Universidade do Minho
Escola de Economia, Gestão e Ciência Política

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The Impact of AI-Based Personalization on Consumer Experience, Trust, Satisfaction and Purchase Intention in E-Commerce

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Conducted under the supervision of:
Professora Doutora Cláudia Maria Neves Simões

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Submitting this final text feels like closing a massive door. This is not simply a master's thesis. To me, it stands as proof of resilience. The last few years brought a lot of personal growth, mixed with moments of very real frustration and doubt. I recognize that this achievement would not have been possible without the support of those around me, and I am sincerely grateful for the encouragement and guidance I have received throughout this journey.

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The Impact of AI-Based Personalization on Consumer Experience, Trust, Satisfaction and Purchase Intention in E-Commerce

Abstract

Bringing Artificial Intelligence (AI) into e-commerce platforms has totally rewritten the consumer experience, through personalized product recommendations. Despite the growing commercial relevance of AI-based personalization, its simultaneous effects on consumer experience, trust, and satisfaction, and the moderating role of privacy concerns remain insufficiently studied, particularly in the Portuguese market.

This research grounds its structural model in two established theories: the Stimulus-Organism-Response (S-O-R) framework and Privacy Calculus Theory. Together, they serve as the foundation for this study's structural model. The study examines how AI-driven personalization (stimulus) influences consumer experience, trust, and satisfaction (organism), which in turn drive purchase intention (response). As a moderating variable, privacy concerns are included. To investigate these relationships empirically, a structured online questionnaire was distributed, yielding 159 valid responses. The sample consisted exclusively of Portuguese consumers, who had made at least one purchase in the past twelve months on a platform featuring AI-based recommendations. Finally, for the statistical validation, the research applied Partial Least Squares Structural Equation Modelling (PLS-SEM) using the SmartPLS 4 software.

Empirical findings from this study clearly demonstrate the value of AI-based personalization, that has significant positive effects on consumer experience, satisfaction and trust. These internal states in turn significantly predict purchase intention. Satisfaction emerged as the strongest predictor of purchase intention, followed by consumer experience and trust. Contrary to what was hypothesized, privacy concerns did not significantly moderate the relationship between AI-based personalization and consumer experience or trust. This finding constitutes empirical evidence for the Privacy Paradox: despite reporting high levels of privacy concern, the item regarding unauthorized data use was the highest-rated item in the questionnaire, respondents' behavioral intentions remained unaffected, consistent with the Privacy Calculus Theory.

This study enriches the existing literature, providing empirical validation of the S-O-R framework in an AI-driven e-commerce context, by extending evidence of the Privacy Paradox

to the Portuguese market, and demonstrating the complementary mediating roles of experience, trust, and satisfaction simultaneously. From a managerial perspective, the findings highlight the strategic importance of investing in accurate, relevant, and transparent recommendation systems, while proactively managing privacy communication as a trust-building tool rather than a mere legal obligation.

Keywords: AI-based personalization; Consumer experience; E-commerce; PLS-SEM; Privacy concerns; Privacy Paradox; Purchase intention; Satisfaction; S-O-R framework; Trust.

O Impacto da Personalização Baseada em IA na Experiência, Confiança, Satisfação e Intenção de Compra do Consumidor no Comércio Eletrónico

Resumo

A integração da Inteligência Artificial (IA) nas plataformas de comércio eletrónico transformou profundamente a experiência de compra do consumidor, através de recomendações de produtos personalizadas. Apesar da crescente relevância comercial da personalização baseada em IA, os seus efeitos simultâneos sobre a experiência, a confiança e a satisfação do consumidor, bem como o papel moderador das preocupações com a privacidade permanecem insuficientemente estudados, em particular no mercado português.

Este estudo fundamenta o seu modelo estrutural em duas teorias consolidadas: o modelo Estímulo-Organismo-Resposta (S-O-R) e a Teoria do Cálculo da Privacidade. Em conjunto, estas teorias constituem a base conceptual do modelo proposto. O estudo examina de que forma a personalização baseada em IA (estímulo) influencia a experiência, a confiança e a satisfação do consumidor (organismo), que por sua vez determinam a intenção de compra (resposta). As preocupações com a privacidade são incorporadas como variável moderadora. Para testar empiricamente estas relações, foi distribuído um questionário online estruturado, do qual resultaram 159 respostas válidas. A amostra foi composta exclusivamente por consumidores portugueses que tinham efetuado pelo menos uma compra nos últimos doze meses numa plataforma com recomendações baseadas em IA. A validação estatística foi realizada através da Modelação por Equações Estruturais de Mínimos Quadrados Parciais (PLS-SEM), com recurso ao software SmartPLS 4.

Os resultados empíricos demonstram claramente o valor da personalização baseada em IA, que exerce efeitos positivos e significativos sobre a experiência do consumidor, a satisfação e a confiança. Estes estados internos predizem significativamente a intenção de compra, com o modelo a explicar 65,7% da sua variância. A satisfação emergiu como o preditor mais forte da intenção de compra, seguida da experiência do consumidor e da confiança. Contrariamente ao que foi hipotetizado, as preocupações com a privacidade não moderaram significativamente a relação entre a personalização baseada em IA e a experiência ou a confiança do consumidor. Este resultado constitui evidência empírica do Paradoxo da Privacidade: apesar de reportarem elevados níveis de preocupação com a privacidade, pois o item relativo à utilização não autorizada de dados foi o mais pontuado do questionário, as

intenções comportamentais dos respondentes não foram afetadas, em consonância com a Teoria do Cálculo da Privacidade.

Este estudo enriquece a literatura existente ao fornecer validação empírica do modelo S-O-R num contexto de comércio eletrónico impulsionado por IA, ao estender a evidência do Paradoxo da Privacidade ao mercado português, e ao demonstrar simultaneamente os papéis mediadores complementares da experiência, da confiança e da satisfação. Do ponto de vista da gestão, os resultados sublinham a importância estratégica de investir em sistemas de recomendação precisos, relevantes e transparentes, gerindo proativamente a comunicação sobre privacidade como uma ferramenta de construção de confiança e não como uma mera obrigação legal.

Palavras-chave: Comércio eletrónico; Confiança; Experiência do consumidor; Intenção de compra; Modelo S-O-R; Paradoxo da Privacidade; Personalização baseada em IA; PLS-SEM; Preocupações com a privacidade; Satisfação.

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List of abbreviations

AI – Artificial Intelligence

AIRS – Artificial Intelligence-based Recommender System

ANOVA – Analysis of Variance

AVE – Average Variance Extracted

CR – Composite Reliability

HTMT – Heterotrait-Monotrait ratio of correlations

IUIPC – Internet Users' Information Privacy Concerns

PII – Personally Identifiable Information

PLS-SEM – Partial Least Squares Structural Equation Modelling

SD– Standard Deviation

S-O-R –Stimulus-Organism-Response (framework)

SPSS – Statistical Package for the Social Sciences

VIF – Variance Inflation Factor

1. INTRODUCTION

This introduction is divided into six sections. It begins by setting out the research context, situating Artificial Intelligence (AI) based personalization within the broader landscape of digital commerce, and highlighting the inherent tension between the benefits of personalization and privacy concerns. The following section presents the central research question and the three specific objectives guiding the study. The third section describes the theoretical framework adopted, the Stimulus-Organism-Response (S-O-R) model and Privacy Calculus Theory, which together provide the conceptual basis for the proposed relationships. The fourth section provides an overview of the methodology, summarizing the quantitative approach, the data collection procedures, and the analytical methods that were used. Section five highlights the main empirical findings and, finally, section six provides an outline of the general structure of the thesis.

1.1 Research Context and Relevance of the Topic

This research looks into how AI-based personalization affects consumer experience, trust, and satisfaction, specifically inside e-commerce platforms. The main reason for doing this study comes down to a growing need of understanding how algorithmic personalization shapes human behavior and decision-making in online environments. E-commerce has grown massively over the last few years, driven by rapid digital transformation and the increasing adoption of emerging technologies (Saleh & Zeebaree, 2025). The implementation of AI completely changes the way customers search for, evaluate, and ultimately buy products online (Kushwah, 2024). Today, more businesses are implementing AI-powered conversational marketing strategies to make shopping feel personal and highly relevant, these tactics boost customer engagement, strengthen brand relationships, loyalty and improve overall return on investment (Gupta et al., 2024).

E-commerce essentially covers any business transaction for goods and services happening digitally, it has moved from being a secondary channel to dominating global retail (Verma et al., 2021). This transformation is fundamentally supported by the growing application of machine learning and deep learning algorithms that analyze vast amounts of user data, such as browsing history, previous purchases, and demographic information, to generate product recommendations that match a shopper's specific tastes (Nalla et al., 2024).

Big players such as Amazon, Shein, Zara, and AliExpress now build their entire value proposition around these personalized systems. Their goal is increasing conversion rates, reducing search effort, and building long-term customer loyalty (Bhardwaj et al., 2024). Older personalization tactics used rigid rules and broad demographic buckets, but AI-driven models are different, they adapt in real time, offering a level of precision and relevance that was previously unattainable (Khamoushi, 2024).

Using AI for personalization is now a major strategic edge for online brands. It directly shapes how consumers view value, satisfaction, trust, and their willingness to buy again (Almeida, 2025). Nevertheless, this trend also prompts critical inquiries. Although personalization makes shopping smoother, it also triggers concerns about mass data collection, a lack of transparency, and the risk of personal info being misused (Sipos, 2025; Saleh & Zeebaree, 2025). Consumers are increasingly aware that their digital behavior is continuously tracked and analyzed, however, paradoxically, they keep using and enjoying the systems that make them nervous, a contradiction captured by the concept of the *Privacy Paradox* (Norberg et al., 2007). So, understanding the mechanisms through which personalization influences consumer behavior, and the degree to which privacy concerns moderate these effects, represents a crucial topic for both researchers and industry professionals.

This study addresses this issue through an empirical investigation into how AI-based personalization shapes consumer experience, trust, and satisfaction in e-commerce platforms, and examines how these internal states turn into an intent to buy. The research further examines whether privacy concerns moderate this process, contributing empirical evidence to the ongoing debate on the role of privacy in AI-driven digital commerce in the Portuguese market.

1.2 Research Problem, Objectives and Methodology

Even though research into AI-based personalization is expanding rapidly, several gaps remain. First, the majority of current research examines the effects of personalization on a single consumer outcome, like satisfaction or purchase intention, without simultaneously considering the interrelated roles of experience, trust, and satisfaction as mediating constructs (Lemon & Verhoef, 2016; Pavlou, 2003). Second, the moderating role of privacy

concerns in the relationship between AI personalization and consumer behavior remains underexplored and empirically contested (Malhotra et al., 2004; Chen et al., 2025). Third, beyond the theory, there is also a geographic bias. Almost all empirical evidence comes from English-speaking or Asian markets, there is the need to investigate these dynamics within Southern European contexts, such as the Portuguese.

Consequently, this research is conducted with alignment with the following research questions: (i) "what is the impact of AI-based personalization on experience, trust, satisfaction and purchase intention in e-commerce platforms? (ii) What is the role of privacy concerns on the relationship between AI-based personalization and consumer experience and trust?"

In order to answer these research questions, the study aims to:

a) Analyze the impact of AI-based personalization on consumer experience, trust, and satisfaction.

b) Evaluate how consumer experience, trust, and satisfaction influence purchase intention.

c) Test the moderating effect of privacy concerns on the relationship between AI-based personalization and consumer experience and trust.

Methodologically, this research follows a positivist and quantitative design. Primary data were collected through a structured online questionnaire distributed via social media platforms, like WhatsApp, Facebook, Instagram, and institutional email between February and March 2026. Participation was restricted to adults who had made at least one online purchase in the previous twelve months on a platform featuring AI-based product recommendations. Following the application of screening criteria and the removal of unengaged responses, a final valid sample of 159 responses was obtained.

Constructs were measured using validated scales adapted from the literature. Srinivasan et al. (2002) and Xu et al. (2011) for AI-based personalization, Rose et al. (2012) for Consumer Experience, Gefen et al. (2003) for Trust, Anderson and Srinivasan (2003) for Satisfaction, Pavlou (2003) for Purchase intention, and Malhotra et al. (2004) for Privacy Concerns. A five-point Likert scale was used to rate each item. Partial Least Squares Structural Equation

Modelling (PLS-SEM) in SmartPLS 4 was used to evaluate hypotheses using the two-step method suggested by Hair et al. (2021).

1.3 Theoretical Framework

To structure this research, the study adopts the S-O-R framework (Mehrabian & Russell, 1974). While it originally came from environmental psychology, the core logic is universal. This model suggests that our environment (the stimulus) influences our internal feelings and thoughts (the organism), which ultimately drives our actions (the response). In the context of this study, AI-based personalization acts as a stimulus. This technology shapes the consumer's internal state, specifically their experience, trust, and satisfaction. Those three feelings then push the consumer toward a final behavioral move, which in this case is purchase intention.

Privacy concerns also play a relevant role as a moderating factor, consistent with the Privacy Calculus Theory (Culnan & Armstrong, 1999; Dinev & Hart, 2006). The theory states that consumers engage in a rational cost-benefit analysis, weighing the perceived benefits of personalization against the perceived risks of data disclosure.

The S-O-R framework was selected because of its well-established suitability for explaining consumer responses to online environmental stimuli (Kexin & Teo, 2023) and provides a clear, three-stage structure that easily integrates all our mediating and moderating variables.

1.4 Structure of the Dissertation

This dissertation is organized into five chapters. Beyond this first chapter introduction, the second chapter presents the literature review, covering the conceptual foundations of AI-based personalization in e-commerce, the main challenges and ethical implications associated with data privacy, the theoretical framework underpinning the study, and the development of the research hypotheses. Chapter three is strictly dedicated to the methodology, including the research design, data collection instrument, sampling procedures, and analytical methods. Next, the fourth chapter delivers the actual empirical results, encompassing the

sociodemographic characterization of the sample, descriptive statistics, the assessment of the measurement model, the evaluation of the structural model, and hypothesis testing. Finally, the fifth chapter delivers the final conclusions. It highlights what this study contributes to both theory and business practice, notes its inherent limitations, and offers a few concrete ideas for future researchers.

2. LITERATURE REVIEW

This chapter establishes the conceptual and theoretical foundations of the study. It begins by presenting the role of AI in personalization within e-commerce, followed by a discussion of the main challenges and ethical concerns related to data privacy. The S-O-R framework is then introduced as the theoretical basis for the proposed conceptual model and research hypotheses. Finally, a summary of the literature review is provided.

2.1 Artificial Intelligence and Personalization in E-Commerce

Artificial Intelligence originated in the 1940s–50s with initial early neuronal modeling and establishment of the Turing Test. The term "AI" was formally introduced in 1956 at the Dartmouth Conference, sparking decades of advancement in symbolic systems, neural networks, and machine learning. Deep learning has further strengthened the use of AI in daily life and business scenarios since 2012 (Shao et al., 2022). Currently, companies are going beyond social media by seeking to create immersive digital experiences that ensure their relevance and modernity in the market. With the use of AI, they enhance customer service through personalization and the recommendation of products and content (Almeida, 2025).

In this sense, e-commerce platforms utilize predictive analytics to personalize recommendations by analyzing users' past behavior, including browsing history, previous purchases, and demographic information. Electronic commerce, or e-commerce, entail all aspects of a business transaction for goods and services conducted over digital platforms. With growing consumer demand for online solutions, many companies are adopting e-commerce strategies to solidify their market presence and to gain a competitive advantage (Verma et al., 2021). The rapid expansion of e-commerce has transformed the way businesses interact with consumers, which therefore require big data analytics and AI to drive actionable insights to improve customer journeys and operational efficiency (Nalla et al., 2024).

This context enhances the relevance of product suggestions, making the shopping experience more tailored, which can lead to higher conversion rates and larger basket sizes (Kushwah, 2024). Consequently, e-commerce has evolved from a simple online transaction system to a dynamic environment that can offer intelligent and adaptive experiences powered by AI technologies.

While traditional personalization techniques rely on static segments and generic offers, AI-based techniques dynamically adapt content based on user behavior and predictive analytics (Khamoushi, 2024). Personalization in e-commerce refers to the strategy of tailoring content, products, services, and shopping experiences offered to online customers based on their characteristics, behaviors, preferences, and individual data (Rolando, 2024). It is important to understand the technological mechanisms that make AI adaptation possible.

2.1.1 AI-Based Personalization: Privacy and Challenges

AI plays a central role in e-commerce by enabling personalized product recommendations. Through deep learning algorithms, platforms process vast amounts of user data to offer tailored suggestions, significantly improving customer engagement, boosting sales, and enhancing the overall shopping experience (Zhang & Xiong, 2024). Technologies such as machine learning and deep learning are used to build recommendation models. These collect and analyze users' personal information and behavioral data allowing e-commerce platforms to identify items similar to those preferred by each consumer (Yin et al., 2025). AI-based personalization further allows e-commerce platforms to anticipate consumer needs by predicting future preferences and offering highly accurate recommendations.

Compared with traditional retail methods, the AI-driven suggestions deliver greater precision and relevance, contributing to a more engaging and insightful shopping experience for consumers (Yin et al., 2025). These mechanisms not only enable real-time adaptations and predictive recommendations, but also directly influence how consumers perceive and interact with e-commerce platforms.

When AI is integrated into e-commerce several benefits emerge, however, there are significant ethical challenges to be considered. Data privacy concerns and algorithmic bias are key issues that must be carefully managed to ensure objectivity and build consumer trust. In order to achieve this, sensitive consumer information should be protected and transparency

in AI decision-making processes are essential in dealing with these challenges. Consequently, the ethical deployment of AI including strict adherence to privacy regulations and the management of algorithmic fairness, is crucial for sustainable business practices and maintaining customer trust (Saleh & Zeebaree, 2025).

Although personalization enhances the shopping experience, it simultaneously introduces concerns about excessive data collection, lack of transparency, and potential misuse of personal information. These risks highlight the need for organizations to adopt ethical safeguards that ensure accountability and clarify how consumer data is used (Sipos, 2025). Consequently, the ethical integration of AI into e-commerce platforms demands the use of strategies that ensure accountability and transparency. This requires measures such as developing clear ethical guidelines that involve privacy and data protection, investing in research and promoting digital literacy among consumers in what concerns the use of AI and the use of their data. Such measures are essential not only to maintain consumer trust and satisfaction but also to promote a fair, inclusive, and sustainable digital marketplace (Ifekanandu et al., 2023).

2.2 The Privacy Paradox and Privacy Calculus

In the context of AI personalization, privacy concerns are best understood through the framework of Internet Users Information Privacy Concerns (IUIPC). According to Malhotra et al. (2004), consumers' apprehensions are not generic but structured around three specific dimensions adopted in this study: (1) collection — the perception that vast amounts of data are being accumulated, often exceeding what is necessary for the transaction; (2) control — the consumer's sense of powerlessness regarding the approval, modification, or deletion of their own data; (3) awareness — the degree of knowledge about the company's privacy practices and the transparency of information usage.

However, research often observes a contradiction in consumer behaviour known as the Privacy Paradox (Norberg et al., 2007). This phenomenon describes the discrepancy between consumers who claim to be highly concerned about their privacy but continue to freely disclose personal information on online platforms in return for benefits.

To explain how these concerns interact with the benefits of AI, this research relies on the Privacy Calculus Theory (Culnan & Armstrong, 1999; Dinev & Hart, 2006). This theory suggests that consumers engage in a rational cost-benefit analysis. They are willing to disclose information if they perceive that the expected benefits outweigh the potential risks of intrusion (Culnan & Armstrong, 1999; Dinev & Hart, 2006).

2.3 Theoretical Framework

The Stimulus-Organism-Response (S-O-R) model, originally introduced by Mehrabian and Russell (1974), has become one of the most influential frameworks for explaining how individuals process and respond to environmental stimuli. According to the model, external stimuli (S) set off internal cognitive and affective states (O), which, in turn, shape behavioral responses (R). Although it was developed for physical environments, the S-O-R framework has been widely adopted in e-commerce due to its strong ability to explain how online stimuli influence consumer perceptions and behaviors.

Recent research shows that this model may be suitable for e-commerce contexts, where digital design elements, recommendation systems, and interactive features function as psychological stimuli. Kexin and Teo (2023) note that stimuli, such as, personalization directly affect consumers' internal evaluation, i.e. trust, satisfaction and emotional involvement. These internal states constitute the organism stage and are fundamental in shaping behavioral outcomes, i.e. purchase intention and continued use of the platform.

Given the focus of this dissertation on evaluating how AI-based personalization (stimulus) shapes consumer experience, trust, and satisfaction (organism) and ultimately influences purchase intention (response), the S–O–R model provides a coherent and theoretically grounded foundation. Its structure aligns naturally with the dynamics of personalized e-commerce environments, making it an appropriate framework to support the development of the conceptual model and research hypotheses.

2.3.1 Conceptual Model and Hypotheses

The proposed research model is based on the S-O-R (Stimulus-Organism-Response) paradigm, suggesting that AI-based personalization (Stimulus) influences the consumer's

internal state (Organism: Experience, Trust and Satisfaction), which, in turn, determines their behavioral response (Purchase Intention). Additionally, the moderating effect of Privacy Concerns is considered. Figure 1 illustrates the structural relationships, where AI-Personalization (Stimulus) influences the internal states of Experience, Trust, and Satisfaction (Organism), which in turn determine Purchase Intention (Response). Additionally, the model integrates Privacy Concerns as a moderating variable affecting the initial stage of this process.

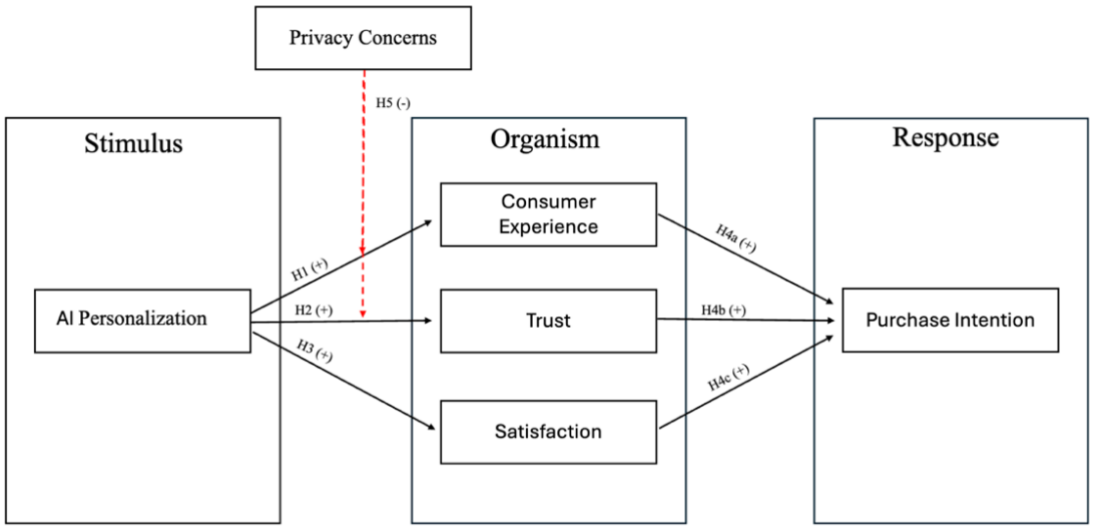


Figure 1: Proposed Conceptual Model based on the S-O-R framework

The rationale of the framework follows two broad ideas. First, the literature suggests that if personalization offers relevant content and consequently reduces the effort required for research, it significantly improves consumer interaction with the platform. Hence, AI, by being accurate, creates a sense of flow and engagement (Rose et al., 2012). In addition, the system's ability to understand the consumer is perceived as a sign of competence, which generates trust (Gefen et al., 2003). Finally, personalization, by satisfying the needs of each consumer, contributes directly to their overall satisfaction (Anderson & Srinivasan, 2003). Therefore, we propose AI personalization as antecedent for customer experience, trust and satisfaction related to e-commerce platforms.

Secondly, according to S-O-R logic, the internal state of the organism determines behavioral response. The literature on e-commerce consistently identifies those consumers

who have positive experiences, trust the platform, and feel satisfied are more likely to convert this predisposition into a purchase. Seminal studies indicate that trust and satisfaction are the main antecedents of online transaction intention, reducing the uncertainty associated with the online environment (Pavlou, 2003). Similarly, a fluid shopping experience acts as a positive reinforcement for repeat purchases. Consequently, we identify consumer experience, trust and satisfaction as antecedents of purchase intention in e-commerce platforms.

We will now see in more detail the research hypotheses.

2.3.2 AI-Based Personalization and Consumer Experience

Customer experience is a multidimensional construct that encompasses the customer's cognitive, emotional, behavioural, sensorial, and social responses to a firm's offerings across the entire purchase journey (Lemon & Verhoef, 2016). In the context of digital commerce, consumer experience refers to the user's overall perception of the value and satisfaction obtained from their interactions with an online platform at all points of contact, that is, from product discovery to post-purchase engagement. Therefore, it can be understood as the result of consistent and personalized interactions between the consumer and the brand (Lemon & Verhoef, 2016).

Artificial intelligence-based recommender systems (AIRSs) play a crucial role in shaping consumer experience within e-commerce environments by promoting personalized and efficient interactions. These systems help customers quickly find products or services that match their preferences, reduce search time, and improve the quality of purchasing decisions. In addition, the perception of reliability, usefulness, and empathy from AIRSs contributes to increasing consumer confidence and satisfaction levels. When implemented well, these systems not only optimize the purchasing journey, but also strengthen the customer's emotional engagement with the brand, creating positive experiences in e-commerce (Chen et al., 2025).

According to Bhardwaj et al. (2024), AI-driven personalization improves consumer experience by significantly increasing conversion rates through tailored product recommendations and marketing materials that closely align with individual preferences. Moreover, there are personalized strategies which reduce cart abandonment by offering customized incentives and timely reminders. These encourage customers to complete their

purchases. Therefore, such personalized experiences promote customer loyalty by keeping track of purchases and nurturing long-term relationships, as consumers feel valued when interactions are adapted to their specific needs.

Overall, AI-based personalization not only simplifies the consumer journey but also transforms it into a more engaging, relevant, and emotionally connected experience, positioning e-commerce brands as more responsive and customer-centric entities. Hence, we propose that:

H1: AI-based personalization positively affects consumer experience in e-commerce platforms.

2.3.3 AI-Based Personalization and Consumer Trust

Trust is a fundamental element of consumer behavior and a determining factor in successful online interactions. In the context of e-commerce, trust can be understood as the consumer's belief in the ability and integrity of the seller or platform to deliver on their promises and resolve concerns and complaints in a transparent and reliable manner. It is a key element in encouraging consumers to make online transactions, share personal information, and build lasting relationships with digital retailers (Hassan et al., 2025).

Consumer trust is essential for successful AI-based personalization, as users are increasingly aware of how their data is collected and used. Trust in digital platforms evolves over time and is influenced by users' previous experiences, their perception of the platform's reliability, and the quality of data management. While personalized and relevant interactions can increase trust, it can quickly diminish if consumers feel a loss of control over their personal data. Transparent communication, clear data use policies, and user consent mechanisms are therefore crucial to reducing perceived risks and enhancing trust in e-commerce platforms (Sipos, 2025). Hence, we propose that:

H2*:* AI-based personalization positively affects consumer trust in e-commerce platforms.

2.3.4 AI-Based Personalization and Consumer Satisfaction

Customer satisfaction is one of the most widely studied concepts in marketing and consumer behavior. According to Oliver (1997), satisfaction results from a cognitive comparison between consumers' expectations and their actual experiences of performance,

leading to positive or negative evaluations depending on whether expectations are met or not. In the context of e-commerce, this evaluation extends to digital interactions, where the effectiveness of personalized recommendations can significantly influence consumers' overall satisfaction with the platform (Abinesh & Dulloo, 2024).

Recent research emphasizes that AI plays a crucial role in shaping satisfaction through the personalization of online experiences. Beyond the browsing experience, personalization directly drives satisfaction by proactively fulfilling consumer needs and reducing search effort, creating an immediate sense of gratification (Anderson & Srinivasan, 2003). Abinesh and Dulloo (2024) found that AI-driven personalization has the strongest positive effect on customer satisfaction, particularly when transparency and user control are integrated into personalization processes. These factors enhance perceptions of relevance, trust, and value, leading to improved engagement and overall satisfaction. The study also highlights that satisfaction is maximized when consumers feel their data is handled responsibly and that the personalization process remains ethical and user centric.

However, as Sipos (2025) points out, excessive or intrusive personalization can generate discomfort, privacy concerns, and a perceived loss of control, which can reduce satisfaction despite technological accuracy. Therefore, maintaining high satisfaction levels in AI-driven environments requires balancing personalization efficiency with transparency and user autonomy. Hence, we propose:

H3**:** AI-based personalization positively affects consumer satisfaction in e-commerce platforms.

In summary, satisfaction in AI-based personalization arises from the balance between technological efficiency and consumer control. When personalization is transparent, respectful of privacy, and aligned with user expectations, it enhances not only satisfaction but also loyalty, trust and the intention to continue engaging with the platform.

2.3.5 AI-Based Personalization and Purchase Intention

Purchase intention refers to a consumer's conscious willingness to engage in a future purchase and represents the behavioural outcome of previous cognitive and emotional evaluations. According to Ajzen's (1991) *Theory of Planned Behavior*, intention is the most direct antecedent of behavior and reflects a consumer's motivation to act. In e-commerce,

purchase intention reflects the consumer's perceived likelihood of completing an online transaction after evaluating platform reliability, information quality, and overall service experience, factors that tend to have greater weight online due to the absence of physical interaction (Gefen et al., 2003).

According to Wang et al. (2023), consumer perception, trust, and attitude are interrelated determinants of purchase intention in e-commerce. Positive consumer perceptions of transparency, product information, and service responsiveness build trust and promote favorable attitudes, which subsequently increase their purchase intention. On the other hand, negative perceptions, such as low service quality or perceived risk, can suppress these effects, indicating that trust and perception together shape how AI-based personalization influences consumers' purchasing decisions.

Research indicates that AI-based personalization can strengthen purchase intention by increasing the relevance and perceived value of recommendations. Singhal et al. (2025) show that personalization improves the consumer decision-making process by increasing convenience and perceived usefulness, but its strongest influence occurs indirectly through trust. When consumers believe that AI systems use their data transparently and responsibly, personalized suggestions increase both satisfaction and willingness to purchase. However, if personalization appears intrusive or raises privacy concerns, trust declines and purchase intent weakens. Thus, we identify consumer experience, trust, and satisfaction as antecedents of purchase intention, and propose that:

H4a: Consumer experience positively affects purchase intention in e-commerce platforms.

H4b: Trust positively affects purchase intention in e-commerce platforms.

H4c: Satisfaction positively affects purchase intention in e-commerce platforms.

2.3.6 The Moderating Role of Privacy Concerns

Although AI personalization offers benefits such as convenience and relevance, it requires the collection of a large amount of personal data. This presents a dilemma, often described as the 'Privacy Paradox' (Norberg et al., 2007). To explain this, we resort to the Privacy Calculation Theory (Culnan & Armstrong, 1999; Dinev & Hart, 2006). This theory suggests that consumers make a rational comparison between benefits and risks. They are

willing to share personal data if they believe that the value they obtain with improved recommendations outweighs the risk of losing privacy (Malhotra et al., 2004; Chen et al., 2025).

However, when consumers have high privacy concerns, regarding the collection and control of their data the perceived risk becomes too high (Malhotra et al., 2004). In this situation, AI personalization is not seen as useful, but rather as intrusive. Therefore, high privacy concerns are expected to reduce the positive impact of personalization on both consumer experience and consumer trust. Following the idea of privacy calculus, when perceived privacy risk is high, driven by a lack of control or awareness, the calculus outcome becomes negative. In such cases, privacy concerns act as a moderator, potentially inhibiting trust and diminishing the positive effects of the personalized experience (Malhotra et al., 2004; Chen et al., 2025). Thus, the following moderation hypotheses are proposed:

H5a: Privacy concerns negatively moderate the relationship between AI-based personalization and consumer experience in e-commerce platforms.

H5b: Privacy concerns negatively moderate the relationship between AI-based personalization and trust in e-commerce platforms.

Table 1 presents a Summary of the proposed hypotheses.

Hypothesis	Summarized Description
H1	AI-based personalization positively affects consumer experience.
H2	AI-based personalization positively affects consumer trust.
H3	AI-based personalization positively affects consumer satisfaction.
H4a	Consumer experience positively affects purchase intention.
H4b	Trust positively affects purchase intention.
H4c	Satisfaction positively affects purchase intention.
H5a	Privacy concerns negatively moderate the relationship between AI-based personalization and consumer experience.

H5b	Privacy concerns negatively moderate the relationship between AI-based personalization and trust.

Table 1: Summary of the research hypotheses.

2.4 Summary of Literature Review

This chapter established the theoretical foundations of the study, adopting the S-O-R framework to analyze the impact of AI-based personalization. The literature review highlighted that while personalization enhances consumer experience, trust, and satisfaction thereby driving purchase intention, this process is not entirely frictionless. The conceptual model integrates Privacy Concerns as a critical moderator, based on the Privacy Calculus Theory. This addition addresses a gap in understanding how privacy perceptions may inhibit the positive effects of AI. Having defined the research hypotheses and the structural model, the following chapter details the quantitative procedures, sampling methods, and statistical tools used to empirically test these relationships.

3. METHODOLOGY

This chapter aims to explain the methodological procedures adopted to empirically test the conceptual model proposed in the literature review. It begins by reaffirming the problem and objectives of the research, followed by the research design. Subsequently, the data collection instrument and sampling techniques are described, ensuring the reliability and validity of the study.

3.1 Research Problem and Objectives

This study aims to understand, in the online context, how AI-based personalization influences consumer experience, trust, and satisfaction, which in turn drive purchase intention. Furthermore, it explores the challenges related to privacy concerns.

Consequently, this research is conducted with alignment with the following research questions: (i)*"what is the impact of AI-based personalization on experience, trust, satisfaction and purchase intention in e-commerce platforms? (ii)* "what is the role of privacy concerns on the relationship between AI-based personalization and consumer experience and trust?".

In order to answer these research questions, the study aims to:

a) Analyze the impact of AI-based personalization on consumer experience, trust, and satisfaction.
b) Evaluate how consumer experience, trust, and satisfaction influence purchase intention.
c) Test the moderating effect of privacy concerns on the relationship between AI-based personalization and consumer experience and trust.

3.2 Research Paradigm

The research paradigm employed in this study can be identified as positivism. According to Mohammad Ali (2024), the positivist paradigm is grounded in the ontological assumption that reality is objective, singular, and exists independently of the researcher's perception. From an epistemological perspective, this approach involves maintaining independence and impartiality towards the object of study, as well as adopting a neutral and

highly objective stance, so as to prevent personal biases from influencing the empirical results (Saunders et al., 2023). This philosophical position is appropriate for the present study, as it seeks to empirically verify a theoretical framework through the collection of numerical data and statistical analysis to reveal cause-and-effect relationships.

In line with the positivist approach, this research follows a deductive reasoning process. As described by Mohammad Ali (2024), positivist research typically uses quantitative analysis and a deductive approach, moving from established theories and empirical observations to specific hypotheses, which are then tested through data collection and analysis to confirm or reject the proposed model. From a methodological perspective, this paradigm supports the selected research design, which is based on a quantitative survey. Through the use of a structured questionnaire with standardized measurement scales, the study aims to objectively quantify consumers' cognitive and affective states, triggered by AI-based personalization and their subsequent behavioral intentions. Finally, the positivist paradigm allows the conclusions to be statistically validated, in this case through Partial Least Squares Structural Equation Modelling (PLS-SEM), which enables the generalization of the results regarding consumer behavior to a larger population (Hair et al., 2021).

3.3 Research Design

Based on the positivist paradigm defined above, this study adopts a quantitative research approach. This approach was selected because the study aims to measure consumer perceptions using numerical data and analyze the relationship between variables using statistical methods (Bell et al., 2022; Saunders et al., 2023).

With regard to its objective, the research design is classified as descriptive and explanatory. According to Saunders et al. (2023), descriptive research seeks to accurately portray the characteristics of a particular phenomenon, situation, or group of people. In this study, it is descriptive in nature, as it portrays the demographic profile of the respondents. Furthermore, explanatory research aims to establish causal relationships between variables (Saunders et al., 2023). Thus, this study is explanatory, as the main objective is to identify how AI-based personalization explains variations in consumer experience, trust, satisfaction, and purchase intention. In addition, the study adopts a cross-sectional design, which means that data were collected at one specific moment (Saunders et al., 2023).

3.4 Data Collection Instrument

In order to test the hypotheses of the proposed conceptual model, a structured online questionnaire was developed and published using Google Forms, with the aim of collecting primary data. This method was chosen because it enables the efficient collection of standardized data from a large and diverse sample of online consumers, while ensuring the anonymity of the respondents (Saunders et al., 2023). The instrument was developed based on the S-O-R framework and followed a rigorous operationalization process to ensure construct validity.

The questionnaire is organized into three main sections to ensure a logical flow for respondents. The first section serves as a triage and contextualization phase. It begins by setting the context for the study's main topic, then identifies users who have interacted with e-commerce platforms that use AI recommendations (e.g. Amazon, Zara, Shein) and connects their responses to a specific recent shopping experience to ensure data accuracy.

The second section comprises the measurement of the model's core constructs based on the S-O-R logic. Specifically, it assesses AI personalization as the stimulus by measuring the perceived relevance and needs correspondence of recommendations. Subsequently, it evaluates the internal states, representing the organism, by measuring consumer experience, encompassing cognitive and affective states, along with trust and satisfaction regarding the website. Furthermore, it assesses purchase intention as the final behavioral response. This section measures privacy concerns as a moderating variable in order to understand potential barriers to adoption. Finally, the third section collects demographic data such as gender, age, location, employment status, educational qualifications, household size and income, as well as the frequency of online shopping. This data is essentially used to characterize the survey sample.

To ensure the reliability of the measurement, the scales were adapted from established studies in the literature. All items were measured using a 5-point Likert scale, ranging from "1 - Strongly Disagree" to "5 - Strongly Agree", which is widely recommended in business research to measure consumer perceptions and attitudes (DeVellis & Thorpe, 2021).

Construct & Source	*Code*	*Measurement Items (Adapted to AI context)*	*Administered Items (Portuguese)*
AI Personalization ***(Srinivasan et al., 2002; Xu et al., 2011)***	***AIP1***	This website makes product recommendations that match my needs.	Este WEBSITE faz recomendações de produtos que correspondem às minhas necessidades.
	AIP2	I feel that the recommendations presented are personalized for me.	Sinto que as recomendações apresentadas são personalizadas para mim.
	AIP3	The website offers product suggestions that I would probably like to buy.	O WEBSITE oferece sugestões de produtos que eu provavelmente gostaria de comprar.
	AIP4	The website seems to understand my shopping preferences based on my browsing history.	O WEBSITE parece compreender as minhas preferências de compra com base no meu histórico de navegação.
Consumer Experience ***(Rose et al., 2012)***	***CX1***	I felt focused when exploring the products suggested by the website.	Senti-me focado(a) ao explorar os produtos sugeridos pelo WEBSITE.
	CX2	I felt that the recommendations helped me stay focused on shopping.	Senti que as recomendações me ajudaram a manter o foco nas compras.
	CX3	I felt I had control over the product choice process.	Senti que tinha o controlo sobre o processo de escolha dos produtos.
	CX4	I felt good browsing the presented suggestions.	Senti-me bem ao navegar pelas sugestões apresentadas.
	CX5	I was pleased with the experience of seeing these recommendations.	Fiquei agradado(a) com a experiência de ver estas recomendações.

	CX6	I felt excited about the products the website showed me.	Senti-me entusiasmado(a) com os produtos que o WEBSITE me mostrou.
Trust	***TR1***	I believe this website is trustworthy.	Acredito que este WEBSITE é de confiança.
	TR2	I feel I can trust the recommendations made by the website.	Sinto que posso confiar nas recomendações feitas pelo WEBSITE.
(Gefen et al., 2003)	***TR3***	I believe the website intends to help me by suggesting products.	Acredito que o WEBSITE tem a intenção de me ajudar ao sugerir produtos.
	TR4	I have no hesitation in following the purchase recommendations of this website.	Não tenho hesitação em seguir as recomendações de compra deste WEBSITE.
Satisfaction	***SAT1***	I am satisfied with my overall experience using the recommendations on this website.	Estou satisfeito(a) com a minha experiência global ao usar as recomendações neste WEBSITE.
(Anderson & Srinivasan, 2003)	***SAT2***	The personalization system met my expectations.	O sistema de personalização correspondeu às minhas expectativas.
	SAT3	I am happy with the relevance of the products shown to me.	Estou contente com a relevância dos produtos que me foram mostrados.
Purchase Intention	***PI1***	It is likely that I will buy products recommended by this website in the future.	É provável que eu compre produtos recomendados por este WEBSITE no futuro.
	PI2	I intend to continue using this website for my purchases.	Tenho a intenção de continuar a usar este WEBSITE para as minhas compras.

(Pavlou, 2003)	***PI3***	I would seriously consider buying a product suggested by the AI of this website.	Consideraria seriamente comprar um produto sugerido pela IA deste WEBSITE.
Privacy Concerns ***(Malhotra et al., 2004)***	***PC1***	I am concerned that the website collects too much personal information about me to make recommendations.	Preocupa-me que o WEBSITE recolha demasiada informação pessoal sobre mim para fazer recomendações.
	PC2	Knowing the website uses AI, I feel my privacy is invaded by losing control over what the AI knows about me.	Sei que o WEBSITE usa IA, pelo que sinto que a minha privacidade é invadida ao perder o controlo sobre o que a IA sabe de mim.
	PC3	I am concerned that my data is used for other purposes without authorization.	Preocupa-me que os meus dados sejam usados para outros fins sem a minha autorização.

Table 2: Constructs, sources and measurement items

3.4.1 Translation and Adaptation Procedure

As the original scales were developed in English, and the questionnaire was designed to study the Portuguese market, it was necessary to carry out a translation and adaptation process to ensure semantic equivalence in Portuguese, a standard and recommended practice in research (Saunders et al., 2023). The items were carefully translated and back-translated to suit the specific context of personalization in e-commerce, ensuring clarity for the target population. Minor adjustments were made to the wording to improve readability, without altering the original meaning of the concepts. The full version of the questionnaire, as presented to respondents, is available in the Appendix.

3.5 Questionnaire Pre-test

A pilot study was conducted to test the data collection instrument prior to the official launch of the survey. According to Saunders et al. (2023), conducting a pre-test is a crucial methodological step to ensure content validity and identify any errors or problems with

understanding the questions. Consequently, this preliminary phase involved a convenience sample of 10 participants who shared characteristics similar to those of the target population. The main objective of this pre-test study was to assess the clarity, readability and logical coherence of the questions, as well as to verify the accuracy of the translation from English into Portuguese (Malhotra, 2019). During this phase, participants were asked to complete the questionnaire and provide feedback on any ambiguous terms, difficulties in interpretation, or technical issues encountered on the platform. The feedback received was highly positive, indicating that the instructions were clear and the items easy to understand. Based on these results, the content validity was confirmed, with only minor layout adjustments made before the questionnaire was deemed suitable for the final data collection.

3.6 Population and Sampling

The target population for this study consists of online consumers who have interacted with e-commerce platforms that use AI-based recommendation systems (e.g. Amazon, Zara, Shein, Worten) at least within the last 12 months. As there is no official list or sampling frame for all such consumers, this study employs a non-probability sampling technique, namely convenience sampling. Convenience sampling was chosen due to time and resource constraints, allowing for the efficient collection of data from accessible members of the population (Etikan et al., 2016). In addition, a snowball sampling strategy was encouraged, in which respondents were invited to share the questionnaire with their network of contacts, thereby increasing the study's reach (Saunders et al., 2023).

The questionnaire was distributed digitally via social media platforms including LinkedIn, Instagram, WhatsApp, and by email. Data collection took place between February and March 2026. Initially, a total of 186 responses were collected. To ensure the suitability of the sample, a screening question was included at the beginning of the survey, restricting participation to individuals who had made an online purchase in the last 12 months on websites using AI recommendations, which reduced the sample to 162 participants.

Subsequently, a data cleaning procedure was performed to identify and remove unengaged responses (e.g., random answering patterns or "straight-lining"). After this process, a final sample of 159 valid responses were obtained. This sample size is considered

adequate PLS-SEM, meeting the minimum requirements suggested by the literature (Hair et al., 2021) to ensure statistical power.

3.7 Data Analysis Method

After the data collection process, the responses were exported to a database for preliminary analysis, where a rigorous data cleaning procedure was conducted to identify and remove invalid responses, such as incomplete questionnaires or unengaged answers. Following this initial screening, the data analysis was performed in two distinct phases. Initially, the demographic profile of the sample was analyzed using descriptive statistics, including frequencies and percentages, to allow for a detailed characterization of the participants and the research context.

Subsequently, to test the proposed conceptual model and the research hypotheses, the study employed PLS-SEM. using the SmartPLS 4 software. PLS-SEM was selected as the most appropriate method for this study based on the recommendations of Hair et al. (2021), as it is particularly suitable for complex models that include both mediating and moderating variables. Furthermore, this method is robust when dealing with non-normal data distributions, which are common in social science research, and aligns with the study's objective of predicting key target constructs (Hair et al., 2021).

In accordance with standard methodological guidelines, the model assessment followed a two-step approach. The first step involved the evaluation of the measurement model to assess the reliability and validity of the constructs (checking for internal consistency, convergent validity, and discriminant validity). Once the measurement quality was confirmed, the second step focused on the evaluation of the structural model to test the relationships between variables and determine the statistical significance of the proposed hypotheses (Hair et al., 2021).

3.8 Ethical Considerations

Ethical considerations were a priority throughout the research process, in strict accordance with the fundamental principles of research ethics (Saunders et al., 2023). All participants were fully informed about the purpose of the study before starting the

questionnaire. Participation was entirely voluntary, and respondents were guaranteed the right to withdraw from the survey at any point in time, without any consequences.

Furthermore, anonymity and confidentiality were strictly guaranteed, as no personal identifiable information (PII), such as names, email addresses or IP addresses was collected. The data obtained were used exclusively for academic research purposes and analyzed in aggregate form, ensuring that no individual response could be linked to a specific participant (Saunders et al., 2023).

4. PRESENTATION AND ANALYSIS OF RESULTS

This chapter focuses on presenting and analyzing the results obtained from the questionnaire. First, the socio-demographic and behavioral characteristics of the sample are presented, followed by descriptive statistics for the variables under study.

4.1 Sample Profile and online shopping familiarity

As summarized in Table 3, the analysis of the statistical frequencies revealed that the final sample for this study consists of 159 participants. Regarding the demographic profile, there is a clear predominance of females, who account for 73.0% of the sample. The sample is predominantly young, with most respondents (65.4%) falling within the 18 to 24 age group. In terms of educational level, a high level of education is evident, with 43.4% holding a bachelor's degree and 39.6% having completed secondary education. Geographically, the municipalities with the highest representation are Vila Real (27.7%) and Braga (16.4%).

In socio-economic terms, a large proportion of the sample consists of students (44.0%), followed by employees (23.3%) and working students (22.6%). Households are mostly composed of 4 people (44.0%), with monthly net household income distributed evenly across the proposed categories. In particular the following ranges stood out: €2,000 to €2,999 bracket (22.6%) and the €1,000 to €1,999 bracket (22.0%).

Finally, with regard to online consumer behavior, respondents demonstrated familiarity with e-commerce, as they make online purchases mainly "a few times a year" (46.5%) or "monthly" (39.0%). Particularly relevant to the context of this study is the fact that most of the sample (86.8%) stated that they had noticed the presence of personalization and product suggestions based on Artificial Intelligence during their browsing experience, which

validates the eligibility of these participants for the analysis of the proposed conceptual model.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	116	73.0
	Male	43	27.0
Age	18-24	104	65.4
	25-34	21	13.2
	35-44	13	8.2
	45-54	9	5.7
	55-64	11	6.9
	65 or older	1	0.6
Education Level	Basic Education	4	2.5
	Secondary Education	63	39.6
	Bachelor's Degree	69	43.4
	Master's Degree	21	13.2
	Doctorate	2	1.3
Current Occupation	Student	70	44.0
	Employed	37	23.3
	Working Student	36	22.6
	Self-employed	12	7.5
	Retired	3	1.9
	Unemployed	1	0.6
Household Size	1 person	13	8.2
	2 people	21	13.2
	3 people	39	24.5
	4 people	70	44.0
	5 people	15	9.4
	6 people	1	0.6
Net Monthly Household Income	Less than 1,000€	13	8.2
	1,000€ to 1,999€	35	22.0
	2,000€ to 2,999€	36	22.6

	3,000€ to 3,999€	27	17.0
	More than 4,000€	16	10.1
	Prefer not to say	32	20.1
Online Shopping Frequency	Rarely	13	8.2
	A few times a year	74	46.5
	Monthly	62	39.0
	Weekly	10	6.3
Noticed AI Personalization?	Yes	138	86.8
	Did not notice	18	11.3
	No	3	1.9

Table 3: Sample Profile and online shopping familiarity

4.2 Descriptive Statistics and Common Method Bias

To ensure the absence of Common Method Bias, Harman's Single Factor Test (Podsakoff et al., 2003) was conducted using IBM SPSS. The principal component analysis, restricted to a single factor and without rotation, revealed that the single extracted factor explains only 44.89% of the total variance. As this value is below the 50% threshold, it is concluded that Common Method Bias does not represent an issue for the present study, confirming the quality and reliability of the collected data.

Table 4 presents the descriptive statistics, particularly the mean and standard deviation, for each of the measurement items in the conceptual model. On a 5-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree), the results indicate an overall positive perception among respondents. The variable with the highest level of agreement was the intention to continue using the website for online shopping, with a mean of 4.09. Meanwhile, the statement with the lowest level of agreement, with a mean of 2.97, relates to the absence of hesitation in following purchasing recommendations. The standard deviations ranged overall between 0.881 and 1.200.

Regarding "AI-based Personalization", respondents demonstrated a strong positive perception, with means ranging from 3.67 to 3.97. Users particularly agreed that the website understands their shopping preferences based on their browsing history (mean = 3.97, SD =

0.924). The standard deviations, mostly remaining below 1.00, indicate a relatively solid consensus among participants, suggesting that the majority clearly recognize the system's ability to tailor product suggestions to their needs.

The concept of “Consumer Experience” received moderate to positive ratings. Although participants reported feeling enthusiastic (mean = 3.67, SD = 0.978) and satisfied (mean = 3.64, SD = 0.916) with the recommendations, the item assessing whether these suggestions helped them stay focused whilst shopping received a slightly lower score (mean = 3.19) and showed the greatest variability within this concept (SD = 1.111). This highlights that, although the emotional and interactive experience is generally positive, the functional impact on the user's focus differs significantly from person to person.

"Trust" was the concept that generated the most contradictory opinions. Although the overall reliability of the website was rated positively (mean = 3.70, SD = 1.118), the statement regarding the absence of hesitation in following purchase recommendations received the lowest score in the entire table (mean = 2.97, SD = 1.099). Furthermore, all items within this construct had standard deviations greater than 1.05. This wider dispersion of responses highlights a group of sceptical users, although many trust the platform in general, there is clear hesitation when it comes to fully trusting the AI's specific purchasing advice.

The concept of "Satisfaction" revealed strong and consistent positive feelings. All evaluation items received consistent scores of around 3.70, with the lowest standard deviations in the table (ranging from 0.905 to 0.950). This combination of high averages and lower variability indicates a strong consensus among respondents, confirming that the AI-based personalization system effectively met their expectations and successfully presented relevant products.

Regarding "Privacy", respondents expressed considerable concern, particularly regarding the possibility of their data being used for other purposes without authorization (mean = 3.92). Interestingly, this construct has the highest standard deviations in the entire study (ranging from 1.136 to 1.200). This indicates a significant polarization among users, as many individuals are very concerned about data collection by AI and feel a loss of control, while a substantial proportion of the sample appears far less concerned, reflecting divided attitudes towards digital privacy.

Finally, "Purchase intention" reflects a very positive behavioural outcome. The highest level of agreement across the entire questionnaire was found in users' intention to continue using the website for their purchases (mean = 4.09), which also revealed a strong consensus (SD = 0.881). Although the specific intention to purchase a product directly suggested by the AI was slightly lower and more varied (mean = 3.54, SD = 1.005), the overall results demonstrate that users are highly willing to maintain their relationship and continue shopping on the platform.

Construct	Measurement Item	Mean	Std. Deviation
AI-based Personalization	This WEBSITE makes product recommendations that match my needs.	3.75	0.946
	I feel that the recommendations presented are personalized for me.	3.67	1.029
	The WEBSITE offers product suggestions that I would likely want to buy.	3.91	0.906
	The WEBSITE seems to understand my shopping preferences based on my browsing history.	3.97	0.924
Consumer Experience	I felt focused while exploring the products suggested by the WEBSITE.	3.36	1.015
	I felt that the recommendations helped me stay focused on my shopping.	3.19	1.111
	I felt I had control over the product selection process.	3.52	1.036
	I felt good navigating the presented suggestions.	3.65	0.974
	I felt enthusiastic about the products the WEBSITE showed me.	3.67	0.978
	I was pleased with the experience of seeing these recommendations.	3.64	0.916
Trust	I believe this WEBSITE is trustworthy.	3.70	1.118
	I feel I can trust the recommendations made by the WEBSITE.	3.58	1.052
	I believe the WEBSITE intends to help me by suggesting products.	3.39	1.152
	I have no hesitation in following the purchasing recommendations of this WEBSITE.	2.97	1.099
Satisfaction	I am satisfied with my overall experience using the recommendations on this WEBSITE.	3.71	0.950
	The personalization system met my expectations.	3.69	0.949
	I am happy with the relevance of the products shown to me.	3.70	0.905
Privacy	I am concerned that the WEBSITE collects too much personal information about me to make recommendations.	3.73	1.200

	I know the WEBSITE uses AI, so I feel my privacy is invaded by losing control over what the AI knows about me.	3.51	1.136
	I am concerned that my data might be used for other purposes without my authorization.	3.92	1.174
Purchase Intention	It is likely that I will buy products recommended by this WEBSITE in the future.	3.74	0.951
	I intend to continue using this WEBSITE for my purchases.	4.09	0.881
	I would seriously consider buying a product suggested by the AI of this WEBSITE.	3.54	1.005

Table 4: Descriptive statistics of the measurement model items

4.2.1 Exploratory Demographic Analysis

Prior to conducting the exploratory demographic analyses, the internal consistency of the composite scores used in this section was verified. As detailed in Section 4.3, all constructs demonstrated satisfactory reliability, with Cronbach's alpha values exceeding the recommended threshold of 0.70, and acceptable values for average variance extracted (AVE) and composite reliability (Hair et al., 2021). This confirms that the composite means used in the following analyses are reliable representations of their respective constructs.

In order to better understand the dynamics of the sample, an analysis was carried out with the aim of observing how certain variables vary across different demographic groups, specifically regarding age and gender. With regard to age, literature frequently suggests that older generations tend to be more skeptical about data sharing and AI technologies. The descriptive analysis of the current sample partially supports this theoretical premise. As illustrated in Table 3, the youngest age group (aged between 18 and 24), which constitutes the vast majority of respondents (n = 104), expressed a moderate level of concern regarding privacy (mean = 3.68). The highest level of concern was observed among the oldest respondents (aged above 54, n = 12), who recorded the highest mean score in the sample (mean = 4.06), followed by the 25–34 age group (mean = 3.90). The remaining groups showed slightly lower and relatively similar levels of concern, with the 35–44 group recording the lowest mean (mean = 3.54). These results suggest a general tendency for older users to express greater privacy concern regarding AI-based personalization, which is consistent with

the broader argument that perceived risks of data collection vary across consumer segments (Malhotra et al., 2004; Chen et al., 2025).

Furthermore, a One-Way ANOVA was conducted to test whether these differences in Privacy Concerns across age groups were statistically significant. For the purposes of this exploratory analysis, Privacy Concerns were operationalized as a composite score, calculated as the mean of the three measurement items (*PC1*, *PC2*, and *PC3*), consistent with the construct's operationalization in the structural model. The results revealed no statistically significant differences between the groups (F (4, 154) = 0.623, p = 0.647). Consequently, although certain demographics displayed slightly higher mean scores descriptively, age is not a statistically significant determinant of privacy concerns within the context of AI-based personalization in this sample.

Group	Count	Sum	Average	Variance			
18-24	104	382.667	3.6795	1.2102			
25-34	21	82.000	3.9048	0.9016			
35-44	13	46.000	3.5385	2.0470			
45-54	9	32.000	3.5556	0.5833			
>54	12	48.667	4.0556	0.7239			
Source of Variation							
Source of Variation	SS	df	MS	F	P-value	F crit	
Between Groups	2.91	4	0.728	0.6229	0.6468	2.4304	
Within Groups	179.875	154	1.168				
Total	182.785	158					

Table 5: Anova: Single Factor

In addition, an exploratory comparison of gender differences revealed an interesting behavioural nuance. With regard to privacy concerns, both genders showed virtually identical levels of concern (Female: mean = 3.72; Male: mean = 3.71). However, regarding purchase intention, female respondents demonstrated slightly greater receptiveness to AI recommendations. Women had a higher mean (mean = 3.86, SD = 0.810) compared to male

respondents (mean = 3.60, SD = 0.843). This suggests that, within this specific sample, women are slightly more inclined to follow AI-driven product suggestions and to remain loyal to the website.

To rigorously examine these gender differences, an independent-samples t-test was conducted. Purchase Intention was similarly operationalized as a composite score representing the mean of its three measurement items (PI1, PI2, and PI3). The results indicated that the difference in Purchase Intention between males and females was not statistically significant (t (73) = 1.690, p = 0.095). Therefore, while female respondents showed a slightly higher mean score in this specific sample, gender does not act as a statistically significant differentiator concerning purchase intention in this sample.

	Female	**Male**
Mean	3.856	3.605
Variance	0.656	0.710
Observations	116.000	43.000
Hypothesized Mean Difference	0.000	
Df	73.000	
t Stat	1.690	
P(T<=t) one-tail	0.048	
t Critical one-tail	1.666	
P(T<=t) two-tail	0.095	
t Critical two-tail	1.993	

Table 6: t-Test: Two-Sample Assuming Unequal Variances

4.3 Evaluation of the Measurement Model

Before proceeding to the structural model and hypothesis testing, it is essential to assess the quality of the measurement model to ensure that the data collected via the questionnaire are reliable and valid (Hair et al., 2021). This assessment focuses on the reliability of the indicators, internal consistency, and convergent validity.

As shown in Table 7, internal consistency is demonstrated, as the Cronbach's alpha and Composite Reliability (CR) values for all constructs exceed the recommended threshold of 0.70, confirming the robustness and internal consistency of the scales used. Furthermore, convergent validity was established, given that the AVE for each construct was above the

reference value of 0.50 (Hair et al., 2021). Thus, the items explain a significant portion of the variance in the constructs.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Purchase	0.840	0.842	0.903	0.757
Trust	0.865	0.878	0.908	0.713
Personalization	0.897	0.900	0.928	0.764
Satisfaction	0.904	0.904	0.940	0.838
Experience	0.878	0.913	0.907	0.625
Privacy	0.908	0.928	0.942	0.844

Table 7: Construct reliability and convergent validity

Following the assessment of convergent validity, discriminant validity was examined to ensure that each construct is empirically unique. This study employed the Heterotrait-Monotrait ratio of correlations (HTMT), which is currently considered the most stringent and reliable criterion.

	Experience	Personalization	Privacy	Purchase	Satisfaction	Trust	Privacy x Personalization
Experience							
Personalization	0.607						
Privacy	0.133	0.048					
Purchase	0.833	0.690	0.095				
Satisfaction	0.788	0.602	0.117	0.866			
Trust	0.757	0.514	0.154	0.784	0.789		
Privacy x Personalization	0.149	0.234	0.067	0.258	0.189	0.178	

Table 8: Discriminant validity (HTMT criterion)

The results in Table 8 show that most HTMT values are below the conservative threshold of 0.85. The correlation between 'Satisfaction' and 'Purchase' (0.866) remains below the 0.90 ceiling suggested by Henseler et al. (2015) for conceptually related constructs. Thus, discriminant validity is fully established, confirming that the model's measures are distinct.

4.4 Evaluation of the Structural Model and Hypothesis Testing

Before testing the structural relationships, it is necessary to assess the model for potential collinearity issues among the predictor constructs (Hair et al., 2021). The Variance Inflation Factor (VIF) was analyzed for all sets of independent variables.

	Experience	Personalization	Privacy	Purchase	Satisfaction	Trust
Experience				2.406		
Personalization	1.053				1.000	1.053
Privacy	1.006					1.006
Purchase						
Satisfaction				2.543		
Trust				2.221		
Privacy x Personalization	1.056					1.056

Table 9: Collinearity statistics (Inner VIF)

As presented in Table 9, all internal VIF values range between 1.000 and 2.543, values that are well below the strict threshold of 3.0 recommended by Hair et al. (2021). This confirms that multicollinearity does not introduce bias into the regression results and that the structural model can be reliably evaluated.

Following the collinearity assessment, the structural model was evaluated using a bootstrapping procedure (5,000 subsamples) to test the significance of the path coefficients (*p*-values) and their respective effect sizes (f^2). According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

	Original sample	Sample mean	Standard deviation	*T* statistics	*P*-values
Experience -> Purchase	0.350	0.348	0.088	3.999	0.000
Personalization -> Experience	0.567	0.571	0.061	9.242	0.000
Personalization -> Satisfaction	0.545	0.547	0.070	7.761	0.000
Personalization -> Trust	0.444	0.450	0.074	6.034	0.000
Privacy -> Experience	-0.122	-0.122	0.078	1.560	0.119
Privacy -> Trust	-0.146	-0.153	0.080	1.831	0.067
Privacy x Personalization -> Experience	-0.019	-0.019	0.081	0.232	0.817
Privacy x Personalization -> Trust	-0.052	-0.053	0.070	0.754	0.451
Satisfaction -> Purchase	0.379	0.379	0.093	4.073	0.000
Trust -> Purchase	0.174	0.179	0.084	2.072	0.038

Table 10: Structural model results (Path coefficients and hypothesis testing)

Predictor Construct -> Target Construct	f^2	**Effect Size**
Experience -> Purchase Intention	0.152	Medium
Personalization -> Experience	0.461	Large
Personalization -> Satisfaction	0.423	Large
Personalization -> Trust	0.244	Medium
Privacy -> Experience	0.022	Small
Privacy -> Trust	0.028	Small
Satisfaction -> Purchase Intention	0.168	Medium
Trust -> Purchase Intention	0.041	Small
Privacy x Personalization -> Experience	0.001	None
Privacy x Personalization -> Trust	0.004	None

Table 11: Effect sizes (f^2)

As shown in the hypothesis and effect size analysis, AI-based Personalization proved to be a critical driver in the model. It exerts a highly significant positive effect on Experience ($p < 0.001$, large effect $f^2 = 0.461$), Trust ($p < 0.001$, medium effect $f^2 = 0.244$), and Satisfaction ($p < 0.001$, large effect $f^2 = 0.423$) thereby statistically supporting hypotheses *H1*, *H2*, and *H3*, respectively.

Furthermore, the antecedents of the target variable all demonstrated significant positive relationships: Experience ($p < 0.001$, medium effect $f^2 = 0.152$), Trust ($p = 0.038$, small

effect f^2 = 0.041), and Satisfaction (p < 0.001, medium effect f^2 = 0.168), significantly increase users' Purchase Intention so hypotheses *H4a*, *H4b*, and *H4c* are also fully supported.

On the other hand, the paths related to Privacy yielded non-significant results and negligible effect sizes. Included both the direct paths from Privacy Concerns to Experience and Trust and the interaction terms (Privacy × Personalization). However, the formal hypotheses *H5a* and *H5b* focus exclusively on the moderating role of Privacy. While the direct effects were also non-significant, the following analysis specifically addresses the interaction effects as hypothesized. Both the direct effects of Privacy on Experience (p = 0.119) and Trust (p = 0.067), as well as its moderating role between Personalization and the outcome variables, were not statistically supported (p > 0.05). Notably, the path from Privacy to Trust, while not significant at the conventional α = 0.05 threshold (p = 0.067), approaches marginal significance, suggesting a tentative negative relationship that warrants further investigation in future studies with larger and more diverse samples. Therefore, hypotheses *H5a* and *H5b* are not supported, this indicates a "Privacy Paradox" in the sample, where privacy concerns do not significantly negate the positive impacts of personalized AI recommendations.

	R-square	R-square adjusted
Experience	0.339	0.326
Purchase	0.664	0.657
Satisfaction	0.297	0.293
Trust	0.232	0.217

Table 12: Coefficient of determination

Finally, the model's predictive accuracy was assessed using the Coefficient of Determination (R^2). As is evident from Table 12, the structural model accounts for 65.7% of the variation in Purchase Intention (R^2_{adjusted} = 0.657). According to Hair et al. (2021), this indicates that the explained variation is moderate (0.50) to high (0.75), thus validating the ability of the model to predict consumer behavior in the AI-driven e-commerce contexts.

The results of the structural model analysis, including the path coefficients, their respective levels of significance, and the R^2 values for the endogenous constructs, are illustrated in Figure 2 below. This graphical representation allows for a comprehensive overview of the validated relationships within the proposed S-O-R Framework.

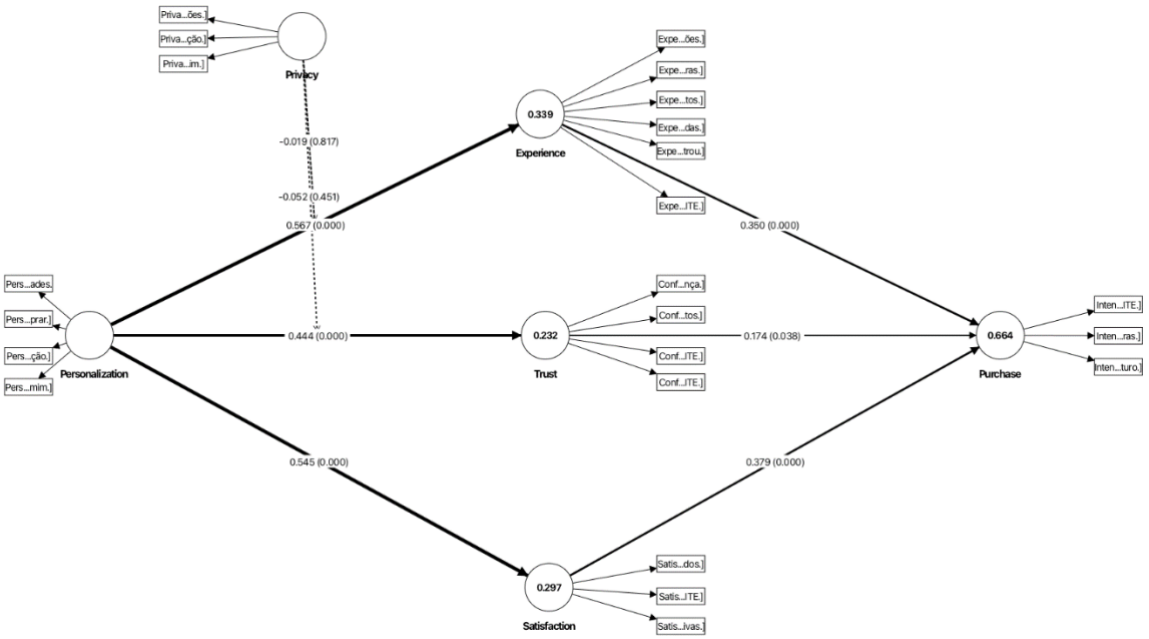


Figure 4: Final structural model with path coefficients and p-values

Finally, to complement the assessment of the model's performance, its predictive relevance was evaluated using the PLSpredict procedure. In accordance with the guidelines set out by Hair et al. (2021), the results presented in Table 13 show that the target construct, Purchase Intention, exhibits a Q^2_{predict} value of 0.329. As this value is considerably higher than the threshold of zero, it confirms that the model has a satisfactory level of predictive relevance for out-of-sample data, further supporting the robustness of the findings.

	$Q^2_{predict}$
Experience	0.287
Satisfaction	0.283
Trust	0.189
Purchase	0.329

Table 13: Results of the predictive relevance (Q^2_{predict})

4.5 Discussion of Results

This section aims to discuss the statistical findings presented in the structural model, contextualizing them within the theoretical framework and the literature reviewed. Based in the S-O-R paradigm introduced by Mehrabian and Russell (1974), the validated model provides empirical evidence of how AI-driven stimuli shape consumers' internal states and subsequent behavioral intentions in e-commerce environments.

The empirical results provide strong support for the stimulus stage of the model. The findings confirm that AI-based Personalization is a crucial determinant of consumers' internal states, significantly and positively influencing Consumer Experience (*H1*), Trust (*H2*), and Satisfaction (*H3*), demonstrating effects of medium to large size.

When comparing the results with literature, they are consistent. As suggested by Bhardwaj et al. (2024) and Chen et al. (2025), AI-driven personalization significantly improves consumer experience by providing tailored product recommendations that reduce search time and meet user preferences. Furthermore, the positive impact on Trust validates the perspective of Hassan et al. (2025) and Gefen et al. (2003), reinforcing that an AI system's ability to accurately understand and assist the consumer is perceived as a sign of competence and reliability. Finally, the strong link to Satisfaction corroborates the findings of Abinesh and Dulloo (2024) and Anderson & Srinivasan (2003), who noted that AI-driven personalization proactively fulfills consumer requirements, creating an immediate sense of gratification when expectations are met.

Regarding the behavioral response, the model confirms that Consumer Experience (*H4a*), Trust (*H4b*), and Satisfaction (*H4c*) all significantly increase the Purchase Intention of users. This validates the core assumption of the S-O-R paradigm in this specific context (Kexin & Teo, 2023), a positive and intelligent digital environment (Stimulus) generates favorable cognitive and emotional evaluations (Organism), which ultimately lead to a concrete behavioral intention to buy (Response). Consistent with Wang et al. (2023) and Pavlou (2003), these internal states act as crucial interrelated determinants that reduce the uncertainty associated with online transactions, directly driving the consumer's motivation to complete a purchase.

Perhaps the most intriguing contribution of this research relates to the rejection of privacy-related hypotheses (*H5a* and *H5b*). While the literature initially hypothesized that high

privacy concerns would reduce the positive impact of personalization (Malhotra et al., 2004), the statistical results revealed that privacy concerns did not significantly moderate the impact of AI-based personalization on Experience or Trust.

This result is particularly significant when analyzed in light of the descriptive data. The three privacy variables showed high mean scores (*PC1* = 3.73, *PC2* = 3.51, *PC3* = 3.92), with concern about unauthorized use of data being the highest across the entire questionnaire. Nevertheless, these same respondents demonstrated a strong purchase intention, and the privacy construct did not exert any significant moderating effect on experience or trust. This quantitative contrast, that is, high reported concern, but unaffected behavior, constitutes the empirical manifestation of the Privacy Paradox in the present study. One possible explanation resides in the context of the active purchase process in which the participants are situated. When the consumer is in a search and purchase decision phase, the immediate benefit of personalized recommendations, such as reduced search effort and more relevant results, tend to dominate cognitive evaluation, relegating privacy concerns to the background (Dinev & Hart, 2006). This statistical outcome is consistent with the Privacy Paradox identified by Norberg et al. (2007), where consumers may express high levels of privacy concern but do not change their actual behavior or perceptions in digital platforms. Furthermore, these results can be explained through the Privacy Calculus Theory (Culnan & Armstrong, 1999; Dinev & Hart, 2006). In the analyzed e-commerce context, the perceived benefits of AI-based personalization, appear to override the perceived risks of data collection.

Although authors such as Sipos (2025) warn that excessive personalization can generate discomfort and a sense of loss of control, the findings of this study suggest that, for this specific sample, the utility of the AI-driven recommendation outweighed the potential privacy cost. This does not necessarily mean that consumers do not care about data collection, but rather that the immediate gratification and efficiency provided by the algorithm currently overshadow their privacy concerns during the purchasing journey.

In summary, the empirical validation of the S-O-R framework in this study shows that AI-based personalization plays a key role in increasing purchase intention by improving consumer experience, strengthening trust, and enhancing satisfaction. Interestingly, the fact that privacy concerns did not have a significant impact suggests that today's online consumers may adopt a more practical mindset when shopping online. Based on these findings, the next chapter will present the main conclusions of this research, detailing both its theoretical

contributions and practical implications for e-commerce managers, while also acknowledging the limitations of the study.

5. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

This chapter summarizes the main findings of the study and its broader implications. It starts by analyzing whether the proposed hypotheses were supported by the results. It then outlines the theoretical and practical contributions of the study. The chapter concludes by acknowledging the study's limitations and offering some recommendations for future academic research in the fields of e-commerce and AI.

5.1 Conclusions

The objective of this study was to answer the following research questions: (i) "what is the impact of AI-based personalization on experience, trust, satisfaction and purchase intention in e-commerce platforms? (ii) What is the role of privacy concerns on the relationship between AI-based personalization and consumer experience and trust?". Based on the S-O-R model, a structural model was developed and empirically tested using PLS-SEM with a sample of 159 online consumers in the Portuguese market.

The empirical findings strongly support the core structure of the proposed model. AI-based personalization was found to have a highly significant and positive impact on the consumer's internal states, specifically enhancing consumer experience, trust, and satisfaction. Consequently, these positive internal evaluations, namely consumer experience, trust, and satisfaction, act as critical drivers for purchase intention. More specifically, the three hypotheses related to the stimulus stage of the model were confirmed. AI-based personalization had a significant positive effect on Consumer Experience and Satisfaction, and a moderate positive effect on Trust. These results indicate that when consumers see recommendations as relevant and tailored to their needs, they respond with greater engagement, more trust in the platform, and a stronger feeling that their expectations have been met.

The hypotheses related with behavioral response stage, Consumer Experience, Satisfaction and Trust demonstrated significant positive effects on Purchase Intention. This indicates that the model has strong predictive power and that the three organism-level

constructs are effective and complementary antecedents of purchasing behavior in AI-driven e-commerce environments.

The most theoretically significant finding of this study relates to the role of privacy. Contrary to the hypothesized moderating effect, Privacy Concerns did not significantly moderate the relationship between AI-based personalization and Consumer Experience or Trust. Notably, even the direct paths from Privacy to Experience and to Trust did not reach conventional statistical significance. This result is particularly surprising, as respondents expressed considerable concerns about privacy, with average scores ranging from 3.51 to 3.92 on a five-point scale, and concern about unauthorized use of their data (mean = 3.92) was the highest-scoring item in the entire questionnaire.

Thus, it can be concluded that, for today's online consumers in the Portuguese market within the context of an active purchasing journey, the immediate utility, convenience, and relevance of AI-driven recommendations appear to outweigh the perceived risks associated with data collection. This contradiction provides strong empirical support for the Privacy Paradox (Norberg et al., 2007), which describes precisely this dissonance between expressed privacy concern and actual disclosure behavior and aligns with the Privacy Calculus Theory (Culnan & Armstrong, 1999; Dinev & Hart, 2006) , which frames data disclosure as a rational cost-benefit evaluation. When the perceived value of personalized recommendations is high enough, through reduced search effort, more relevant suggestions, and a smoother purchase journey, consumers are willing to tolerate a certain level of perceived privacy risk. Within an active purchase context, where the consumer is already motivated to buy, the cognitive weight of the benefit side of this calculus appears to dominate, pushing privacy concerns to the background.

Additionally, it was found that demographic variables such as age and gender were not statistically significant differentiating factors in this study. Although older respondents reported slightly higher privacy concerns and female respondents showed marginally higher purchase intention, neither difference reached statistical significance. This suggests that the effectiveness of AI-based personalization, as well as the Privacy Paradox itself, transcends these demographic differences.

5.2 Theoretical Contributions

From an academic perspective, this research provides several important contributions. First, it validates the applicability and robustness of the S-O-R paradigm in the contemporary context of AI-driven digital commerce, contributing to a growing body of literature that adapts environmental psychology models to digital consumer behavior. By conceptualizing AI personalization as the stimulus, consumer experience, trust, and satisfaction as organism-level states, and purchase intention as the behavioral response, the study provides an empirically validated structural model that can serve as a theoretical reference for future research in this domain.

This study also contributes to enriching the literature on the Privacy Paradox and Privacy Calculus Theory. It provides quantitative evidence that while consumers articulate strong privacy concerns, their actual behavioral intentions are overwhelmingly driven by the functional and emotional benefits of personalized experience. Furthermore, the borderline path from Privacy Concerns to Trust warrants further investigation and may indicate that, at higher levels of privacy concern or with more diverse samples, a significant moderating effect could emerge.

5.3 Practical Contributions

Beyond its theoretical contributions, this study yields actionable insights for managers, digital marketers and decision-makers in the e-commerce industry, particularly those operating in or expanding into the Portuguese market. Since AI-driven personalization has a significant impact on both Consumer Experience and Satisfaction, e-commerce managers should prioritize investing in advanced recommendation systems and conversational AI. Recommendations that closely match users' browsing history and purchase preferences are not just a convenience feature, but a strategic factor in consumer loyalty and purchasing behavior. Platforms operating in Portugal should consider localizing their recommendation algorithms to reflect Portuguese consumer preferences and seasonal buying patterns.

It is indeed important to invest in the overall quality of the digital experience, as it has been found that Consumer Experience is a significant predictor of Purchase Intention. In turn, managers should ensure that AI-based recommendations are presented in an intuitive and visually appealing format, to improve navigation rather than confuse the user. Special

attention should be given to the items with the lowest scores in the Consumer Experience construct, notably whether recommendations help users stay focused on their shopping, this suggest that current implementations may sometimes distract rather than assist consumers.

Although trust is the least significant predictor of Purchase Intention, it remains statistically significant and strategically relevant. The lowest average score across the entire study was for the item asking whether consumers had no hesitation in following the website's purchase recommendations, which reveals that, although consumers generally trust the platform, they remain cautious when it comes to following AI suggestions. Managers should invest in transparency mechanisms, such as explaining why a product is recommended, what data is being used and how, to bridge this gap between general trust and behavioral trust.

Lastly, even though privacy concerns did not significantly influence consumer behavior in this study, their high descriptive scores should not be ignored from a management perspective. Concerns about unauthorized data use proved to be the highest-scoring item in the questionnaire and may indicate a potential risk. If privacy expectations are not proactively managed, they could become a challenge as regulatory scrutiny increases and consumers become more digitally aware. Managers should not treat privacy communication as a legal compliance exercise, but as a tool for building trust. Thus, e-commerce platforms should adopt transparent data policies and clearly communicate how AI algorithms use personal data to generate recommendations.

5.4 Limitations and Future Research

Despite its useful findings, as with any research, this study is not without limitations, and it is important to acknowledge them so that future research can avoid repeating the same mistakes and further deepen our understanding. The initial limitation pertains to the cross-sectional approach of data collection, which captures consumers' perceptions at a single point in time. The swift advancement of AI technology and the increasing public debate regarding data ethics indicate that consumer trust and privacy concerns are constantly changing. Conducting a longitudinal study would be useful for tracking how these perceptions evolve as consumers become more familiar with AI-driven environments.

Additionally, a significant limitation of the research is found in the sample composition, which is predominantly made up of young, highly educated Portuguese consumers. This may

be because the questionnaire was distributed using convenience and snowball sampling. Although this method has some advantages, there are serious disadvantages, such as the risk that the sample is not representative. This limits the generalizability of the results, although it provides a deep understanding of this specific segment, natives of the digital world, the results may not be fully generalizable to older age groups or different cultural contexts, where privacy norms and e-commerce behaviors may differ significantly. Future research should test the model across diverse cultural contexts and broader demographic segments to determine if the Privacy Paradox is applicable on a global level.

A noteworthy discovery from this research is the marginal significance of the relationship between Privacy Concerns and Trust. Future studies could benefit from exploring this connection by employing larger and more varied demographic groups. A stronger direct or moderating effect of privacy might emerge in populations with greater digital literacy or a deeper understanding of data protection regulations.

In conclusion, this study provides empirical support for the relevance of AI-based personalization as a strategic asset in e-commerce, demonstrating its ability to enhance the consumer experience, build trust, increase satisfaction, and eventually drive purchase intention. The non-significance of the privacy hypotheses raises an important discussion about the practical limits of privacy concerns as a behavioral barrier in the current e-commerce landscape, a discussion that becomes increasingly urgent as AI technologies become more widespread and data collection more extensive. The findings presented here provide a foundation for future research and a set of practical insights for managers seeking to unlock the full potential of AI-driven personalization in a responsible and effective manner.

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Appendix — Questionnaire (Portuguese Version)

O Impacto da Personalização baseada em IA na Experiência do Consumidor em Plataformas de E-Commerce

Este questionário insere-se no âmbito da minha dissertação de Mestrado em Gestão e Negócios na Escola de Economia, Gestão e Ciência Política da Universidade do Minho.

O principal objetivo é perceber como os recursos de personalização da Inteligência Artificial (IA) utilizados por plataformas de venda online influenciam a experiência de compra online.

A sua participação é voluntária e anónima. Os dados recolhidos serão utilizados exclusivamente para fins de investigação académica. O questionário demora aproximadamente 5 minutos a ser preenchido.

Agradeço, desde já, a sua disponibilidade e colaboração.

Luana Baptista — PG55480 — Mestrado em Gestão e Negócios — luanabaptista001@gmail.com

** Indica uma pergunta obrigatória.*

Secção 1 — Contextualização

Quando navega num website (p. ex. Amazon, Zara, Shein ou AliExpress), encontra frequentemente uma secção com produtos ou conteúdos sugeridos com base no seu comportamento anterior, como pesquisas realizadas, produtos visualizados ou compras passadas. Este tipo de sugestões é geralmente gerado por sistemas automáticos que personalizam a experiência de navegação a cada utilizador, através de tecnologias de inteligência artificial (IA).

1. Nos últimos 12 meses, efetuou alguma compra online num Website que lhe ofereceu recomendações personalizadas de produtos (p. ex. Amazon, Shein, Zara, AliExpress ou outros websites de comércio)? *****

Marcar apenas uma opção.

☐ Sim

☐ Não

2. Por favor, indique em que website suportado por IA realizou a sua última compra online. *****

Marcar apenas uma opção.

☐ Amazon

☐ AliExpress

☐ Shein

☐ Temu

☐ Worten

☐ Zara

☐ Outra: _____

3. Durante a sua experiência nesse website suportado por IA, notou alguma personalização como sugestões de produtos baseadas no que viu ou comprou anteriormente? *****

Marcar apenas uma opção.

☐ Sim

☐ Não

☐ Não reparei

Secção 2 — O Estímulo (Personalização baseada em IA)

Considerando o Website suportado por IA onde realizou a sua última compra online — daqui para a frente designado por WEBSITE — por favor responda às questões abaixo.

4. Personalização baseada em IA. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	1 Discordo Totalmente	2	3	4	5 Concordo Totalmente
Este WEBSITE faz recomendações de produtos que correspondem às minhas necessidades.	○	○	○	○	○
Sinto que as recomendações apresentadas são personalizadas para mim.	○	○	○	○	○
O WEBSITE oferece sugestões de produtos que eu provavelmente gostaria de comprar.	○	○	○	○	○
O WEBSITE parece compreender as minhas preferências de compra com base no meu histórico de navegação.	○	○	○	○	○

Secção 3 — A Sua Experiência, Confiança e Satisfação

5. Experiência do Consumidor. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	1 Discordo Totalmente	2	3	4	5 Concordo Totalmente
Senti-me focado(a) ao explorar os produtos sugeridos pelo WEBSITE.	○	○	○	○	○
Senti que as recomendações me ajudaram a manter o foco nas compras.	○	○	○	○	○
Senti que tinha o controlo sobre o processo de escolha dos produtos.	○	○	○	○	○
Senti-me bem ao navegar pelas sugestões apresentadas.	○	○	○	○	○
Fiquei agradado(a) com a experiência de ver estas recomendações.	○	○	○	○	○
Senti-me entusiasmado(a) com os produtos que o WEBSITE me mostrou.	○	○	○	○	○

6. Confiança. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	**1** **Discordo Totalmente**	**2**	**3**	**4**	**5** **Concordo Totalmente**
Acredito que este WEBSITE é de confiança.	○	○	○	○	○
Sinto que posso confiar nas recomendações feitas pelo WEBSITE.	○	○	○	○	○
Acredito que o WEBSITE tem a intenção de me ajudar ao sugerir produtos.	○	○	○	○	○
Não tenho hesitação em seguir as recomendações de compra deste WEBSITE.	○	○	○	○	○

7. Satisfação. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	1 Discordo Totalmente	2	3	4	5 Concordo Totalmente
Estou satisfeito(a) com a minha experiência global ao usar as recomendações neste WEBSITE.	○	○	○	○	○
O sistema de personalização correspondeu às minhas expectativas.	○	○	○	○	○
Estou contente com a relevância dos produtos que me foram mostrados.	○	○	○	○	○

Secção 4 — Intenção de Compra e Privacidade

8. Intenção de Compra. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	1 Discordo Totalmente	2	3	4	5 Concordo Totalmente
É provável que eu compre produtos recomendados por este WEBSITE no futuro.	○	○	○	○	○
Tenho a intenção de continuar a usar este WEBSITE para as minhas compras.	○	○	○	○	○
Consideraria seriamente comprar um produto sugerido pela IA deste WEBSITE.	○	○	○	○	○

9. Privacidade. Por favor, indique o seu grau de concordância com as seguintes afirmações em relação ao WEBSITE. *****

Escala: 1 = Discordo Totalmente; 5 = Concordo Totalmente. Marcar uma opção por linha.

Item	1 Discordo Totalmente	2	3	4	5 Concordo Totalmente
Preocupa-me que o WEBSITE recolha demasiada informação pessoal sobre mim para fazer recomendações.	○	○	○	○	○
Sei que o WEBSITE usa IA, pelo que sinto que a minha privacidade é invadida ao perder o controlo sobre o que a IA sabe de mim.	○	○	○	○	○
Preocupa-me que os meus dados sejam usados para outros fins sem a minha autorização.	○	○	○	○	○

Secção 5 — Dados Demográficos

Para finalizar, são solicitados alguns dados gerais apenas para fins estatísticos e de caracterização da amostra. Relembra-se que todas as respostas são anónimas e confidenciais.

10. Qual é o seu género? *****

Marcar apenas uma opção.

☐ Feminino

☐ Masculino

☐ Outro

☐ Prefiro não responder

11. Qual é a sua faixa etária? *****

Marcar apenas uma opção.

☐ 18–24

☐ 25–34

☐ 35–44

☐ 45–54

☐ 55–64

☐ 65 ou mais

12. Em que concelho reside? *****

Resposta aberta: _____

13. Qual a sua situação profissional atual? *****

Marcar apenas uma opção.

☐ Estudante

☐ Trabalhador-Estudante

☐ Empregado por conta de outrem

☐ Trabalhador independente

☐ Desempregado

☐ Reformado

14. Qual é o seu nível de escolaridade mais elevado (concluído)? *****

Marcar apenas uma opção.

☐ Ensino Básico (9.º ano ou inferior)

☐ Ensino Secundário (12.º ano)

☐ Licenciatura

☐ Mestrado

☐ Doutoramento

15. Quantas pessoas compõem o seu agregado familiar (incluindo o próprio)? *****

Resposta aberta: _____

16. Qual o rendimento mensal líquido do seu agregado familiar? *****

Marcar apenas uma opção.

☐ Menos de 1.000 €

☐ De 1.000 € a 1.999 €

☐ De 2.000 € a 2.999 €

☐ De 3.000 € a 3.999 €

☐ Mais de 4.000 €

☐ Prefiro não responder

17. Com que frequência faz compras online? *****

Marcar apenas uma opção.

☐ Semanalmente

☐ Mensalmente

☐ Algumas vezes por ano

☐ Raramente

— Fim do questionário —