesses to strike a balance between consistency and human-centric engagement in customer journeys.

2.2. AI IN RETAIL

Retail has evolved into a highly dynamic environment shaped by digital transformation and shifting consumer expectations. In addition to its conventional role in distribution and logistics, the retail sector today serves as a multifaceted interaction arena where brands, technologies, and consumers intersect. The acceleration of this change is driven by the expansion of digital channels, data-driven services, and technology-mediated interfaces, which collectively transform the creation and experience of value (Ramos et al., 2021; Reinartz et al., 2019).

Artificial Intelligence (AI) is changing how companies interact with clients and provide value in the service sector. It is often thought of as being used in smart manufacturing and process optimization. However, its application in service settings, particularly in retail, has transformed the way people shop by making it more personalized, efficient, and user-friendly across all channels (Grewal et al., 2020; Huang & Rust, 2018). AI supports finding products and interacting with them after purchase, ensuring a consistent and relevant experience tailored to the situation (Heinonen et al., 2013; Helkkula et al., 2012). Smart mirrors and virtual try-on systems are examples of tools that combine the real and digital worlds. AI plays a crucial role in client engagement strategies (Rangaswamy et al., 2020).

To improve inventory management, logistics, and customer service through advanced technologies, retailers are progressively adopting AI-driven solutions. Virtual assistants, AI-driven recommendation systems, and automated checkout processes are increasingly prevalent tools designed to enhance consumer experiences (Guzman & Lewis, 2020; Hoyer et al., 2020).

A particularly relevant framework in this setting is the distinction between utilitarian and hedonic shopping values. Hedonic value includes pleasure, emotional stimulation, and rich experiences, whereas utilitarian value is associated with objective actions and functional efficiency (Babin et al., 1994; Jones et al., 2006). Both forms of value impact consumer satisfaction and loyalty, and their concurrent existence makes retail an optimal setting to investigate the influence of intelligent systems on both the rational and emotional aspects of the customer experience.

AI-driven recommendation systems are among the most significant applications of intelligent automation. These systems do more than suggest products. They utilize real-time consumer data and personalization algorithms to inform selection planning, promotional targeting, and customer retention strategies (Bleier et al., 2018; Chang & Park, 2024; Tyrväinen et al., 2020). These systems utilize real-time data on browsing history, purchasing trends, contextual information, and behavioral signals to create highly personalized experiences that cater to the needs of each consumer (Guzman & Lewis, 2020; Hoyer et al., 2020).

These improvements, on the other hand, have some challenges. The successful implementation of AI requires more than technical infrastructure, as it demands organizational alignment across people, processes, structure, and culture (Bleier et al., 2018; Chang & Park, 2024; Tyrväinen et al., 2020). An excessive reliance on automation may lead to a decrease in face-to-face communication, potentially harming emotional connection and the sense of authenticity in brand encounters (Valenzuela et al., 2024). Additionally, ethical issues such as data privacy, algorithmic bias, and a lack of transparency have given rise to the concept of Corporate Digital Responsibility (CDR). This means that companies should be transparent and honest when utilizing AI in customer-facing roles (Kaplan & Haenlein, 2019; Scarpi & Pantano, 2024).

In summary, the use of AI in service industries, particularly retail, enables the personalization of services based on data and enhances operational flexibility. However, to maximize its benefits, companies must strike a balance between automating operations and designing experiences that prioritize people and emotions.

2.3. OPTIMISM (OP)

Parasuraman (2000) defines optimism as a fundamental component of technology readiness, which is the positive conviction of an individual that technology can produce advantageous results, including increased efficiency, flexibility, and control in daily activities. This attitude suggests that people

generally believe technology can improve their lives and help them achieve their personal or professional goals.

In the context of AI-driven recommendation systems, optimism facilitates the interaction between users and intelligent tools by reducing initial resistance and promoting a more open and constructive approach. P Individuals who display a strong sense of optimism tend to expect favorable experiences with automated services, believing that these technologies will simplify tasks and enhance their satisfaction with purchases (Fu et al., 2023; Pillai et al., 2020).

Building on this perspective, optimism has a substantial positive impact on perceived ease of use (PEOU), even though its influence on perceived utility (PU) was not consistently supported across contexts (Nugroho & Fajar, 2017). Means optimistic users may approach technology with fewer psychological barriers, but they still critically evaluate its functional value, particularly in unfamiliar or mandatory contexts. This subtle difference suggests that optimism primarily benefits emotional openness and perceptions of usability, rather than direct evaluations of performance outcomes.

In online stores, where people commonly interact with AI systems indirectly or through built-in features such as product suggestions and smart filters, optimism can influence how people perceive these features, perceiving them as either helpful or intrusive (Tyrväinen et al., 2020). People who are optimistic are more to view algorithmic help as a means to gain power rather than a way to manipulate others.

Furthermore, Huang and Rust (2020) observe that optimism fosters an emotional bond with AI by fostering expectations of convenience and personalization. This aligns with the findings of Maduku et al. (2023), who discovered that optimism plays a significant role in fostering positive Attitudes Toward AI emerging technologies, especially in the presence of trust and transparency.

This study suggests that optimism has a favorable effect on both the perceived value and ease of use of AI recommendation systems in retail settings.

H1a: *Optimism (OP) positively influences Perceived Usefulness (PU).*

H1b: *Optimism (OP) positively influences Perceived Ease of Use (PEOU).*

H1c: *Optimism (OP) positively influences Attitude Toward AI (ATU).*

2.4. Hedonic Value (HV)

Hedonic value is the experiential and affective benefits that consumers derive from interacting with a product or service, in addition to its utilitarian function (Etemad-Sajadi & Ghachem, 2015). In the retail sector, this dimension is particularly significant, as purchasing is often driven by self-expression, novelty, and enjoyment rather than strict necessity (Bridges & Florsheim, 2008). Pleasure, excitement, and aesthetic satisfaction are some of the hedonic qualities that can be added to digital encounters to make them more memorable and emotionally engaging for customers (Ha & Jang, 2010).

Personalized, interactive, and context-aware technologies are employed in AI-powered retail environments to generate hedonic value. According to Kim et al. (2021), intelligent recommendation systems can generate emotional engagement by providing recommendations that correspond with consumers' browsing habits, attitudes, and preferences. These interactions transcend mere utility by offering a sense of comprehension and enjoyment, which are essential stimulants of hedonic satisfaction.

Customer loyalty is significantly influenced by hedonic experiences, particularly when consumers establish emotional connections with a brand through digital environments that are both visually appealing and pleasurable (Etemad-Sajadi & Ghachem, 2015). This emotional connection can be strengthened through AI personalization, where recommendations incorporate not only functional relevance but also stylistic and identity-based preferences.

According to Tyrväinen et al. (2020), personalization strategies that align with consumers' aesthetic preferences and identity expressions, such as style or tone, can enhance hedonic value by satisfying psychological requirements for self-relevance and uniqueness. This connection between emotion and identity makes hedonic value a powerful force in buying situations involving AI.

Hedonic value also affects how people perceive things, such as their value and ease of use. According to Kim et al. (2021), consumers' attitudes and intentions can be significantly influenced by positive emotive responses to AI systems, particularly when the technology is perceived as both beneficial and enjoyable. Retailers who incorporate emotionally appealing features into AI-driven systems are more likely to increase satisfaction, foster repeated use, and stimulate favorable word-of-mouth behavior.

In conclusion, hedonic value plays a crucial role in comprehending how consumers react to AI-driven recommendation systems, as it reflects the emotional richness of digital interactions. This research posits that hedonic value has a positive impact on the overall customer experience and attitudes toward AI technologies.

H2a: *Hedonic Value (HV) positively influences Perceived Usefulness (PU).*

H2b: *Hedonic Value (HV) positively influences Perceived Ease of Use (PEOU).*

H2c: *Hedonic Value (HV) positively influences Attitude Toward AI (ATU).*

2.5. TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM) is a fundamental paradigm that helps us understand how people adopt new technology in various contexts (Mustofa et al., 2025). Davis (1989) presented the well-known predecessor, TAM, which is grounded in underlying perceptions such as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), to help determine a user's Attitude Towards AI (ATU) and subsequently their behavioral intention and actual use behavior.

As identified by Venkatesh et al., (2003), evaluating user acceptance even before a prototype is completed helps a firm know in advance what might prevent adoption and the details of a user-centered design. With AI-enabled services, customer acceptance is primarily based on their perceived ease of use and perceived benefits of intelligence when dealing with intelligent systems. It is suggested that interactive natural-language interface formats, such as chatbots and virtual assistants, play an essential role in improving user-perceived ease and usefulness (Prentice et al., 2020).

2.5.1. PERCEIVED USEFULNESS

Perceived Usefulness (PU) is defined as the extent to which an individual believes that utilizing a specific technology would improve their performance or experience (Davis, 1989). In AI-driven customer-facing services, PU indicates consumers' belief that the system can effectively address problems, minimize waiting times, and provide tailored experiences.

Davis and Venkatesh (2000) assert that technology must demonstrate clear benefits during its earliest implementation stages to achieve widespread adoption. AI-driven recommendation systems in retail enhance perceived usefulness by aligning product suggestions with customer preferences, hence increasing relevance and engagement (Huang & Rust, 2018). This concept originates from evaluating the extent to which a system fulfills your requirements (Venkatesh & Davis, 2000).

Also, PU is important for how people feel and what they plan to do. Studies have demonstrated that people are more passionate and committed to technologies that they think are useful (Amsal et al., 2021; Pitardi & Marriott, 2021). This makes PU an even more important factor in forecasting not only consumption but also customer engagement in AI-mediated settings.

H3: *Perceived Usefulness (PU) positively influences Attitude Toward AI (ATU).*

H4: *Perceived Usefulness (PU) positively influences Customer Experience (CX).*

2.5.2. PERCEIVED EASE OF USE

Perceived Ease of Use (PEOU) refers to the degree to which a user expects a technology to be effortless (Davis, 1989). In AI-driven customer experience (CX), this includes user-friendly interfaces, intuitive chatbot conversations, and seamless digital interactions.

According to Prentice et al., (2020), AI systems with natural and conversational interfaces make people less resistant to automation by making it seem easier to learn. Research in areas such as smart technology and e-commerce has shown that the ease of use has a significant impact on whether people will utilize a product (Lee et al., 2023; Yousafzai et al., 2007).

H5: *Perceived Ease of Use (PEOU) positively influences Perceived Usefulness (PU).*

H6: *Perceived Ease of Use (PEOU) positively influences Attitude Toward AI (ATU).*

2.5.3. ATTITUDE TOWARD AI

Attitude Toward AI (ATU) is a measure of an individual's comprehensive assessment of technology, which can be either positive or negative (Davis, 1989). This attitude is a critical predictor of subsequent technology adoption and behavioural intention (Ajzen & Cote, 2008; Yousafzai et al., 2007).

Attitudes are shaped by trust, perceived ease of use (PEOU), and perceived usefulness (PU) in AI-driven automation (Yao et al., 2024). A favorable disposition enhances the inclination to adopt technology, but skepticism, often linked to perceived over-automation or insufficient transparency, may diminish involvement (Zhang et al., 2021). To foster positive sentiments, firms should prioritize user empowerment, emotional intelligence, and transparent communication in their AI design process.

Additionally, ATU is linked to the emotional connection between the user and technology. Research indicates that individuals with favourable perceptions of AI technologies are more likely to investigate and interact with these systems, particularly when they regard them as beneficial and user-friendly (Prentice et al., 2020; Santiago et al., 2024). In this sense, Attitude Toward AI serves as a bridge between functional beliefs, such as perceived usefulness and ease of use, and actual behavioural engagement (Venkatesh & Davis, 2000).

H7: *Attitude Toward AI (ATU) has a positive influence on Customer Experience (CX).*

2.6. CUSTOMER EXPERIENCE

Customer experience (CX) is widely recognized as a strategic factor in relationship marketing and value creation. It is the customer's internal and subjective reaction to a brand, whether it is direct or indirect (Tyrväinen et al., 2020). CX is further conceptualized by Lemon and Verhoef (2016) as the comprehensive perception that results from a sequence of cognitive, emotional, and behavioral responses that occur during the consumer journey.

The retail industry has prioritized physical environments as essential components of the consumer experience. Servicescape (Bitner, 1992) is a concept that emphasizes the impact of retail environments on consumer behavior through environmental signals. But the increasing growth of digital technologies is changing these touchpoints. AI systems are being increasingly integrated by retailers to enhance merchandising, streamline operations, and provide seamless omnichannel interactions (Bernoff, 2019). Automated checkouts, smart shelves, and real-time stock management are examples (Scarpi & Pantano, 2024). In contrast, retail still values the social and aesthetic aspects of shopping in stores (Alexander & Varley, 2025).

Although early research primarily concentrated on task-oriented and transactional components of CX (Verhoef et al., 2009), more recent studies have emphasized its affective and social dimensions. For example, in the fashion retail sector, the presence of purchasing companions has been demonstrated to influence purchase decisions and improve the hedonic quality of the experience (Borges et al., 2010). On the other hand, general retail focuses on practical benefits, such as speed, convenience, and efficiency, with fewer socially oriented touchpoints (Ylilehto et al., 2021).

CX is naturally complex and evolves in response to how people think, feel, sense, and act (Hsiao et al., 2020; Shi et al., 2025). As consumers interpret and re-interpret experiences based on personal context and evolving expectations, it also interacts closely with value perceptions (Heinonen et al., 2013; Helkkula et al., 2012). Consumer experience (CX) is frequently associated with self-expression, brand aesthetics, and hedonic value in retail, whereas it is influenced by price sensitivity, functionality, and availability in grocery or general retail (Balasubramanian et al., 2005; Batra & Ahtola, 1991).

As AI-powered recommendation systems become increasingly central to digital service environments, their influence on customer experience is becoming more evident. These systems personalize content, facilitate decision-making, and reduce friction across digital and mobile channels, enhancing both the

efficiency and emotional quality of the journey. Bleier et al. (2018) suggest that personalized suggestion information, when regarded as pertinent and timely, enhances satisfaction and strengthens emotional ties with the brand.

From a design perspective, fluidity across channels, enabled by AI recommendations and context-aware systems, contributes to a seamless experience. It has been demonstrated that smooth transitions across platforms, devices, and retail settings promote a cognitive state of "flow," which raises engagement and happiness in omnichannel contexts (McLean & Wilson, 2019).

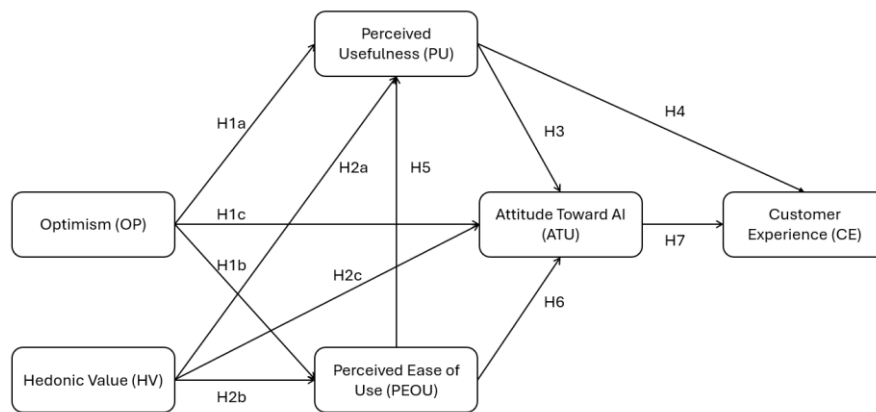
Moreover, CX in AI-mediated environments is shaped by users' trust in algorithmic decisions and their perceived control over personalization features. The integration of transparency, user autonomy, and contextual relevance has demonstrated an ability to amplify emotional reactions and confidence in AI systems, thereby enhancing the overall experience (Singh & Singh, 2024; Valenzuela et al., 2024).

Finally, CX extends beyond the moment of transaction. According to experiential consumption theory, customers co-create meaning through their experiences across multiple timeframes—before, during, and after consumption (Cova & Carú, 2007; Helkkula & Dube, 2015). This non-linear understanding reinforces the need to examine CX holistically, considering both functional and symbolic dimensions, especially in AI-enhanced environments where digital interactions replace or complement human service.

3. METHODOLOGY

As illustrated by previous literature, customer responses to AI-powered services are shaped by both cognitive evaluations and emotional predispositions. Accordingly, this study proposes an integrated model that combines constructs from the Technology Acceptance Model (TAM) with psychological and experiential factors—including Optimism, AI Anxiety, Hedonic Value, and Personalization. The model aims to examine how these dimensions influence consumers’ overall customer experience (CX) with intelligent recommendation systems in the retail context. Figure 1 presents the conceptual model, which was developed to identify which drivers are most decisive in shaping trust, engagement, and satisfaction in AI-mediated environments.

Figure 1 - Conceptual Model



3.1. MEASURES

The measurement items for each construct were applied to AI-powered recommender systems in an online retail context, utilizing prior validated scales to adapt them. All constructs were measured by reflective multi-item scales with responses recorded on a seven-point Likert scale (1 = Totally Disagree to 7 = Totally Agree). More explicitly, AI Personalization items were derived from Tyrväinen et al. (2020), while the hedonic value construct operationalization was following Ghachem and Etemad-Sajadi (2015). Optimism items came from Fu et al. (2023) and Perceived Ease of Use from Maduku et al. (2023). The Perceived Usefulness scale was adapted from Kasilingam (2020), and AI Anxiety was derived from Huang and Li (2020). Attitudes toward AI were measured using items adapted from Tiago et al. (2024), and Customer Experience was assessed using items from Bawack et al. (2021).

A full list of the adapted measurement items may be found in Appendix 1. The survey was again pre-tested for clarity and content validity prior to full deployment.

3.2. PARTICIPANTS

Data were collected from May 2025 to June 2025 using the Qualtrics online platform and distributed across various social media platforms, including Instagram, WhatsApp, and LinkedIn. Resulting in a total of 431 responses and 300 valid responses. Respondents who willingly agreed to participate were required to confirm their agreement by clicking the “Agree” button on a starting page that described the purpose of the study. Then, participants were asked to report their perceptions and attitudes toward AI-based recommendation systems based on their awareness or any level of prior exposure, including indirect interactions, such as encountering personalized product suggestions or chatbot interfaces while browsing in digital commerce environments.

Females were more strongly represented in the sample (60.7%), and nearly half of the respondents were between 18 and 24 years old (47.7%). Detailed statistics are reported in Table 1.

Upon analyzing participant behavior, 105 respondents (35%) expressed a preference for online purchasing, while 65% favored buying at physical retail establishments. This indicates a sustained customer inclination for the tactile experience of trying on apparel and engaging with things physically. Moreover, only 114 participants indicated any engagement with automation systems, of which 54 were people who favored online purchasing. This signifies a favorable correlation between exposure to automated technology and a preference for digital retail settings, underscoring the potential impact of intelligent systems on consumer purchasing behavior.

Table 1 - Demographic profile of respondents

Characteristics	Attribute	Frequency	Percentage (%)
Gender	Female	182	60,7%
	Male	118	39,3%
	Others	0	0%
Age	18 – 24	143	47,7%
	25 - 34	101	33,7%
	35 - 44	26	8,7%
	45 – 54	21	7%

	+55	9	3%
Education	Basic School	50	16,6%
	High School	131	43,7%
	Bachelor's degree	98	32,7%
	Master's degree	12	4%
	Doctoral degree	11	3,7%
	Other	0	0%
Occupation	Student	67	22,3%
	Worker	190	63,3%
	Self-Worker	29	9,7%
	Homemaker	1	0,33%
	Unemployed	11	3,7%
	Retired	2	0,7%

3.3. DATA ANALYSIS

To evaluate the structural relationships among the latent constructs, this study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS version 4.1.1.4. The structural model was tested using SmartPLS, employing standard estimation procedures that included the analysis of path coefficients, coefficients of determination (R^2), and predictive relevance indicators (Q^2) to assess the model's explanatory power and robustness. The significance of the estimated path coefficients was determined through bootstrapping with 5,000 resamples, in line with Hair et al. (2017).

AI Anxiety (AIA) and AI Personalization (AIP) were excluded from the final model due to low explanatory power and non-significant effects, indicating that these variables did not have a direct impact on customer experience in this context. Additionally, several measurement items, such as PU5, OP5, CX1, CX4, CX5, and CX10, were removed during the model refinement process due to weak factor loadings or insufficient contribution to construct reliability.

4. RESULTS

4.1. RELIABILITY AND VALIDITY OF MEASURES

The evaluation of the measurement model commences with Table 2, which presents the descriptive statistics for all observed items. The mean values range from 3.47 to 5.26, suggesting a strong inclination among respondents towards favourable assessments of the constructs. Standard deviations range from 1.10 to 1.55, indicating a sufficient degree of diversity in answers. The skewness and kurtosis values remained within acceptable thresholds. All skewness values were below 3.0, and kurtosis values were below 10.0, suggesting no major deviations from normality (Kline, 2015). While partial least squares structural equation modelling does not necessitate multivariate normality, the nearly symmetric and mesokurtic distribution of item responses enhances the robustness and interpretability of the findings (Hair et al., 2017).

Table 2 - Descriptive Statistics

Name	Mean	Median	Standard deviation	Excess kurtosis
HV_1	4.883	5.000	1.193	0.839
HV_2	4.453	4.000	1.384	0.321
OP_1	4.480	5.000	1.345	-0.213
OP_2	5.257	5.000	1.267	1.279
OP_3	4.433	5.000	1.553	-0.512
OP_4	4.840	5.000	1.349	0.548
OP_5	4.123	4.000	1.617	-0.694
PU_3	4.113	4.000	1.435	-0.505
PU_1	4.657	5.000	1.402	0.423
PU_5	4.627	5.000	1.454	-0.086
PU_4	4.333	4.000	1.450	-0.513
PU_2	4.687	5.000	1.468	-0.133
PEOU_1	4.707	5.000	1.257	0.590
PEOU_2	4.390	5.000	1.514	-0.689
PEOU_3	4.437	4.000	1.451	-0.455
PEOU_4	5.037	5.000	1.289	0.943
ATU_1	4.023	4.000	1.365	-0.302
ATU_2	3.377	3.000	1.493	-0.804
ATU_3	4.593	5.000	1.433	-0.013
ATU_4	4.147	4.000	1.414	-0.216
ATU_5	4.087	4.000	1.494	-0.482
CX_1	4.497	5.000	1.453	-0.060
CX_2	4.487	5.000	1.455	-0.057
CX_3	3.567	4.000	1.534	-0.845
CX_4	4.197	4.000	1.483	-0.420
CX_5	4.333	5.000	1.515	-0.273
CX_6	4.113	4.000	1.433	-0.256
CX_7	4.220	4.000	1.494	-0.486
CX_8	4.300	4.000	1.502	-0.456

CX_9	4.107	4.000	1.484	-0.557
CX_10	4.853	5.000	1.542	0.186

Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

As shown in Table 3, the outer loadings indicate that all items are strongly associated with their respective constructs, supporting the internal consistency of the measurement model. Moreover, each item loads more highly on its assigned construct than on any of the others, confirming that the constructs are empirically distinct from one another. This dual pattern of strong within-construct associations and weaker cross-construct correlations provides evidence of both convergent and discriminant validity, as outlined by Hair et al. (2017).

Table 3 - Convergent Validity

Item	Outer Loading	ATU	CE	HV	OP	PEOU	PU
ATU_1	0.784	0.784	0.603	0.5	0.599	0.543	0.612
ATU_2	0.789	0.789	0.628	0.464	0.577	0.382	0.536
ATU_3	0.804	0.804	0.576	0.585	0.619	0.519	0.583
ATU_4	0.902	0.902	0.657	0.597	0.609	0.518	0.661
ATU_5	0.912	0.912	0.683	0.617	0.639	0.528	0.68
CX_2	0.791	0.651	0.791	0.457	0.589	0.502	0.771
CX_3	0.75	0.577	0.75	0.339	0.487	0.349	0.531
CX_6	0.863	0.613	0.863	0.423	0.568	0.434	0.631
CX_7	0.842	0.62	0.842	0.449	0.557	0.41	0.647
CX_8	0.8	0.564	0.8	0.426	0.504	0.399	0.509
CX_9	0.835	0.627	0.835	0.426	0.509	0.391	0.558
HV_1	0.931	0.626	0.477	0.931	0.581	0.504	0.483
HV_2	0.919	0.594	0.483	0.919	0.506	0.469	0.43
OP_1	0.849	0.646	0.56	0.537	0.849	0.479	0.547
OP_2	0.807	0.551	0.47	0.478	0.807	0.426	0.586
OP_3	0.823	0.61	0.58	0.465	0.823	0.389	0.572
OP_4	0.889	0.633	0.615	0.503	0.889	0.45	0.684
PEOU_1	0.855	0.573	0.508	0.512	0.519	0.855	0.524
PEOU_2	0.703	0.348	0.252	0.298	0.27	0.703	0.333
PEOU_3	0.845	0.517	0.433	0.433	0.455	0.845	0.407
PEOU_4	0.811	0.435	0.412	0.417	0.374	0.811	0.395
PU_1	0.853	0.682	0.696	0.484	0.669	0.476	0.853
PU_2	0.848	0.584	0.634	0.412	0.526	0.509	0.848
PU_3	0.852	0.596	0.603	0.383	0.612	0.387	0.852

PU_4	0.906	0.669	0.678	0.425	0.641	0.443	0.906
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Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

Reliability and validity assessment results for the measurement model are shown in Table 2. All latent variables showed an excellent composite reliability, indicating internal consistency and stability in the measurement of the constructs. Furthermore, Cronbach's alphas were above 0.70, providing additional evidence of scale reliability (Hair et al., 2017).

Table 4 - Reliability and validity of constructs

Construct	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	Average variance extracted (AVE)
ATU	0,894	0,899	0,923	0,706
CX	0,898	0,902	0,922	0,663
HV	0,831	0,834	0,922	0,855
OP	0,863	0,867	0,907	0,710
PEOU	0,821	0,848	0,881	0,649
PU	0,888	0,891	0,922	0,749

Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

Convergent validity was ascertained through indicator loadings and average variance extracted (AVE). An indicator shares a bigger proportion of variance with its construct when convergent validity is supported. All retained items had loadings above 0.70, while AVE values were above 0.50, indicating that the constructs account for at least half of the variance in their respective indicators (Fornell & Larcker, 1981).

Table 5 - Heterotrait-Monotrait Ratio (HTMT) Matrix

Construct	ATU	CE	HV	OP	PEOU	PU
ATU						
CX	0,835					
HV	0,764	0,598				
OP	0,826	0,746	0,694			
PEOU	0,677	0,574	0,622	0,596		
PU	0,820	0,834	0,572	0,807	0,603	

Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

Two complementary approaches were employed to assess discriminant validity. Firstly, the Fornell-Larcker criterion was used, in which the square root of a construct's AVE must be compared with its correlations with other constructs. In all cases, the diagonal values in the correlation matrix exceeded the inter-construct correlations, indicating that the constructs are empirically distinct.

Table 6 - Fornell-Larcker criterion for discriminant

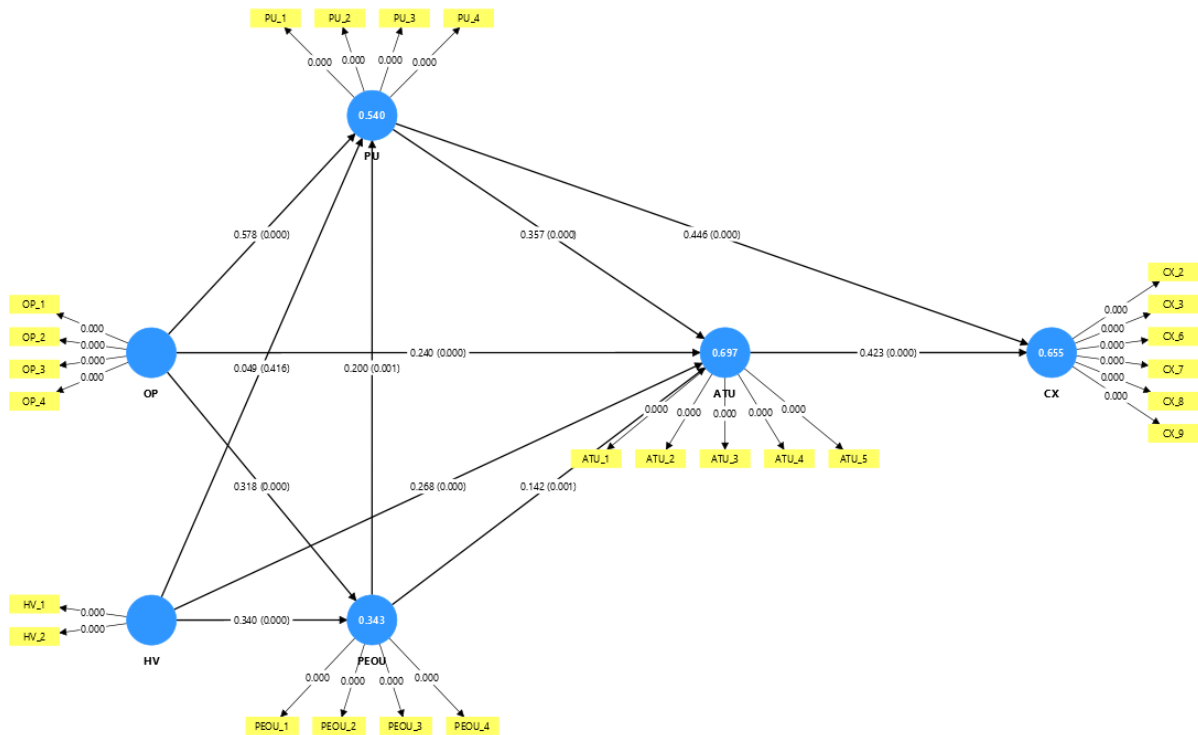
Construct	ATU	CE	HV	OP	PEOU	PU
ATU	0,840					
CX	0,750	0,814				
HV	0,660	0,519	0,925			
OP	0,725	0,662	0,589	0,843		
PEOU	0,594	0,513	0,527	0,518	0,806	
PU	0,734	0,757	0,494	0,710	0,525	0,865

Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

4.2. STRUCTURAL MODEL EVALUATION

The structural model was evaluated using standard PLS-SEM procedures, including model fit, explanatory power (R^2), path coefficients (β), effect sizes (f^2), and predictive relevance (Q^2), following Hair et al. (2017) guidelines. The Standardized Root Mean Square Residual (SRMR) was 0.064, which is below the recommended value of 0.08 (Henseler et al., 2011), indicating a good overall model fit.

Figure 2 - Structural Model



Note: Values shown on arrows represent path coefficients (β), with p-values in parentheses; HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

By using bootstrapping, the resulting path coefficients, *t*-statistics, *p*-values, and 95% bias-corrected confidence intervals are presented in Table 5. Most hypothesized relationships were statistically significant ($p < 0.05$), with confidence intervals that did not include zero, thus confirming the robustness of the proposed model. Only the path from Hedonic Value (HV) to Perceived Usefulness (PU) was not significant ($\beta = 0.049$, $t = 0.813$, $p = 0.416$; CI [-0.070; 0.163]), indicating a weak or absent direct effect in this context.

Table 7 - PLS-SEM Bootstrapping Results

Path	β (Original Sample)	Sample Mean (M)	Standard Deviation (STDEV)	T-value	P-value	CI Lower (2.5%)	CI Upper (97.5%)
ATU → CX	0.423	0.425	0.053	7.986	0.0	0.315	0.524
HV → ATU	0.268	0.269	0.048	5.603	0.0	0.173	0.36
HV → PEOU	0.34	0.336	0.072	4.732	0.0	0.194	0.476
HV → PU	0.049	0.046	0.06	0.813	0.416	-0.07	0.163
OP → ATU	0.24	0.238	0.056	4.309	0.0	0.14	0.359

OP → PEOU	0.318	0.322	0.062	5.098	0.0	0.194	0.439
OP → PU	0.578	0.577	0.051	11.421	0.0	0.474	0.669
PEOU → ATU	0.142	0.143	0.041	3.469	0.001	0.058	0.218
PEOU → PU	0.2	0.202	0.058	3.467	0.001	0.086	0.31
PU → ATU	0.357	0.356	0.054	6.546	0.0	0.251	0.466
PU → CE	0.446	0.445	0.056	8.013	0.0	0.328	0.55

Note: HV = Hedonic Value; OP = Optimism; PU = Perceived of Usefulness; PEOU = Perceived Ease of Use; ATU = Attitude Toward AI; CX = Customer Experience

In terms of explanatory power, the model demonstrated moderate to high levels of explained variance. Specifically, Customer Experience (CE) was explained at $R^2 = 0.655$, Attitude Toward AI (ATU) was explained at $R^2 = 0.697$, and Perceived Usefulness (PU) was explained at $R^2 = 0.540$, which are greater than the 0.50 threshold recommended by Hair et al. (2019) and indicate high explanatory relevance for the model. On the other hand, Perceived Ease of Use (PEOU) produced R^2 values of 0.343, respectively. Although not as high, these values are acceptable in exploratory models and suggest that additional predictors may be necessary to adequately explain these constructs (Chin, 1998; Venkatesh & Davis, 2000).

The path coefficient analysis confirmed most of the hypothesized relationships proposed in the conceptual model. Optimism (OP) was a strong and significant predictor of PU ($\beta = 0.578$, $p < 0.001$), PEOU ($\beta = 0.318$, $p = 0.001$), and ATU ($\beta = 0.240$, $p = 0.047$), supporting H1a, H1b, and H1c. These findings indicate that individuals with a positive predisposition toward technology tend to evaluate AI systems as more useful, intuitive, and appealing.

Hedonic Value (HV) had a significant effect on PEOU ($\beta = 0.340$, $p = 0.002$), supporting H2b. However, its impact on PU ($\beta = 0.049$, $p = 0.065$) and ATU ($\beta = 0.268$, $p = 0.560$) was not statistically significant, meaning that H2a and H2c are not supported. These results suggest that while emotional engagement enhances perceived ease of use, it does not directly shape perceptions of usefulness or user attitude in this context.

Perceived Ease of Use (PEOU) had a positive influence on ATU ($\beta = 0.142$, $p = 0.002$), supporting H6. However, its effect on PU ($\beta = 0.200$, $p = 0.429$) was not statistically significant. Thus, H5 is not supported. This implies that ease of use alone may not be a decisive factor in how useful consumers perceive AI systems to be, particularly in more advanced or automated environments.

Perceived Usefulness (PU) significantly predicted both Attitude Toward AI (ATU) ($\beta = 0.357$, $p < 0.001$) and Continuance Experience (CX) ($\beta = 0.446$, $p < 0.001$), hence corroborating H3 and H4, respectively. These findings confirm the fundamental premise of the Technology Acceptance Model (TAM), which posits that perceived utility is crucial in fostering favorable attitudes and improving user experience (Davis, 1989; Venkatesh et al., 2003).

Table 8 - Path coefficients

Hypotheses	Path Coefficients (β)	p-value
H1a	0,578	0,0
H1b	0,318	0,001
H1c	0,240	0,047
H2a	0,049	0,065
H2b	0,34	0,002
H2c	0,268	0,56
H3	0,357	0,0
H4	0,446	0,0
H5	0,200	0,429
H6	0,142	0,002
H7	0,423	0,0

Finally, ATU showed a strong positive effect on CE ($\beta = 0.423$, $p < 0.001$), confirming H7 and highlighting its mediating role between cognitive evaluations and experiential outcomes. This supports the idea that attitudes toward AI systems translate into more favorable customer experiences.

The effect sizes (f^2) for PU \rightarrow CX and PU \rightarrow ATU were moderate to considerable, signifying that perceived utility significantly influences both attitudes and experiences. The impacts of PEOU, OP, and HV were little to moderate, aligning with Cohen's (1988) f^2 interpretation standards. These findings underscore the crucial yet supplementary role of usability and emotional predispositions in technology acceptance.

Finally, the Q^2 values for CX and ATU were positive, validating the model's predictive significance for essential outcome components (Hair et al., 2017). These findings substantiate the extended TAM framework utilized in this study, demonstrating that both cognitive evaluations (e.g., perceived usefulness, ease of use) and emotional predispositions (e.g., optimism, hedonic value) significantly affect attitudes and customer experiences in AI-mediated retail settings.

Table 9 - Verification of hypothesis

Hypotheses	Result
H1a - Optimism positively influences Perceived Usefulness.	Supported
H1b - Optimism positively influences Perceived Ease of Use.	Supported
H1c - Optimism positively influences Attitude Toward AI.	Supported
H2a - Hedonic Value positively influences Perceived Usefulness.	Not supported
H2b - Hedonic Value positively influences Perceived Ease of Use.	Supported
H2c - Hedonic Value positively influences Attitude Toward AI.	Not supported
H3 - Perceived Usefulness positively influences Attitude Toward AI.	Supported
H4 - Perceived Usefulness positively influences Customer Experience.	Supported
H5 - Perceived Ease of Use positively influences Perceived Usefulness.	Not supported
H6 - Perceived Ease of Use positively influences Attitude Toward AI.	Supported
H7 - Attitude Toward AI has a positive influence on Customer Experience.	Supported

4.3. COMMON METHOD BIAS

Since all constructs in the model, including cognitive (PU, PEOU), emotional (HV), dispositional (OP), and experiential (CX), were measured using self-reported responses in a single questionnaire, it was crucial to evaluate the possible influence of Common Method Bias (CMB) on the reliability of the results.

To reduce this risk, both statistical and procedural measures were implemented. Collinearity was statistically evaluated using the entire collinearity test proposed by Kock (2015), which examines both vertical and lateral collinearity using Variance Inflation Factors (VIFs) for all indicators. Consistent with Hair et al. (2017), elements exhibiting VIF values exceeding five were eliminated to guarantee a robust model estimate. All maintained components demonstrated acceptable VIF values (varying from 1.45 to 4.44), confirming the absence of multicollinearity and suggesting that common method bias is unlikely to jeopardize the structural estimates.

Various approaches were employed throughout the construction of the questionnaire to reduce method bias, including randomizing item order, separating constructs into separate blocks, and employing diverse response phrasings. These solutions reduced response consistency issues and improved the dependability of the data gathered. Statistical and procedural protections collectively

ensure that common method bias was sufficiently mitigated in the evaluation of the expanded TAM model utilized for AI-based recommendation systems.

5. DISCUSSION

This study examined the psychological and technological influences on users' perceptions and experiences using AI-driven recommendation systems in the retail industry. By augmenting the Technology Acceptance Model (TAM) to incorporate emotional (Hedonic Value), dispositional (Optimism), and experiential (consumer Experience) variables, the results provide a multifaceted perspective on the impact of intelligent technologies on consumer contact and engagement.

This discovery was the essential mediating function of Perceived Usefulness (PU), substantially predicted both Attitude Toward AI (ATU) and Customer Experience (CX), supporting the original Technology Acceptance Model (TAM) assertion that perceptions of utility are fundamental to technology acceptance (Davis, 1989; Venkatesh & Davis, 2000). This aligns with the findings of Kasilingam (2020) and Tyrväinen et al. (2020), which suggest that personalization and problem-solving abilities in AI-enhanced systems enhance users' confidence in the system's value, resulting in improved attitudinal and experiential outcomes.

Perceived Ease of Use (PEOU) showed an indirect yet significant impact. Although its direct effect on CX was not substantiated, PEOU had a considerable influence on PU and ATU. This corroborates the theoretical framework presented by Venkatesh et al. (2003), which posits that perceived ease of use indirectly promotes behavioral engagement by enhancing perceptions of usefulness. Furthermore, this aligns with Prentice et al. (2020), who noted that interfaces, such as chatbots and voice assistants, enhance user comfort and familiarity. The lack of a direct correlation between Perceived Ease of Use (PEOU) and Customer Experience (CX) indicates that usability alone does not adequately influence experiential quality, in contrast to research such as McLean and Wilson (2019), which emphasized the importance of seamless experiences in fostering cognitive flow in omnichannel retail.

Regarding Optimism (OP), the results confirmed its strong effect on both PU and PEOU, reinforcing its function as a psychological enabler. This finding is consistent with the technology readiness framework proposed by Parasuraman (2000) and the results of Fu et al. (2023), which identified optimism as a key antecedent of openness to intelligent automation. Optimistic users generally engage with AI systems with diminished psychological barriers, viewing them as more advantageous and user-friendly, a finding corroborated by Fu et al., 2023 in online service contexts.

Perceived Ease of Use (PEOU). This substantiates the assertion by Kim et al. (2021) that emotionally engaged recommendation experiences diminish friction and enhance the impression of comfort. However, its non-significant effects on PU and ATU indicate that emotional appeal alone may not be enough to influence perceived utility or adoption intent. These results contrast with studies such as

Etemad-Sajadi & Ghachem (2015) and Tyrväinen et al. (2020), which emphasized the role of identity-aligned personalization in building favorable perceptions. A plausible explanation is that in practical retail environments, users prioritize functional relevance over hedonic stimulation, especially when navigating utilitarian tasks.

The constructs AI Anxiety (AIA) and AI Personalization (AIP) were omitted from the final model due to their low explanatory power and insignificant correlations with CX and ATU. This discovery contrasts with existing literature highlighting the significance of trust and control in influencing AI interactions (e.g., Kaplan & Haenlein, 2019; Scarpi & Pantano, 2024). A plausible explanation is that, within the examined retail setting, consumers do not regard AI personalization as intrusive, nor do they encounter considerable worry regarding the system's operation. Future studies may investigate whether these impacts are influenced by variables such as transparency or perceived control, or whether they gain significance in high-sensitivity sectors, such as healthcare or financial services.

Finally, Attitude Toward AI (ATU) emerged as a robust predictor of Customer Experience (CX), reinforcing the idea that user attitudes not only drive usage intention but also enhance affective and experiential engagement. This aligns with the view of Yousafzai et al. (2007) and Prentice et al. (2020), who found that attitudes serve as a bridge between beliefs and emotional responses. Moreover, this finding expands the traditional TAM scope beyond adoption behavior to include outcomes related to customer satisfaction and brand connection, as argued by Santiago et al. (2024) and Singh & Singh (2024).

This study offers empirical evidence that cognitive and emotional mechanisms collaboratively influence customer responses to AI systems in retail. Although perceived value is the primary motivator, elements such as optimism and emotional involvement significantly enhance perceived ease and the whole experience. These observations underscore the need for creating AI solutions that are not only efficient and intelligent but also intuitive and emotionally responsive to user needs.

6. CONCLUSIONS

This study investigated user perceptions and experiences of AI-driven recommendation systems in retail, enhancing the Technology Acceptance Model (TAM) with emotive (Hedonic Value), dispositional (Optimism), and experiential (Customer Experience) components. The validated model offers a comprehensive understanding of how cognitive assessments and emotional elements interact to influence attitudes and overall user experiences.

The results confirm that Perceived Usefulness has a primary influence on both Attitude Toward AI and Customer Experience, underscoring the crucial importance of functional advantages in technology adoption. Furthermore, optimism surfaced as a significant psychological precursor, shaping users' judgments of both usability and system value. Although Hedonic Value made a minor contribution, primarily by enhancing perceptions of usability, it still highlights the importance of emotionally engaging interfaces in user evaluations.

The study methodologically illustrates the appropriate use of PLS-SEM for verifying complex models that encompass both cognitive and affective components. The modified measurement tools demonstrated reliability and validity in the setting of intelligent recommendation systems.

This research offers practical assistance for designing AI-driven recommendation systems in retail. It underscores the necessity to focus not only on utility and usability but also on user expectations, emotional impact, and cognitive ease. Retailers seeking to adopt intelligent automation should prioritize interfaces that are intuitive, transparent, and engaging, while preserving customer trust and personalization without being intrusive.

The study, while contributory, is constrained by its cross-sectional methodology, reliance on self-reported variables, and sector-specific focus. Future studies should employ longitudinal and mixed-method approaches to evaluate the progression of user perceptions over time and in various circumstances.

In conclusion, user adoption of intelligent recommendation systems is not exclusively dictated by technological functionality. It originates from the interaction of intellectual assessment, emotional involvement, and personal inclinations. As AI progressively revolutionizes customer-facing services, its efficacy will hinge not only on its intelligence but also on its profound comprehension and reverence for human values.

6.1. THEORETICAL CONTRIBUTIONS

This study enhances technology acceptance theory by presenting and validating an extended model that incorporates cognitive, affective, and dispositional characteristics within the framework of AI-powered recommendation systems.

This study enriches the traditional TAM by shifting its focus away from behavioural intention, instead attempting to make the acceptance theory match the new concept of engagement and enjoyment within the realm of digital retail settings, with customer experience being the highest priority.

The incorporation of Optimism as a consistent, trait-level predictor of system perceptions provides a dispositional viewpoint into acceptance models, reinforcing recent appeals for the integration of personality-based elements into consumer technology frameworks. The confirmation of Hedonic Value as a determinant of usability perception establishes a connection between affective involvement and cognitive evaluation, hypothesizing the relationship between affective product experience design and user acceptance factors.

The elimination of AI Anxiety and AI Personalization, owing to their insignificance, underscores the relevance of contextual and boundary factors in the generalizability of models. This encourages additional theoretical investigation into the timing and applicability of these structures, especially in industries where automation is standard or personalization is anticipated.

Collectively, these contributions provide a more comprehensive and psychologically informed framework for AI acceptance, expanding the theoretical perspective used to assess intelligent service technologies.

6.2. PRACTICAL IMPLICATIONS

This study offers multiple practical insights for designing, implementing, and communicating intelligent recommendation systems in customer-oriented settings. The significant influence of Perceived Usefulness (PU) on both Attitude Toward AI (ATU) and Customer Experience (CX) underscores the need for creating systems that effectively support users in achieving their objectives.

Practitioners must prioritize functionalities that provide evident usefulness, including precise and pertinent recommendations, transparent algorithmic reasoning, and decision-making support. To expedite adoption, these characteristics must be explicitly conveyed during onboarding and reinforced through interface design.

Second, the significant relationship between Perceived Ease of Use (PEOU) and both PU and ATU highlights usability as a strategic concern, particularly in early adoption phases. Interfaces must be intuitive, responsive, and cognitively efficient, thereby reducing effort and enhancing user confidence. To promote positive first impressions and sustained engagement, feedback loops must be clear, and navigation must be easy.

The influence of Optimism (OP) suggests that previous expectations and predispositions shape users' views of AI. Organizations might gain advantages from strategic communication initiatives that portray intelligent systems as supportive, empowering, and congruent with user values. Communications highlighting advantages such as convenience, customization, and user autonomy may particularly appeal to those who are inclined to perceive technology favorably.

Finally, the validation of Hedonic Value (HV) as a factor influencing perceived usability suggests that emotional engagement should not be overlooked. In addition to improving the user experience, systems that use visually appealing design, playful interaction components, or individualized indicators may also increase acceptance by making the interaction more pleasurable.

These findings indicate that optimizing AI-powered recommendation systems necessitates a balance of functional utility, usability, positive framing, and emotional resonance.

6.3. LIMITATIONS

The study offers both practical and theoretical insights into the implementation of intelligent recommendation systems, although several limitations must be acknowledged. The study employed a cross-sectional survey approach, which limited its capacity to establish causal inferences. Although PLS-SEM is adept for theory construction and predictive modeling, longitudinal or experimental methods are necessary to evaluate the temporal stability and causal direction of the observed connections.

Secondly, all dimensions were assessed using self-reported data, which is inherently vulnerable to biases, such as social desirability and CMB. Despite the implementation of procedural (e.g., item randomization) and statistical (e.g., collinearity checks) controls, future research could strengthen measurement validity by integrating survey data with behavioral metrics, usage logs, or multi-source assessments.

Third, the study focused on a specific form of AI interaction, recommendation systems in a retail context, which, while improving ecological validity, may limit the generalizability of findings to other

sectors or technologies. User perceptions and responses could vary depending on the domain, system maturity, or interaction complexity. Thus, applying the model to sector-specific use cases (e.g., healthcare, finance, education) is a promising avenue for future research.

Fourth, excluding some constructs from the final model due to low explanatory power. AI Personalization and AI Anxiety influence the results, as they do not have significant relationships with the outcome variables. The impact of the final results is due to a lack of significant relationships with the outcome variables. This could be attributed to measurement limitations or the absence of mediating variables that apply to them (e.g., trust, perceived intrusiveness). Future studies could use more context-sensitive operationalizations of these constructs or investigate their indirect effects in moderated or mediated models.

Fifth, this study did not conduct a multigroup analysis (MGA) to examine potential differences among customer groups (e.g., gender, age, or shopping preferences), despite using bootstrapping to estimate standard errors and test the significance of structural correlations. If structural relationships differ significantly between subgroups, failing to account for population heterogeneity may result in biased PLS-SEM results. This research concentrated on general consumer perceptions; however, subsequent studies should investigate the consistency of these effects across other user profiles (Sarstedt et al., 2011).

The sample was confined to a singular cultural and language setting, potentially impacting the external validity of the findings. Cultural attitudes on automation, experience with AI, and digital literacy may affect perceptions of utility, usability, and trustworthiness. Investigating varied people and markets might enhance the model's broader validation. The limitations specified do not negate the study's findings but rather point to strong areas for continued calibration and refinement of the model to enhance human–AI interaction knowledge.

6.4. FUTURE RESEARCH

To further develop and broaden our understanding of how users interact with intelligent recommendation systems, several research directions are suggested in light of the identified constraints.

Longitudinal research is recommended to investigate how user attitudes toward AI systems evolve. Perceived Usefulness and Attitude Toward AI are variables that may change due to increased exposure,

familiarity, or system enhancements. Temporal emphasis enables researchers to determine the stability and direction of acceptance, rather than being dependent on static measurements.

Secondly, subsequent research should investigate mediating and moderating mechanisms, mainly psychological and contextual elements that may indirectly affect user experience. Although certain variables, such as AI Anxiety and AI Personalization, may be insignificant in this study, they could still influence outcomes through intermediary factors like trust, perceived risk, or user control. Incorporating these principles may offer a more thorough understanding of how cognitive and emotional processes influence AI acceptance.

Third, the model could be improved by integrating external variables derived from comprehensive theoretical frameworks, such as social impact, reported delight, or algorithmic transparency. These dimensions have been recognized in pertinent literature as significant predictors of user acceptability, and their incorporation may enhance explanatory power, especially for components such as PU and PEOU, which produced modest R^2 values in this study.

The present study concentrated on a broad implementation of recommendation systems in the retail sector. Further study should evaluate the model within specific domains, such as healthcare, education, or financial services, and across various user segments, including generational, cultural, and professional categories. This would facilitate a more precise comprehension of whether the observed connections are context-dependent or universally applicable.

Future research should incorporate multigroup analysis (MGA) utilizing methodologies such as the permutation-based approach or the nonparametric confidence set method (Sarstedt et al., 2011). This would facilitate a more nuanced comprehension of the stability of the links identified in this study—specifically those among optimism, perceived usefulness, and customer experience—across various demographic or behavioral segments. This approach would enhance the external validity of the findings and reveal potential moderating effects of group participation.

Researchers are urged to employ mixed-method approaches to obtain more comprehensive and nuanced insights. The integration of quantitative modeling with qualitative interviews, user testing, or experience sampling may reveal motivational and emotional aspects that structured surveys could neglect. This methodological diversity would enhance a more human-centered and iterative comprehension of user interaction with AI-enabled devices.

By exploring these pathways, future research can enhance acceptance models and more effectively match AI system design with the changing expectations, demands, and behaviors of consumers.

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APPENDIX A - MEASUREMENT ITEMS BY CONSTRUCT

Construct	Construct Abbreviation	Item ID	Original item	Adapted item	Study
Hedonic Value	HV	HV1	The interaction with the virtual agent is pleasant	The interaction with AI recommendation systems is pleasant	Ghachem, L., Etemad-Sajadi, R., 2015
		HV2	The interaction with the virtual agent is funny	The interaction with AI recommendation systems is funny	
AI Personalization	AIP	AIP1	This retailer can provide me with personalized deals/ads that are tailored to my activity context.	AI recommendation systems can provide me with personalized deals/ads that are tailored to my activity context.	Tyrväinen et al., 2020
		AIP2	This retailer can provide me with more relevant promotional information that is tailored to my preferences or personal interests.	AI recommendation systems can provide me with more relevant promotional information that is tailored to my preferences or personal interests.	
		AIP3	This retailer can provide me with the kind of deals/ads that I might like.	AI recommendation systems can provide me with the kind of deals/ads that I might like.	
Optimism	OP	OP1	New online shopping technologies, like chatbots, assist in decent life quality.	New online shopping technologies, like AI recommendation systems, assist in decent life quality.	Fu et al., 2023
		OP2	New online shopping technologies, like chatbots, are convenient for people.	New online shopping technologies, like AI recommendation systems, are convenient for people.	
		OP3	New online shopping technologies, like chatbots, help people to manage their shopping properly.	New online shopping technologies, like AI recommendation systems, help people to manage their shopping properly.	
		OP4	New online shopping technologies, like chatbots, are helpful in making my life efficient and effective.	New online shopping technologies, like AI recommendation systems, are helpful in making my life efficient and effective.	
		OP5	I like new online shopping technologies, chatbots, as it provides more freedom to me while shopping online.	I like new online shopping technologies, AI recommendation systems, as it provides more freedom to me while shopping online.	
Perceived Ease of Use	PEOU	PEOU1	My interaction with this digital assistant is clear and understandable.	My interaction with AI recommendation systems is clear and understandable.	Maduku et al., 2023
		PEOU2	My interaction with this digital assistant does not require mental efforts.	My interaction with AI recommendation systems does not require mental efforts.	
		PEOU3	It is easy to use this digital assistant to do what I want it to do.	It is easy to use AI recommendation systems to do what I want it to do.	
		PEOU4	I find this digital assistant easy to use.	I find AI recommendation systems easy to use.	
Perceived Usefulness	PU	PU1	Chatbots for shopping will be useful to me.	AI recommendation systems for shopping will be useful to me.	Kasilingam, D. L., 2020
		PU2	Using chatbots for shopping will enable me to accomplish transactions quickly.	Using AI recommendation systems for shopping will enable me to accomplish transactions quickly.	
		PU3	Using chatbots for shopping will increase my productivity.	Using AI recommendation systems for shopping will increase my productivity.	
		PU4	Using chatbots for shopping will enhance my effectiveness.	Using AI recommendation systems for shopping will enhance my effectiveness.	
		PU5	Using chatbots for shopping would enable me to accomplish shopping tasks fast.	Using AI recommendation systems for shopping would enable me to accomplish shopping tasks fast.	
AI Anxiety	AIA	AIA1	I'm afraid that artificial intelligence (AI) will monitor my behavior.	I'm afraid that artificial intelligence (AI recommendation systems) will monitor my behavior.	Huang, J. Li, J., 2020

		AIA2	I'm worried that AI will collect too much of my personal information.	I'm worried that AI recommendation systems will collect too much of my personal information.	
		AIA3	AI's predictions of my preferences, such as well recommended ads or web pages, make me feel that my privacy is violated.	AI recommendation systems predictions of my preferences, such as well recommended ads or web pages, make me feel that my privacy is violated.	
		AIA4	I worry that humans have special feelings (such as love or adoration) for super AI .	I worry that humans have special feelings (such as love or adoration) for super AI recommendation systems.	
		AIA5	I am disturbed that AI can deceive (for example, enticing people to buy goods).	I am disturbed that AI recommendation systems can deceive (for example, enticing people to buy goods).	
Attitude Toward AI	ATU	ATU1	Technology makes everything work better.	AI recommendation systems makes everything work better.	Santiago et al., 2024
		ATU2	Technology is very important in life.	AI recommendation systems is very important in life.	
		ATU3	I am comfortable using new technologies.	I am comfortable using AI recommendation systems.	
		ATU4	I really enjoy using new technologies.	I really enjoy using AI recommendation systems.	
		ATU5	I am very motivated to use new technologies	I am very motivated to use AI recommendation systems	
Customer Experience	CX	CX1	My smart speaker helps me to accomplish my shopping tasks more quickly.	AI recommendation systems helps me to accomplish my shopping tasks more quickly.	Bawack et al., 2021
		CX2	My smart speaker makes it easier to complete my shopping tasks.	AI recommendation systems makes it easier to complete my shopping tasks.	
		CX3	My smart speaker helps me save money when it comes to shopping tasks.	AI recommendation systems helps me save money when it comes to shopping tasks.	
		CX4	My smart speaker improves my shopping performance.	AI recommendation systems improves my shopping performance.	
		CX5	My smart speaker enhances my shopping effectiveness.	AI recommendation systems enhances my shopping effectiveness.	
		CX6	My smart speaker helps me review and eliminate errors in my shopping tasks.	AI recommendation systems helps me review and eliminate errors in my shopping tasks.	
		CX7	My smart speaker helps me to meet my future shopping target.	AI recommendation systems helps me to meet my future shopping target.	
		CX8	My smart speaker helps me acquire new shopping knowledge.	AI recommendation systems helps me acquire new shopping knowledge.	
		CX9	My smart speaker helps me acquire new shopping skills.	AI recommendation systems helps me acquire new shopping skills.	
		CX10	My smart speaker helps me to come up with innovative shopping ideas.	AI recommendation systems helps me to come up with innovative shopping ideas.	

APPENDIX B - ETHICS COMMITTEE REPORT

This is to certify that

Project No.: **DDMKT2025-7-99707**

Project Title: **How is Artificial Intelligence and service automation influencing customer experience and customer engagement?**

Principal Researcher: **Lorena Crepaldi Oliveira Zanata**

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 7/9/2025.

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, 7/9/2025

NOVA IMS Ethics Committee

ethicscommittee@novaims.unl.pt

APPENDIX C - QUESTIONNAIRE

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Caro Participante,

O meu nome é Lorena Zanata e convido-o a participar neste inquérito, que está a ser realizado no âmbito da minha Tese de Mestrado em Data Driven Marketing, na NOVA IMS

Este estudo visa compreender como o sistema de recomendação inteligente afeta os sentimentos e interações dos clientes com as marcas.

Para participar, deverá ter 18 anos ou mais, independentemente de já ter utilizado esta tecnologia anteriormente. A participação levará aproximadamente 5 minutos, dependendo do tempo que demorar a responder a cada pergunta.

A participação é completamente voluntária e não envolve riscos. Pode interromper o inquérito a qualquer momento sem necessidade de justificar a sua decisão e não existem respostas certas ou erradas.

Todos os dados recolhidos serão mantidos de forma anónima e confidencial, sendo utilizados exclusivamente para fins académicos. Se tiver alguma dúvida, não hesite em contactar-me para: 20230208@novaims.unl.pt

Agradeço imenso o seu tempo e colaboração.
Lorena Zanata.



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Ao clicar em "Concordo em participar no estudo", confirma que foi informado sobre o seguinte:

- Deve ter 18 anos ou mais;
- A sua participação é voluntária e não envolve riscos;
- A informação que fornecer será tratada com a máxima privacidade e confidencialidade, sendo utilizada apenas para fins académicos.

Por favor, selecione a opção que corresponde ao seu consentimento para participar neste estudo:

Concordo em participar no estudo

Não concordo em participar no estudo



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Qual o seu gênero?

- Feminino
- Masculino
- Outros

Qual a sua faixa etária?

- < 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55+

Qual o seu nível de educação mais elevado completado?

- Ensino Básico
- Ensino Secundário
- Licenciatura
- Mestrado
- Doutoramento
- Outro

Qual a sua atividade profissional principal?

- Estudante
- Empregado
- Trabalhador independente
- Dona de casa
- Desempregado
- Reformado

Qual é a sua principal preferência de compras?

- Loja online
- Lojas físicas

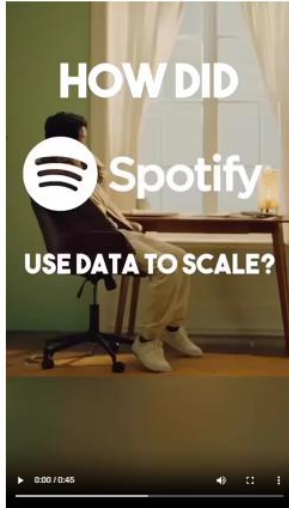
Já interagiu com algum sistema de recomendação inteligente enquanto fazia compras (ex: recomendações feitas por IA)?

- Sim
- Não



0% 100%

Por favor, analise cuidadosamente o seguinte vídeo, que ilustra como a inteligência artificial (IA) pode personalizar a sua interação com a marca.



0% 100%

Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	2. Discordo	3. Discordo parcialmente	4. Nem concordo nem discordo	5. Concordo parcialmente	6. Concordo	7. Concordo totalmente
O sistema de recomendação inteligente pode fornecer-me os tipos de ofertas/anúncios que eu poderia gostar.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente pode fornecer-me informações promocionais mais relevantes, adaptadas às minhas preferências ou interesses pessoais.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente pode fornecer-me ofertas/anúncios personalizados adaptados ao meu contexto de atividade.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



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Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	2. Discordo	3. Discordo parcialmente	4. Nem concordo nem discordo	5. Concordo parcialmente	6. Concordo	7. Concordo totalmente
A interação com os sistemas de recomendação inteligentes é agradável.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A interação com os sistemas de recomendação inteligentes é divertida.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	2. Discordo	3. Discordo parcialmente	4. Nem concordo nem discordo	5. Concordo parcialmente	6. Concordo	7. Concordo totalmente
Novas tecnologias de compras online, como os sistemas de recomendação inteligentes, contribuem para uma boa qualidade de vida.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Novas tecnologias de compras online, como os sistemas de recomendação inteligentes, são convenientes para as pessoas.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Novas tecnologias de compras online, como os sistemas de recomendação inteligentes, ajudam as pessoas a gerir melhor as suas compras.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Novas tecnologias de compras online, como os sistemas de recomendação inteligentes, são úteis para tomar a minha vida mais eficiente e eficaz.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Gosto das novas tecnologias de compras online, como os sistemas de recomendação inteligentes, pois proporcionam-me mais liberdade enquanto faço compras online.



0% 100%

Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

1. Discordo totalmente 2. Discordo parcialmente 3. Nem concordo nem discordo 4. Concordo parcialmente 5. Concordo totalmente

Terho receio de que o sistema de recomendação inteligente monitore o meu comportamento.

Estou preocupado que o sistema de recomendação inteligente coleccione demasiadas informações pessoais minhas.

As previsões feitas pelo sistema de recomendação inteligente sobre as minhas preferências, como anúncios ou páginas recomendadas, fazem-me sentir que a minha privacidade está a ser violada.

Sinto-me incomodado com o facto de o sistema de recomendação inteligente poder enganar (por exemplo, incluindo as pessoas a comprar produtos).



Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	2. Discordo	3. Discordo parcialmente	4. Nem concordo nem discordo	5. Concordo parcialmente	6. Concordo	7. Concordo totalmente
Usar sistemas de recomendação inteligentes para fazer compras aumentará a minha produtividade.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Usar sistemas de recomendação inteligentes para fazer compras será útil para mim.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Usar sistemas de recomendação inteligentes para fazer compras permitirá que eu complete as transações rapidamente.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Usar sistemas de recomendação inteligentes para fazer compras aumentará a minha eficiência.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Usar sistemas de recomendação inteligentes para fazer compras permitirá que eu realize tarefas de compras rapidamente.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com o sistema de recomendação inteligente é clara e compreensível.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com o sistema de recomendação inteligente não requer esforço mental.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
É fácil usar o sistema de recomendação inteligente para fazer o que eu quero que ele faça.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Eu acho o sistema de recomendação inteligente fácil de usar.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	Discordo	Discordo parcialmente	Nem concordo nem discordo	Concordo parcialmente	Concordo	7. Concordo totalmente
Os sistemas de recomendação inteligentes fazem com que tudo funcione melhor.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Os sistemas de recomendação inteligentes são muito importantes na vida.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sinto-me confortável ao utilizar sistemas de recomendação inteligentes.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gosto muito de utilizar sistemas de recomendação inteligentes.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Estou muito motivado(a) para utilizar sistemas de recomendação inteligentes.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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Com base no vídeo que acabou de ver e na sua própria experiência, indique o seu nível de concordância com as seguintes afirmações (1 = Discordo completamente e 7 = Concordo totalmente):

	1. Discordo totalmente	Discordo	Discordo parcialmente	Nem concordo nem discordo	Concordo parcialmente	Concordo	7. Concordo totalmente
O sistema de recomendação inteligente ajuda-me a realizar as minhas tarefas de compras mais rapidamente.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente facilita a conclusão das minhas tarefas de compras.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente ajuda-me a poupar dinheiro quando se trata de tarefas de compras.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente melhora o meu desempenho nas compras.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O sistema de recomendação inteligente melhora a minha eficácia nas compras.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

O sistema de recomendação inteligente ajuda-me a alcançar o meu objetivo de compras futuro.

O sistema de recomendação inteligente ajuda-me a adquirir novos conhecimentos sobre compras.

O sistema de recomendação inteligente ajuda-me a adquirir novas habilidades de compra.

O sistema de recomendação inteligente ajuda-me a ter novas ideias para as compras.



0% ————— 100%

We thank you for your time spent taking this survey.
Your response has been recorded.



NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa