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The role of artificial intelligence personalisation in e-commerce: Customer purchase decisions in the retail sector

Authors:
Kebashnee Moodley[1]
Lavina Sookhdeo[2]

Affiliations:
[1]Department of Information Systems, Faculty of Commerce, Law and Management, University of the Witwatersrand, Johannesburg, South Africa

[2]Wits Business School, Faculty of Commerce, Law and Management, University of the Witwatersrand, Johannesburg, South Africa

Corresponding author:
Kebashnee Moodley
kebashnee.moodley@wits.ac.za

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Background: Online shopping in South Africa grew significantly during the pandemic, highlighting its potential across income groups. Leveraging artificial intelligence (AI) is crucial for e-commerce businesses to enhance customer experiences and stay competitive in the digital age.

Objectives: This study aimed to explore how AI-driven personalisation in e-commerce influences customer purchase decisions in the retail sector in South Africa.

Method: A quantitative approach within a post-positivist paradigm assessed how factors such as perceived usefulness (PU), perceived ease of use (PEU), relative advantage (RA), and voluntariness of use (VOU) impact purchase intention (PI), repeat purchase intention (RPI), and loyalty (LO). Data were collected through a 5-point Likert scale survey distributed to 175 South African e-commerce consumers using convenience sampling, with structural equation modelling (SEM) used for analysis.

Results: The study showed mixed results. Perceived usefulness had a negative but insignificant impact on purchase decisions, possibly because of unmet expectations or price sensitivity. Perceived ease of use also showed a negative but insignificant effect, suggesting that ease alone is insufficient if personalisation quality is lacking. Conversely, relative advantage and voluntariness of use positively influenced purchase decisions, with customers valuing time savings and control over their data.

Conclusion: This study highlights the importance of AI-driven personalisation in South African e-commerce, emphasising the balance between functional and emotional factors to build customer loyalty and influence purchase decisions in a growing market.

Contribution: The study offers practical implications for African businesses and suggests further research into generative AI and cross-country comparisons.

Keywords: artificial intelligence; personalisation; e-commerce; loyalty; purchase intention; repeat purchase intention.

Introduction

E-commerce provides the environment in which artificial intelligence (AI)-powered personalisation features are deployed, enabling businesses to tailor customer interactions based on individual preferences and behaviours. This research specifically examined online shoppers' perceptions regarding the utilisation of these personalisation features within the e-commerce framework, focusing on their influence on customer experience (CE), purchase intention (PI), repeat purchase intention (RPI) and loyalty (LO).

In today's pervasive connectivity and abundant information era, consumers are continuously linked through various devices such as wearables, mobile phones, laptops and cars (eds. Raj, Soundarabai & Augustine 2023). Consumers can access extensive product and service information from multiple sources and conduct transactions across various digital platforms anytime, anywhere (Raj et al. 2023). Therefore, organisations must establish a digital presence and invest in digital channels. The coronavirus disease 2019 (COVID-19) pandemic has emphasised the importance of traditional brick-and-mortar businesses adopting digitalisation and expanding into e-commerce to remain competitive and meet the demands of changing consumer behaviours (Vijayakumar 2023).

The global e-commerce landscape is steadily growing. Retail e-commerce sales worldwide reached 5.8 trillion United States (US) dollars in 2023 and are projected to increase by 39%, surpassing 8 trillion US dollars by 2027 (Kalinin 2024). While Asia, particularly China, dominates global e-commerce revenue, Africa lags with the lowest share (Kalinin 2024). In South Africa, the e-commerce market ranks 51st globally but has seen significant growth, accelerated by the COVID-19 pandemic (Heyns & Kilbourn 2022). Despite this growth, South Africa's e-commerce sector remains relatively underdeveloped. User penetration is expected to rise, particularly among lower-income segments, indicating further potential for expansion (Svotwa 2023).

However, simply having an online presence is not enough for e-commerce companies to succeed. To maintain competitiveness, they must go beyond offering products and competitive prices and focus on delivering superior customer experiences (Heyns & Kilbourn 2022). Personalisation has emerged as a critical strategy for enhancing customer experience in e-commerce. By leveraging available customer data, e-commerce businesses can create tailored interactions that make customers feel valued and engaged (Felix & Rembulan 2023). The Fourth Industrial Revolution, characterised by hyper-automation and hyper-connectivity, is driven by disruptive technologies such as AI, Big Data and the Internet of Things (Heyns & Kilbourn 2022). Companies that embrace these technologies to deliver personalised customer experiences will gain a significant competitive advantage (Vijayakumar 2023). Artificial intelligence, in particular, plays a pivotal role in creating personalised e-commerce experiences, allowing businesses to better meet the needs and expectations of their customers. Therefore, organisations must adopt these technologies to thrive in the rapidly evolving digital landscape and ensure long-term success.

Therefore, this study investigated the capabilities of AI that enable the personalisation of features in e-commerce and examined how these features influence customer purchase decision-making in South Africa.

The main research question that emerged was: How does AI personalisation in an e-commerce context influence PI, RPI and LO? This will be investigated throughout the study.

Research problem

In today's highly competitive e-commerce landscape, businesses must continuously innovate to attract and retain customers, ensuring sustained revenue and long-term viability (Wang et al. 2023). Traditional strategies, such as competitive pricing and unique product offerings, are becoming less effective as they can be easily replicated by competitors, particularly in an era where consumers have instant access to information and price comparison tools (NielsenIQ 2023; Krasia 2023). Economic pressures drive consumers to compare prices across multiple online platforms in search of the best deal, as they aim to maximise the value of their purchases amid rising living costs and inflation. This heightened price sensitivity is further fuelled by the ease with which consumers can access a wide range of options, making it easier to identify and choose the most cost-effective solution (Wang et al. 2023). As a result, businesses face increasing pressure to deliver competitive prices and strong value propositions to retain price-conscious customers.

In this environment, online retailers are under pressure to differentiate themselves by offering superior customer experiences. Global brands like Amazon, Netflix and Uber have set high expectations for seamless, personalised interactions, prompting local e-commerce businesses to adopt similar strategies (CMO Council 2022; Reekie, Stewart & Ahlfeldt 2022). In developed markets, AI is widely used for personalised recommendations, predictive analytics and automated customer service, enhancing both customer satisfaction and operational efficiency. For example, Amazon's recommendation algorithms and Netflix's content suggestions rely heavily on AI to drive engagement and sales (Reekie et al. 2022). Similarly, AI-driven chatbots and personalised marketing transform customer service in companies like Uber (Reekie et al. 2022). The launch of Amazon in South Africa in 2024 has further elevated competition, with its global dominance expected to raise customer expectations (Edwards 2023). To compete, local e-tailers must leverage emerging technologies like AI to create personalised shopping experiences that resonate with consumers and foster loyalty. However, despite the potential of AI to transform e-commerce personalisation, its application remains underexplored in developing markets like South Africa (Heyns & Kilbourn 2022).

Rationale of the study

While previous studies have focused on AI-driven personalisation primarily in the form of recommendation engines (Abinesh & Dulloo 2024; Banik, Banik & Annee 2024; Vijayakumar 2023), there is a gap in empirical research on how customers perceive and respond to various AI personalisation features such as chatbots, predictive analytics, content curation and sentiment analysis (Bhuiyan 2024). Most research tends to be either experimental or technical, overlooking the consumer perspective and how AI influences their shopping behaviours (Wang et al. 2023). Artificial intelligence applications in e-commerce have primarily been studied in markets such as Portugal (Da Silva et al. 2022), the USA (Hoyer 2020) and China (Lee 2019), with limited focus on the African context, despite the rapid growth of e-commerce in the region, particularly following the COVID-19 pandemic. Previous research suggests that sensory appeal can influence customers' perceptions of product performance and impact purchase intentions (Bleier, Harmeling & Palmatier 2019; Vasconcelos et al. 2021). The sensory dimension refers to how an e-commerce platform engages customers' senses (Bleier et al. 2019), including sight, hearing, touch, taste and smell, as well as aesthetic pleasure, excitement, satisfaction and a sense of beauty (Gentile, Spiller & Noci 2007). In an online environment, this pertains to the representational richness of the digital space (Bleier et al. 2019).

Thus, this study aimed to fill this gap by focusing on South Africa, providing insights into how AI can enhance the online shopping experience and drive customer loyalty in the African market. By exploring AI's broader applications beyond recommendation engines, this research contributes to a deeper understanding of how personalised experiences influence purchase decisions, repeat purchases and overall customer loyalty. The findings will not only enrich the existing body of literature but also offer practical implications for e-commerce businesses looking to invest in AI to improve customer engagement and retention.

Literature review and theoretical framework

This section examines the key concepts relevant to AI personalisation in e-commerce and its influence on customer decision-making. It begins by defining essential terms, including *e-commerce, customer experience, artificial intelligence (AI), personalisation, purchase intention, repeat purchase intention* and *loyalty*. The section then introduces the research questions, presents the theoretical framework guiding the study and concludes with a proposed conceptual model that explores AI's role in personalising e-commerce experiences and shaping customer behaviour.

Background and topic definition

The COVID-19 pandemic underscored the critical role of e-commerce in ensuring business sustainability, especially in South Africa, where online shopping has surged in popularity (Chen, Le & Florence 2021; Torry 2020). E-commerce, defined as the buying and selling of goods and services via the Internet (Wang et al. 2023), offers consumers convenience, competitive prices and flexible payment options (NielsenIQ 2023). The rapid growth of e-commerce has created a highly competitive landscape, driven by local and global giants like Amazon (African Retail 2023; Amazon 2023). In this environment, businesses must prioritise exceptional customer experiences to differentiate themselves and foster customer loyalty (Ameen et al. 2021; Khrais 2020).

At the heart of this is customer experience, which refers to the total interaction a customer has with a business across all touchpoints, from browsing to post-purchase (Lemon & Verhoef 2016; Rahmawati & Arifin 2022). Personalisation, which leverages AI to tailor content, recommendations and engagement to individual customer preferences, is a key driver of improved customer experience. By enhancing the relevance and value of interactions, personalisation plays a significant role in influencing PI, RPI and LO (Kaptein & Parvinen 2015; Sujata et al. 2019). In e-commerce, loyalty is typically defined as the tendency of customers to return to a website because of its personalised features (Kim & Baek 2018; Yoon et al. 2013). Purchase intention refers to a customer's likelihood of making a purchase based on the perceived value of the personalised experience (Pappas et al. 2016), while RPI reflects the likelihood of a customer making subsequent purchases from the same retailer (Chiu et al. 2014; Rose et al. 2012).

Artificial intelligence technologies such as machine learning, predictive analytics and deep learning enable the delivery of highly personalised experiences by analysing vast amounts of consumer data, predicting customer preferences and adapting recommendations in real time (Ameen et al. 2021; Wang et al. 2023). These capabilities have a profound impact on customer decision-making in e-commerce, making personalisation a crucial factor in driving online sales (Kalinin et al. 2024).

Purchase intention

A central goal of AI-enabled personalisation is to positively influence PI, the likelihood that a customer will make a purchase (Wang et al. 2023). This study explored how various factors, such as perceived usefulness (PU), perceived ease of use (PEU), relative advantage (RA) and voluntariness, influence online shoppers' purchase decisions on e-commerce platforms. By personalising the shopping experience, AI can reduce decision-making time, highlight relevant products and enhance the perceived value, all of which increase the likelihood of a customer deciding to purchase.

Repeat purchase intention

In addition to encouraging initial purchases, AI-enabled personalisation seeks to drive RPI, the likelihood that customers will return to make subsequent purchases (Wang et al. 2023). This research explored how PU, PEU, RA and Voluntariness influence customers' decisions to revisit e-commerce platforms for future purchases. Personalisation that adapts to individual preferences and anticipates future needs can build ongoing customer satisfaction and trust, making it more likely that customers will return for repeat transactions.

Loyalty

Finally, AI-enabled personalisation plays a key role in building loyalty, the emotional connection that customers form with a brand over time. By recognising and catering to individual preferences, personalised experiences help customers feel valued, which fosters trust and satisfaction. This research examined how PU, PEU, RA and voluntariness of use (VOU) contribute to customer loyalty in e-commerce settings. A personalised shopping experience that aligns with a customer's desires and needs and allows for control over their engagement with the platform, can cultivate long-term loyalty, encouraging customers to return, recommend the brand to others and continue purchasing.

Therefore, the literature sets the foundation for understanding how AI-driven personalisation shapes customer behaviour in e-commerce. Through a theoretical lens and a proposed conceptual model, the research aimed to uncover the critical factors influencing purchase decisions, repeat purchases and brand loyalty in the rapidly evolving digital marketplace.

Artificial intelligence capabilities enabling e-commerce personalisation

Artificial intelligence technologies have the potential to revolutionise customer experience in e-commerce by offering powerful capabilities for personalisation. While AI is not a new concept, advancements in computational power, sophisticated algorithms and data storage have exponentially increased its capabilities (Ergen 2019). The following AI competencies are critical for personalisation in e-commerce:

Machine learning

Machine learning (ML) is a core AI component that enables systems to learn and improve from data without explicit programming (Kaplan & Haenlein 2019). By analysing customer behaviour and patterns, ML algorithms can predict future actions and personalise content effectively (Jakhar & Kaur 2020). Machine learning helps e-commerce businesses process large datasets, identify trends and optimise the customer experience (Rana, Jain & Santosh 2023).

Artificial neural networks

Inspired by the human brain, artificial neural networks (ANNs) are designed to simulate human learning by identifying patterns in data through a multi-layered architecture (Ergen 2019). Artificial neural networks are used to process complex customer data and make decisions based on past interactions. This technology enables deep insights into customer preferences and behaviour, enhancing personalisation (Jakhar & Kaur 2020).

Deep learning

A subset of machine learning, deep learning utilises neural networks with multiple layers to analyse unstructured data more accurately than traditional machine learning methods (Ergen 2019). Deep learning is particularly effective at processing large volumes of data and learning from experiences without human intervention, which allows for more sophisticated customer insights (Goodfellow et al. 2016).

Natural language processing

Natural language processing (NLP) enables computers to interpret human language, facilitating customer interactions through chatbots, virtual assistants and sentiment analysis (Kashyap, Sahu & Kumar 2022; Sujata et al. 2019). By analysing customer feedback, reviews and social media posts, NLP helps businesses understand customer emotions and perceptions, which can inform personalised recommendations (Kang et al. 2020).

Expert systems

Expert systems replicate human decision-making by utilising machine learning and deep learning to process big data. These systems aggregate expert knowledge to automate decision-making processes and offer personalised solutions to customers (Matsuzaka & Yashiro 2023; Tan 2017).

Computer vision

Computer vision allows machines to interpret visual data, such as product images and customer interactions, by using machine learning and deep learning algorithms (Yang & Liu 2021). This capability is crucial for personalising e-commerce experiences, such as recommending products based on visual preferences or assisting with virtual try-ons (Farinella et al. 2013).

The integration of AI into e-commerce personalisation has revolutionised how businesses engage with customers, offering experiences tailored to individual preferences and behaviours. As discussed, AI personalisation features such as recommendation engines, chatbots, content curation, predictive analytics and sentiment analysis are transforming the online shopping landscape, providing a competitive edge for businesses in a saturated market.

Artificial intelligence personalisation features in e-commerce

Artificial intelligence capabilities in e-commerce enable the creation of deeply personalised experiences by leveraging large datasets to understand customer behaviour and preferences. The ability to analyse real-time interactions allows businesses to anticipate customer needs and enhance the shopping journey in a way that traditional methods cannot replicate. Some of the most impactful AI-driven personalisation tools are discussed in the following paragraphs.

Recommendation engines

Artificial intelligence-powered recommendation engines are a cornerstone of personalised online shopping. These systems use machine learning algorithms to analyse customers' past behaviour, preferences and browsing patterns to suggest products that align with their tastes. The advantage of AI in this context is its ability to continuously learn and refine its recommendations, offering products that are not just based on previous purchases but also on contextual factors like location, weather and even time of day (Necula & Păvăloaia 2023). This can drive up-sell and cross-sell opportunities, tailoring product suggestions at every stage of the purchase journey (Moura et al. 2021).

Chatbots and virtual assistants

Artificial intelligence chatbots and virtual assistants are increasingly used to enhance customer service and improve engagement. These tools, powered by NLP and ML, allow for 24/7 customer interaction, providing instant responses to product inquiries and facilitating the purchase process (Alnefaie et al. 2021). More sophisticated virtual assistants go beyond simple queries and can handle complex tasks, offering an even higher level of personalisation by learning from each interaction (Dilmegani 2023). This not only improves efficiency but also builds emotional connections with customers, contributing to a sense of being valued (Chen et al. 2021).

Content curation

Artificial intelligence enables the dynamic curation of content, ensuring that customers are presented with the most relevant product images, videos and information (Hoyer et al. 2020). For new visitors, AI can display best-selling items, while returning customers may see products based on their browsing history or items left in their cart (Chaudhuri et al. 2018; Sujata et al. 2019). By customising the homepage layout and product suggestions throughout the shopping journey, businesses can reduce decision fatigue and enhance the shopping experience.

Predictive analytics

Predictive analytics uses AI algorithms to anticipate customer behaviour, predicting what customers are likely to purchase next based on their historical data and browsing patterns. This can also extend to predicting the effectiveness of certain marketing strategies for individual users, improving the timing and relevance of promotions (Gupta & Joshi 2022). Such insights enable businesses to target customers with personalised offers at the right moment, increasing conversion rates.

Sentiment analysis

Artificial intelligence-driven sentiment analysis offers the ability to gauge customer emotions through their interactions with the website, reviews or social media comments. This analysis is enabled by NLP, which helps businesses understand whether a customer's experience is positive, neutral, or negative. By tailoring customer interactions based on sentiment, businesses can foster better customer relations, address concerns quickly and refine marketing messages to align with customers' emotional states (Sujata et al. 2019).

Influence of artificial intelligence personalisation on customer purchasing decision-making

Personalisation not only enhances customer experience but can also significantly impact customer purchasing decision-making through purchase intention, repeat purchase intention and customer loyalty (Wang et al. 2023). When executed well, AI personalisation makes customers feel more connected to the brand, as the business can demonstrate a deep understanding of their preferences and provide them with highly relevant product suggestions (Kim & Baek 2018). This connection can foster greater customer engagement, making them more likely to return to the site and make repeat purchases.

Studies have shown that personalisation positively influences customer loyalty, with personalised experiences leading to higher levels of satisfaction and trust (Sujata et al. 2019; Tyrväinen, Karjaluoto & Saarijärvi 2020). The personalised content, whether it be through targeted recommendations, custom-tailored offers or emotive customer support, helps build a sense of brand loyalty by showing that the retailer is committed to providing value beyond a simple transaction.

In addition to loyalty, AI personalisation can also improve purchase intention. According to Pappas et al. (2017), personalised content and tailored messaging increase persuasion, making customers more likely to purchase. For instance, AI-powered recommendation engines that incorporate a customer's past behaviour, preferences and contextual information can dramatically reduce decision-making time and offer customers exactly what they need when they need it, boosting conversion rates and sales (Rana et al. 2023; Wu et al. 2017).

Finally, it is essential to recognise that AI personalisation is now expected by many consumers. When it is absent or poorly executed, it may drive customers towards competitors offering more tailored experiences (Lindecrantz, Tjon Pian Gi & Zerbi 2020). This expectation means that businesses must continuously innovate and ensure that their AI-driven personalisation features are of high quality and integrated seamlessly into the overall user experience.

This leads to the following hypothesis for further research:

H1: Personalisation in an e-commerce context positively influences PI, RPI and LO.

Theoretical framework

This study utilises two key theoretical models to examine the impact of AI-driven personalisation on customer behaviours in e-commerce: the *Technology Acceptance Model (TAM)* and the *Diffusion of Innovation Theory (DOI).*

Technology acceptance model

Technology acceptance model, proposed by Davis (1989), serves as the foundation for understanding how users adopt new technologies. Technology acceptance model identifies two primary factors influencing technology adoption: *perceived usefulness* and *perceived ease of use*. Perceived usefulness refers to the extent to which a user believes that using a technology enhances their task performance, such as increasing efficiency or reducing time spent on tasks. Perceived ease of use refers to the perceived effort and difficulty involved in using the technology. According to Davis, these two factors are strongly correlated with users' current and future technology usage. However, PU is found to have a stronger impact on adoption than PEU, suggesting that users may tolerate some complexity if the technology provides clear benefits. In the context of this study, TAM is applied to understand how AI personalisation features on e-commerce sites influence customer perceptions of usefulness and ease of use and how these perceptions, in turn, affect attitudes toward the technology, customer experience and behaviours such as PI, RPI and LO.

Diffusion of innovation theory

Diffusion of innovation theory, as outlined by Rogers (2003), explains how innovations spread through a social system over time. The theory categorises adopters into five groups: Innovators, Early Adopters, Early Majority, Late Majority and Laggards. Rogers identifies five key attributes that influence the adoption of new technologies: *relative advantage, complexity, trialability, compatibility* and *observability*. Relative advantage is the perceived superiority of an innovation over existing solutions and is considered a key factor in adoption. Complexity refers to how difficult the innovation is to use, while trialability relates to how easily a user can experiment with the innovation before full adoption. Compatibility measures how well the innovation aligns with users' existing values and experiences, and observability refers to how visible the outcomes of the innovation are to others.

For this study, relative advantage was identified as a critical factor in assessing the perceived benefits of AI personalisation features on e-commerce sites compared to traditional retail or non-personalised online shopping platforms. The complexity attribute overlaps with the TAM's PEU and was excluded to avoid redundancy. Similarly, observability was not considered relevant as the focus of this study was on individual customer perceptions rather than the visibility of the innovation's outcomes to others. Trialability was also excluded because e-commerce customers have unlimited opportunities to interact with personalisation features, making this attribute less relevant to the study's focus on the intentional use of personalisation. Additionally, the compatibility attribute was integrated into the PU construct, as it relates to how well AI personalisation aligns with customer needs and preferences.

Building on Rogers' work, Moore and Benbasat (1991) introduced the concept of *voluntariness of use*, which addresses the extent to which the adoption of an innovation is perceived as voluntary. This construct is particularly relevant in the context of AI personalisation, where customers may be concerned with their control over personal data for personalised experiences. Thus, RA and VOU were selected as the primary constructs to explore their impact on CE, PI, RPI and LO.

These two theoretical frameworks, TAM and DOI, provide a robust foundation for examining how AI personalisation features are adopted by e-commerce consumers, how they influence customer behaviours and the factors that contribute to the success of such innovations in the online shopping environment.

Conceptual framework

Building on TAM and DOI, the conceptual framework for this study integrates key constructs from both models to examine how AI-driven personalisation influences customer behaviours in e-commerce. These theoretical frameworks provide a comprehensive understanding of technology adoption and innovation diffusion, which are essential for analysing the role of AI personalisation in shaping the CE, PI, RPI and LO.

From TAM, the core constructs of PU and PEU were integrated to explore how customers perceive the benefits and usability of AI personalisation features on e-commerce platforms. These constructs are critical in determining how likely consumers are to adopt AI technologies, which, in turn, influences their interactions with the e-commerce site and their decision-making process.

The DOI contributes further by introducing the RA and VOU constructs, which are crucial in understanding how consumers assess the value and control over AI personalisation. Relative advantage focuses on how much more beneficial AI personalisation is perceived to be compared to traditional shopping experiences, while voluntariness of use highlights the importance of customers feeling in control of their personal information when engaging with personalised features.

The integration of these constructs results in a conceptual model that seeks to explain how AI personalisation influences customer experience, which then affects key behavioural outcomes like PI, RPI and LO. The proposed model positions PU and RA as primary drivers of customer engagement with AI personalisation, while PEU and VOU influence the ease and willingness of customers to interact with these technologies.

Figure 1 illustrates the proposed conceptual framework, highlighting the interrelationships between the constructs and how they collectively influence customer behaviours in an e-commerce context. The next section will provide a detailed explanation of each attribute and its relevance to the study's objectives, elaborating on how these factors contribute to a deeper understanding of the impact of AI personalisation on consumer decision-making.

Conceptual framework: Artificial intelligence-powered personalisation (Sookdeo & Moodley 2024)

Perceived usefulness

Derived from the TAM, *perceived usefulness (PU)* in AI personalisation for e-commerce refers to the degree to which shoppers believe these features enhance their shopping experience by making tasks like finding products, obtaining support and making purchase decisions more effective, relevant and efficient (Wang et al. 2023). Studies by Liang et al. (2012) and Wang et al. (2023) show a positive correlation between PU and the adoption of AI personalisation, indicating

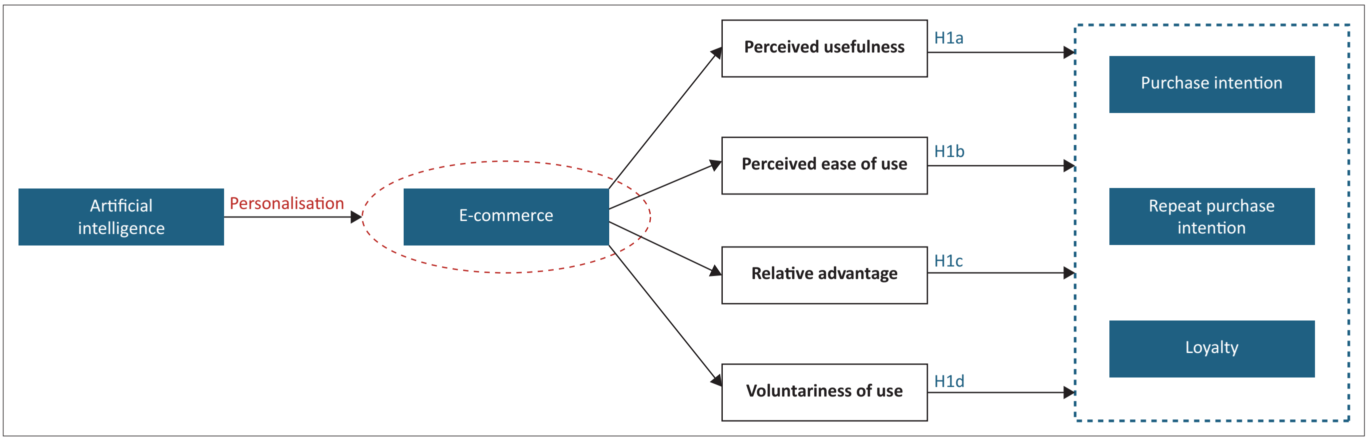

FIGURE 1: Conceptual framework.

that when customers perceive these features as helpful, they are more likely to engage with and trust the platform.

This leads to the proposed sub-hypothesis:

> **H1a:** Perceived usefulness positively influences purchase intention, repeat purchase intention and loyalty.

Specifically, PU enhances purchase intention by streamlining the decision-making process as AI personalisation presents relevant product recommendations based on preferences, browsing history and contextual factors like location or weather, reducing cognitive effort and increasing the likelihood of conversion (Liang et al. 2012; Wang et al. 2023). Similarly, repeat purchase intention is fostered when customers perceive AI personalisation as consistently valuable, offering tailored promotions or reminders of previously viewed items. This ongoing relevancy enhances convenience, encouraging customers to return for future purchases (Chen et al. 2021). Lastly, loyalty is built when customers perceive the personalisation as genuinely useful in meeting their needs, fostering trust and emotional connection with the brand. Over time, AI-driven personalised experiences, such as tailored recommendations and loyalty rewards, strengthen customer satisfaction and brand engagement, making customers more likely to remain loyal and recommend the brand to others (Mileva 2023). Thus, the relationship between PU and these key outcomes forms a dynamic feedback loop when AI personalisation is perceived as useful; it drives greater engagement, repeat purchases and loyalty, creating long-term customer relationships and sustained brand preference.

Perceived ease of use

Perceived ease of use, as defined in the TAM, refers to the degree to which customers believe that AI-powered personalisation features in e-commerce are easy to use, requiring minimal effort, time and cognitive resources (Wang et al. 2023). The impact of PEU on PI, RPI and LO is significant. Firstly, PEU positively influences PI by making the shopping process more seamless and intuitive. When AI personalisation features are easy to navigate, customers can quickly find relevant products and make purchasing decisions with less cognitive load. This ease of use encourages customers to act on their buying intentions. Wang et al. (2023) highlight that PEU enhances the utilisation of AI personalisation, which directly leads to higher purchase likelihood. Secondly, PEU fosters RPI by creating a frictionless shopping experience that customers are likely to return to. If personalisation tools are easy to use and consistently deliver relevant recommendations, customers are more inclined to revisit the platform for future purchases. Research by Chen et al. (2021) supports this by showing that ease of use in personalised features builds a foundation for future engagement.

Thirdly, PEU contributes to loyalty by ensuring a hassle-free, satisfying experience that encourages customers to form a lasting connection with the brand. A smooth, effortless interaction with AI personalisation features makes customers feel understood and valued, which enhances trust and fosters long-term loyalty. As customers become more accustomed to the ease of use, their likelihood to return, recommend the platform and engage in repeat purchases increases (Svotwa et al. 2023). In summary, PEU influences PI, RPI and LO through its role in making the shopping experience more efficient, engaging and user friendly, with research from Wang et al. (2023) and Chen et al. (2021) confirming its positive impact on these outcomes.

Therefore, the following sub-hypothesis was proposed:

> **H1b:** Perceived ease of use in an e-commerce context positively influences purchase intention, repeat purchase intention and loyalty.

Relative advantage

In the context of e-commerce, businesses can gain a competitive advantage by offering unique features or benefits that differentiate them from competitors, such as AI-enabled personalisation. Relative advantage is a key factor in determining competitive advantage, as it captures customers' perceptions that an innovation (in this case, AI-powered personalisation) is more beneficial than traditional alternatives (like non-personalised e-commerce sites or physical stores).

The study examined how customers perceive AI-enabled personalisation as providing a relative advantage over traditional shopping options, such as physical stores or non-personalised online shopping experiences. This perceived superiority can enhance a customer's PI, as they are more likely to engage with e-commerce sites that offer tailored recommendations and streamlined shopping experiences that meet their specific needs. By delivering relevant and timely information, AI personalisation reduces the effort required to make a purchase decision, increasing the likelihood of purchase.

Relative advantage also influences RPI. E-commerce platforms with AI personalisation can create ongoing value by offering personalised promotions, product recommendations and reminders of previously browsed items, making the experience more convenient. Customers perceive these tailored features as a continued benefit, increasing their intention to return to the site for subsequent purchases. In contrast, sites without these personalised features may not offer the same level of convenience or satisfaction, leading to a decreased likelihood of repeat visits.

Lastly, RA plays a crucial role in fostering *loyalty*. When customers feel that an e-commerce site offers distinct, personalised advantages over its competitors, whether it is through personalised promotions, recommendations, or a seamless experience, they are more likely to develop a stronger emotional connection with the brand. This sense of satisfaction and trust built through perceived benefits encourages long-term loyalty, as customers are more inclined to return to the site over time and recommend it to others.

Thus, RA directly impacts PI, RPI and loyalty by enhancing the perceived value of AI personalisation in e-commerce. The greater the perceived benefits of AI-powered features compared to traditional shopping experiences, the more likely customers are to engage with the brand, make repeat purchases and remain loyal over time. Thus, the following hypothesis is proposed:

H1c: Relative advantage of AI personalisation in e-commerce positively influences purchase intention, repeat purchase intention and loyalty.

Voluntariness of use

In the context of the DOI theory, VOU refers to the degree to which customers perceive their use of an innovation such as AI-driven personalisation in e-commerce as voluntary or within their control (Wang et al. 2023). This concept centres on customers' ability to decide whether or not their personal information is used to enhance their shopping experience through personalisation, which can influence their overall interaction with the platform.

Research supports the idea that when customers feel they have control over their personal information, they are more likely to engage with personalised features. For instance, Cecere and Rochelandet (2013) found that websites with clear and transparent privacy policies tend to attract more customers, although they also caution that such policies can sometimes create an illusion of control without guaranteeing real compliance. Similarly, Potoglou, Palacios and Feijóo (2015) showed that privacy concerns significantly impact consumers' online shopping behaviour, with many preferring retailers who ask for minimal personal data.

This study aimed to explore whether the ability to voluntarily choose the use of personal information for personalisation impacts PI, RPI and LO. When customers perceive that the use of personalisation features is voluntary, they tend to view the experience more positively, aligning with their preferences and enhancing their sense of control over the shopping process.

This autonomy increases their investment in the process and, ultimately, their likelihood of making a purchase, as voluntary participation is linked to higher engagement and satisfaction. As customers perceive the personalisation as more relevant and useful to their needs, PI increases.

Similarly, the VOU influences RPI. Customers who feel they have the freedom to opt into personalisation without pressure are more likely to return for future purchases. This voluntary engagement fosters a sense of control, making the experience more satisfying and reinforcing the likelihood of repeated interactions with the brand. As customers continue to opt into personalisation features based on their preferences, they develop a deeper relationship with the brand, which boosts RPI.

Furthermore, VOU plays a crucial role in building loyalty. When customers voluntarily adopt personalised features, they develop a stronger emotional connection to the brand, perceiving it as responsive to their needs and preferences. Over time, this sense of autonomy and satisfaction fosters trust, a key driver of loyalty. Customers who feel that their choices are respected and that the personalised experience benefits them are more likely to stay loyal to the brand, recommend it to others and continue engaging in repeat transactions.

Therefore, the hypothesis that VOU positively influences PI, RPI and LO is supported by the idea that when customers have the freedom to choose their level of engagement with personalisation, they are more satisfied, more invested and more committed to the brand. This sense of control not only enhances their shopping experience but also strengthens their ongoing relationship with the platform.

Thus, the following sub-hypothesis was proposed:

H1d: Voluntariness of use in an e-commerce context positively influences purchase intention, repeat purchase intention and loyalty.

Research methods and design

The research methodology was employed to gain insights into customer perceptions of AI personalisation within an e-commerce context. It clarifies the research design, target population, sampling method and the research instrument utilised, followed by an overview of the data collection process and strategies for analysis and interpretation. Ethical considerations are also discussed.

Research approach

A quantitative research approach was embraced in this study within a post-positivist paradigm. This paradigm acknowledges the existence of multiple realities and recognises that measuring or knowing all variables is impractical. The quantitative approach was chosen to investigate the relationships between PU, PEU, RA and VOU and their effects on PI, RPI and LO, specifically within the context of AI personalisation on E-commerce platforms. This approach allowed for a detailed analysis of how AI-driven personalisation features influence key customer behaviours, such as the likelihood of purchasing, returning for repeat transactions and developing long-term loyalty to e-commerce sites that utilise personalised experiences. By examining these factors, the study aimed to provide insights into how AI personalisation shapes customer decision-making and enhances the overall shopping experience.

Research design

A cross-sectional survey with standardised questions using a 5-point Likert scale was employed to comprehensively explore various aspects of participants' experiences with e-commerce platform personalisation features. This design facilitated diverse participant feedback on the multiple variables under investigation.

Data collection methods

Digital surveys were utilised as the primary method for data collection because of their efficiency in reaching a large and diverse pool of respondents quickly.

Population and sample

The population for this study comprised South African individuals who use e-commerce platforms to purchase goods and services. The sample size was determined using the respondent-per-variable ratio proposed by Kass and Tinsley (1979). Kass and Tinsley (1979) recommend surveying 5–10 participants for each variable, up to a maximum of 300. Given that the research instrument included 35 variable measures, the required minimum sample size was 175 participants. Because of practical constraints in identifying a specific target sample group, a non-probability convenience sampling method was employed. Non-probability convenience sampling, based on participant availability and willingness, was cost-effective and efficient, making it suitable for a survey-based design with limited time and resources. While convenience sampling may introduce bias and does not ensure a representative sample, it was appropriate for this study's goal of understanding consumer behaviour within the South African e-commerce context. Saunders et al. (2019) support the use of convenience sampling, recognising its practical advantages despite its inherent limitations. Future research could improve generalisability by employing probability sampling.

The research instrument

The research instrument used for data collection was an online survey comprising four key sections. The first section outlined the research objectives and explained AI-enabled personalisation features. The second section sought participant consent to opt into the survey, while the third section gathered demographic information. The fourth section assessed AI-enabled personalisation features on e-commerce sites, focusing on the latent variables outlined in the conceptual framework. These variables were measured using scales adapted from established sources, as shown in Table 1.

The survey employed a 5-point Likert scale (Likert 1932) to capture participants' opinions on AI personalisation features across the six key variables. The 5-point Likert scale was chosen because it offers a balanced and straightforward method for capturing respondents' attitudes towards AI-driven personalisation features. It provides a simple and easily understood range of responses, from strongly agree to strongly disagree, with a neutral midpoint that allows for an accurate representation of varying levels of opinion. This scale also facilitates efficient data analysis, as it allows for both descriptive and inferential statistics, including techniques like factor analysis. Moreover, the Likert scale is widely used in social science research, ensuring that the findings are comparable to previous studies. The combination of ease of use, precision and compatibility with statistical methods makes the 5-point Likert scale a practical choice for this research.

To analyse the data, exploratory factor analysis (EFA) was initially conducted to examine the relationships between the multiple variables and determine whether they could be consolidated into a smaller set of fundamental factors (Field 2018). Exploratory Factor Analysis helped validate the measurement scales and rationalise the variables into key

TABLE 1: Variables and measurement sources.

Variable	Measurement source
Perceived usefulness and perceived ease of use	Davis (1989)
Relative advantage	Loiacono et al. (2007); Moore and Benbasat (1991)
Voluntariness of use	Moore and Benbasat (1991)
Loyalty	Srinivasan et al. (2002)
Purchase intention	Putrevu and Lord (1994)
Repeat purchase intention	Loiacono et al. (2007)

Please see the full reference list of this article Moodley, K. & Sookhdeo, L., 2025, 'The role of artificial intelligence personalisation in e-commerce: Customer Purchase Decisions in the Retail Sector', *South African Journal of Information Management* 27(1), a1926. https://doi.org/10.4102/sajim.v27i1.1926 for more information.

factors for further analysis. Subsequently, confirmatory factor analysis (CFA) was performed to assess how well the data fit the conceptual model and to evaluate the reliability and validity of the constructs (Hair et al. 2019). Confirmatory Factor Analysis provided insights into both convergent validity (the correlation between variable items within a factor) and discriminant validity (the distinction between different factors) (Hair et al. 2019). Finally, structural equation modelling (SEM) was applied to test the relationships between the independent variables (PEU, PU, RA and VOU) and the dependent variables (CE, PI, RPI and LO). Structural equation modelling, as described by Hair et al. (2019), allows for simultaneous analysis of interdependent relationships among measurement items and constructs, integrating features of factor analysis and regression techniques.

Data collection procedure

The primary data collection tool used in this study was an online survey, chosen for its efficiency, cost effectiveness and ability to reach a broad and diverse sample of participants. The population consisted of South African participants who use e-commerce platforms to purchase goods and services, to determine their perceptions of personalisation features. The survey was created using Qualtrics survey software provided by the university, with participant data securely stored on the platform. It was distributed via social media channels, resulting in 284 responses.

Outliers, defined as responses that significantly differ from the rest of the sample population on one or more variables (Field 2018; Hair et al. 2019), were identified during pre-analysis to ensure sample representativeness. Standardised scores were used to detect outliers, with a threshold of ±3.29 (Field 2018). Responses falling outside this range were considered outliers and removed. After outlier removal, the final sample size was reduced from 284 to 204.

Data analysis strategies and interpretation

For the analysis of descriptive and inferential statistics, IBM SPSS version 28 was used, enabling a comprehensive understanding of the data through various techniques. Descriptive statistics helped summarise the characteristics of the sample, providing key insights into the demographic and behavioural traits of participants. To explore relationships between variables and reduce data complexity, EFA was applied. Exploratory factor analysis was used to validate and consolidate the 35 variables into a smaller, more manageable set of factors, streamlining the measurement process for subsequent analysis (Field 2018; Hair et al. 2019).

Confirmatory factor analysis was performed using IBM SPSS AMOS version 28 to assess the construct validity of the model and ensure that the data fit the hypothesised relationships. Confirmatory factor analysis was critical in verifying the accuracy and reliability of the measurement model, testing both convergent and discriminant validity (Hair 2019). This step ensured that the constructs, such as PU and PEU, were valid and reliable representations of the factors they were intended to measure.

For the structural analysis of interrelationships between variables, SEM with AMOS was employed, chosen over partial least squares SEM (PLS-SEM) because of its superior ability to handle complex, multivariate data, particularly with a sample size of 204 participants (Mpinganjira 2014). Unlike PLS-SEM, which is typically used for smaller samples or exploratory research (Chin 2010), SEM is more suited for testing theory-driven models with established relationships among variables (Hair et al. 2019). Structural Equation Modelling offers a more robust and precise analysis of model fit and causal relationships, providing deeper insights into how AI personalisation influences customer behaviours such as PI, RPI and LO. Its ability to assess both measurement and structural models simultaneously, along with its capacity to handle missing data, makes SEM a comprehensive tool for analysing complex relationships (Hair et al. 2017). Therefore, SEM with AMOS was the optimal choice for this study's confirmatory analysis, allowing for a clearer understanding of the mechanisms driving customer decision-making in AI-powered e-commerce environments.

To ensure the validity of both the inner and outer models, the conceptual model was rigorously tested for fit indices and construct validity. Reliability and validity were key factors in evaluating the model's robustness. The model's reliability was assessed through Cronbach's alpha and composite reliability scores, with a threshold of >0.7 indicating acceptable reliability for all variables. All variables achieved scores above this threshold, confirming their reliability.

In addition to reliability, both convergent and discriminant validity were assessed. Convergent validity was determined by examining the factor loadings and average variance extracted (AVE), with all items achieving standardised factor loadings above 0.60 and AVE values exceeding 0.50, indicating strong convergent validity (Hair et al. 2017). Discriminant validity, which ensures that the factors are distinct from one another, was also evaluated, with all factors showing adequate separation. These results, presented in Table 2 and Table 3, highlight the quality of the measurement model and reinforce the validity of the conceptual framework.

The Fornell and Larcker (1981) criteria were used to assess the discriminant validity of the model. According to this approach, the square root of the AVE values is presented in bold, running diagonally in Table 3. The other values in the table represent the inter-variable correlations. For discriminant validity to be established, the bold values (representing the square roots of AVE) must be higher than the off-diagonal values in the corresponding rows and columns. This criterion was met for all variables, confirming that discriminant validity was achieved. Additionally, as shown in Table 3, the maximum shared variance (MSV) scores for each variable were lower than their respective AVE values, further supporting the evidence of discriminant validity.

Results

This section presents the outcomes of the research study hypotheses testing (through path analysis) and situates the results within the context of the literature review.

Path analysis results

The estimated path coefficients of the structural model (in Table 4) were analysed to evaluate alignment with the hypotheses.

Hypothesis testing (conceptual model)

After conducting CFA, SEM was employed to examine the structural model relationship between the independent variables, namely PEU, PU, RA and VOU and their influence on customer purchase decision.

Structural equation modelling analysis began by inputting the CFA results into AMOS, using regression imputation to generate new variables corresponding to the latent constructs from the CFA. These latent variable scores were then used to create a path diagram that represented the

TABLE 2: Reliability and convergent validity.

Factors	Items	Standardised factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted	Maximum shared variance
Perceived usefulness	PU45	0.76	0.86	0.86	0.56	0.44
	PU44	0.77				
	PU43	0.64				
	PU42	0.78				
	PU41	0.79				
Perceived ease of use	PEU55	0.84	0.86	0.87	0.57	0.26
	PEU54	0.80				
	PEU53	0.71				
	PEU52	0.67				
	PEU51	0.73				
Voluntariness of use	VOU72	0.80	0.76	0.76	0.61	0.38
	VOU71	0.76				
Customer experience	CE88	0.83	0.85	0.85	0.64	0.47
	CE87	0.81				
	CE86	0.78				
Purchase decision	RPI112	0.84	0.94	0.94	0.63	0.46
	RPI111	0.82				
	PI103	0.80				
	PI102	0.87				
	PI101	0.79				
	LO96	0.84				
	LO95	0.67				
	LO93	0.83				
	LO92	0.70				
	LO91	0.78				
Relative advantage	RA64	0.78	0.77	0.77	0.54	0.47
	RA63	0.71				
	RA62	0.70				

PU, perceived usefulness; PEU, perceived ease of use; VOU, voluntariness of use; CE, customer experience; RPI, repeat purchase intention; PI, purchase intention; RA, relative advantage; LO, loyalty.

TABLE 3: Discriminant validity results.

Variables	Voluntariness of use	Perceived usefulness	Perceived ease of use	Relative advantage	Customer experience	Purchase decision
Voluntariness of use	**0.78**	-	-	-	-	-
Perceived usefulness	0.41	**0.75**	-	-	-	-
Perceived ease of use	0.44	0.49	**0.75**	-	-	-
Relative advantage	0.53	0.66	0.51	**0.73**	-	-
Customer experience	0.58	0.49	0.47	0.69	**0.81**	-
Purchase decision	0.62	0.45	0.41	0.65	0.67	**0.79**

Note: The square root of AVE values is depicted in bold font, running diagonally in the Table 3. The other values listed indicated the inter-variable correlations. For discriminant validity to hold true, the bold values needed to be higher than other values in the corresponding rows and column where they were located. This was the case for all variables which indicated that discriminant validity was achieved.

TABLE 4: Regression weights.

Hypothesis	Path analysis	Estimate	S.E.	C.R.	*p*	Outcome
H1a	Perceived usefulness--> Purchase decision	-0.162	0.10	-1.54	0.12	Rejected
H1b	Perceived ease of use--> Purchase decision	-0.040	0.07	-0.59	0.56	Rejected
H1c	Relative advantage--> Purchase decision	0.778	0.10	7.45	***	Accepted
H1d	Voluntariness of use--> Purchase decision	0.377	0.05	7.13	***	Accepted

Estimate, Estimate of regression weights; s.e., standard error of regression weights; C.R., critical ratio for regression weight – regression weight estimate and/or estimated standard error.

relationships between the variables. The diagram illustrated the dependency relationships, with arrows indicating the direction of influence from independent to dependent variables, while double-sided, curved arrows were used to represent correlations between factors (Hair et al. 2019). Path analysis was conducted to assess the strength of these relationships, with the imputed factor scores from the CFA used in the analysis. Hypothesis testing focused on evaluating the impact of PEU, PU, RA and VOU on PI.

The study investigated these key factors' influence on customer behaviour in the context of AI personalisation in e-commerce. Perceived ease of use assesses how user-friendly AI features, like personalised recommendations, are for customers, with smoother, more intuitive experiences likely boosting PI. Perceived usefulness reflects whether AI personalisation adds value to the shopping experience, making it easier for customers to find relevant products, thus enhancing PI and RPI. Relative advantage evaluates whether customers perceive AI-driven personalisation as superior to non-personalised shopping experiences or traditional retail, with a positive perception increasing purchase intention and loyalty. Lastly, VOU examines whether customers feel they have control over their engagement with AI personalisation features; when customers can voluntarily opt into personalised experiences, it fosters trust and autonomy, leading to higher PI, RPI and LO. In essence, these factors collectively determine how AI personalisation influences customer engagement and decision-making in e-commerce.

The path diagram in AMOS, shown in Figure 2, illustrates the hypothesised relationships between key constructs such as PEU, PU, RA, VOU and their impact on PI, RPI and LO in the context of AI personalisation. After scoring, the unstandardised scores are presented in Figure 3, with standardised scores displayed in Figure 4. These results are then discussed concerning the impact of AI personalisation on customer purchase decision-making, as outlined in the hypotheses.

Model fit

The SEM model fit statistics were first evaluated and indicated a good fit overall for the conceptual model.

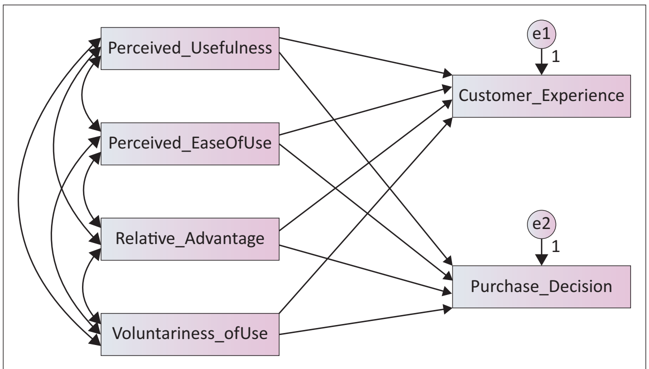

FIGURE 2: Path diagram for hypotheses testing before scoring.

Statistical results are depicted in Table 5 and include root mean square residual (RMR) = 0.010, goodness of fit index (GFI) = 0.976 and comparative fit index (CFI) = 0.982. Root mean square error of approximation (RMSEA) did not meet the acceptable threshold level of <0.08 with a score of 0.269.

Discussion

Discussion of H1: Personalisation in an e-commerce context positively influences purchase decision

This section discusses the results of the study concerning the existing literature, providing insights into how AI-driven personalisation impacts customer purchase decisions in e-commerce.

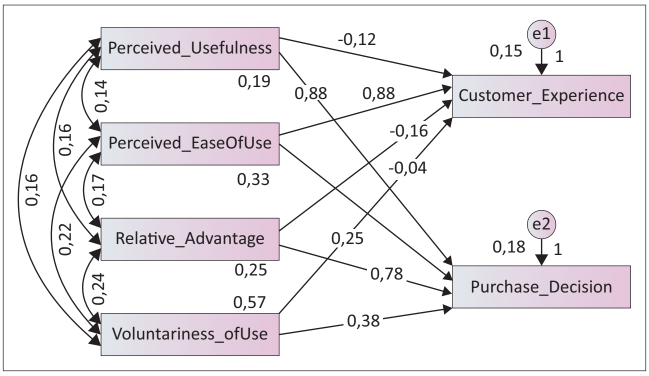

FIGURE 3: Measurement model results – Unstandardised values.

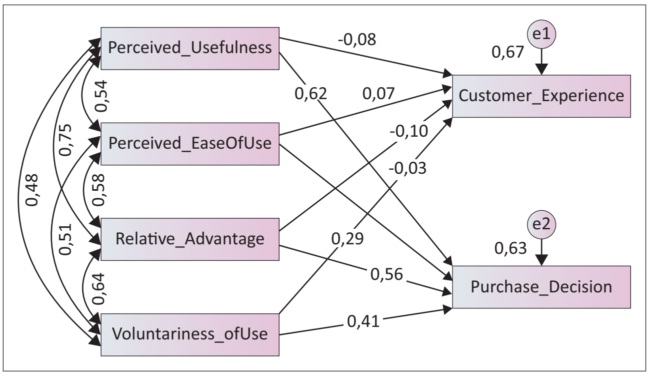

FIGURE 4: Measurement model results: Standardised values.

TABLE 5: Structural model fit statistics.

Category	Indicator	Acceptance level	Model score
Model fitness indicators			
χ^2	*p*-value	> 0.05	0.00
	χ^2	Not applicable	15.73
	df	Not applicable	1.00
Absolute fit	RMSEA	< 0.08	0.27
	GFI	> 0.90	0.98
	RMR	< 0.05	0.01
	Chi-square/*df*	< 3.0	15.73
Incremental fit	CFI	> 0.90	0.98
	NFI	> 0.90	0.98
	IF	> 0.90	0.98

RMSEA, root mean square error of approximation; GFI, goodness of fit index; RMR, root mean square residual; CFI, comparative fit index; NFI, normed fit index; IF, incremental fit; *df*, degrees of freedom; χ^2, Chi-square.

Sub-hypothesis H1a: Perceived usefulness and purchase decision

The findings for Sub-hypothesis H1a indicated a negative and insignificant correlation between PU and purchase decision, which contrasts with the conclusions drawn by previous studies (Rana et al. 2023; Stanley 2022) that suggested personalisation benefits, such as increased relevance and tailored experiences, contribute to enhanced customer satisfaction and positive purchase outcomes. One possible explanation for this discrepancy lies in the quality of personalisation execution.

Previous research underscores that personalisation must meet or exceed customer expectations to foster positive outcomes (Gao et al. 2022). If personalisation fails to anticipate or align with customer preferences, it may not result in the desired effect on purchase decisions (Mileva 2023; Tyrväinen et al. 2020). Furthermore, customers who feel that a retailer truly understands their needs and offers meaningful, relevant content are more likely to engage with the brand and make future purchases (Kim & Baek 2018; Stanley 2022). If personalisation fails to evoke such a sense of connection, it may not enhance purchase decisions. Additionally, Pappas et al. (2017) suggested that personalisation's influence could be diminished when customers have specific shopping goals, such as finding the best price or a specific product brand. Under these circumstances, factors like price sensitivity or product availability could outweigh the effects of personalisation, leading to a lower impact on purchase decisions.

Sub-hypothesis H1b: Perceived ease of use and purchase decision

The negative but insignificant relationship between PEU and purchase decision (Sub-hypothesis H1b) was rejected. Similar to PU, this finding may also be explained by customers' specific shopping goals (Pappas et al. 2017). While ease of use is often viewed as a critical factor for engagement, it does not guarantee that customers will make a purchase if the personalisation fails to meet their specific expectations.

Furthermore, even if personalisation features are easy to use, if they do not deliver satisfactory or relevant recommendations, they can negatively affect purchase intent (Kim & Baek 2018; Tyrväinen et al. 2020). This suggests that ease of use alone is insufficient to drive purchase decisions, particularly if the personalised content or recommendations do not align with customers' needs.

Sub-hypothesis H1c: Relative advantage and purchase decision

The findings for Sub-hypothesis H1c revealed a positive and significant relationship between relative advantage and purchase decision, which supports the hypothesis that customers who perceive clear advantages in AI-driven personalisation are more likely to make purchases. This result aligns with previous research highlighting the benefits of AI-driven personalisation in e-commerce, such as enhancing product relevance, improving customer satisfaction and reducing time and effort during the shopping process (Mileva 2023; Stanley 2022). Customers who perceive AI personalisation as offering distinct advantages over traditional shopping methods are more likely to engage with the platform and increase their purchase intent. This reinforces the notion that AI can improve the overall shopping experience by providing tailored, efficient and relevant recommendations that resonate with customers' preferences.

Sub-hypothesis H1d: Voluntariness of use and purchase decision

The positive relationship between VOU and purchase decision, as proposed in Sub-hypothesis H1d, was confirmed. This finding suggests that customers who feel they have control over how their data is used for personalisation are more likely to trust the platform and proceed with purchases. Transparency in data usage, particularly regarding privacy, plays a crucial role in building trust and reducing concerns about personal data security. This aligns with research by Cecere and Rochelandet (2013), who found that platforms with transparent information privacy policies tend to attract larger customer bases and experience higher revenue. When customers perceive that they have control over their personal information, they are more confident in their decision to engage with AI-driven personalisation, which positively influences their purchase behaviour (Lee et al. 2019).

In summary, the findings of this study highlight the importance of relative advantage and voluntariness of use in driving customer purchase decisions in AI-enabled e-commerce environments. These results suggest that customers value personalised experiences that offer clear benefits and control over their data. However, PU and PEU were not found to significantly influence purchase decisions, indicating that these factors alone may not be sufficient to drive engagement in the context of AI personalisation. This suggests that e-commerce platforms must consider not only the functionality of their personalisation features but also the broader customer experience, including trust, relevance and privacy, to foster meaningful engagement and drive purchase behaviour.

Conclusion

This study highlighted the critical role of AI-driven personalisation in e-commerce and its influence on customer purchase decisions. While RA and VOU emerged as key drivers of engagement with AI personalisation, PEU and PU did not significantly impact purchase decisions. These findings suggest that for AI personalisation to be successful, it must provide not only convenience but also emotional value that resonates with customer needs. E-commerce platforms should focus on offering personalised experiences that deliver clear advantages, such as more relevant recommendations while ensuring customers feel in control of their data. Opt-in privacy policies and transparent data usage are vital for fostering trust and encouraging repeat purchases.

While this study has contributed to the body of knowledge by empirically assessing the impact of AI personalisation on purchase decisions, there are limitations to consider. Firstly, the study was limited to participants in South Africa, and as a result, the findings may not be generalisable to other country contexts. Further research could extend this work to other African countries or compare results across different global markets to examine the broader applicability of the findings. Secondly, the study relied on participants' individual shopping experiences on e-commerce sites and the personalisation features available on those platforms. To ensure that participants had a good understanding of the features being evaluated, examples of AI personalisation were provided in the survey. This could have influenced responses, as participants may have based their answers on their perceptions of those features rather than their actual experiences.

In conclusion, this study answers the research objectives by identifying key factors influencing AI personalisation adoption in South Africa's e-commerce market. However, the unexpected findings regarding PU and PEU suggest that future research should explore deeper aspects of customer experience, including trust, privacy concerns and emotional engagement, to provide a more comprehensive understanding of the factors driving purchase decisions.

Recommendations

With the rapid expansion of e-commerce in South Africa, personalised experiences aimed at enhancing customer satisfaction and gaining a competitive edge can be considered essential (Lindecrantz et al. 2020). Without such personalisation features, e-commerce platforms risk losing customers to competitors, a concern exacerbated by the impending entry of industry giants like Amazon, known for their leadership in e-commerce personalisation and customer experience (Amazon 2023; Statista 2023).

The study underscores the critical role of personalisation in the survival and success of online shopping platforms. While AI technology holds significant potential for delivering enhanced personalisation features, meticulous attention to solution execution is paramount to ensure a positive impact on customer purchase decisions.

E-commerce AI personalisation features should prioritise ease of use and accessibility in design to minimise customer effort and streamline their shopping journey. For instance, offering multiple search formats such as text, image and voice searches can reduce the time spent by customers and foster a positive brand sentiment (Rana et al. 2023). Content curation functionality can further tailor the experience for both new and existing customers by adjusting website layouts (Gupta & Joshi 2022; Mileva 2023).

Moreover, personalisation features must not only be user friendly but also deliver tangible value to customers in exchange for their personal information. Customers need assurance that their data is being utilised to understand their preferences effectively and anticipate their needs (Mileva 2023; Tyrväinen et al. 2020). This necessitates high accuracy and relevance in recommendation options, leveraging AI-driven insights from various data sources like purchase history, browsing behaviour and contextual information (Ameen et al. 2021; Necula & Păvăloaia 2023).

Furthermore, predictive analytics techniques can be employed to target prospective customers with personalised offers and promotions at optimal points in their shopping journey to drive conversion (Gupta & Joshi 2022). Chatbot agents used for online customer support should be efficient and effective in problem solving to enhance customer experience and perceptions of organisational innovation (Chen et al. 2021).

However, functional features alone may not suffice to elicit a positive emotional response from customers. Features that evoke enjoyment and foster an emotional connection to the brand are crucial for increasing engagement and building customer loyalty (Ameen et al. 2021; Gao et al. 2022). Integrating recognition attributes and sensory enjoyment elements can further enhance the personalisation experience (Ameen et al. 2021; Chaudhuri et al. 2018).

Additionally, organisations should explore AI-driven recommendation systems extending to augmented reality and virtual assistants for a more immersive experience (Necula & Păvăloaia 2023). Anthropomorphic features integrated into chatbots, and virtual assistants can create a more human-like interaction, fostering emotional connections and perceptions of value (Chen et al. 2021; Mileva 2023).

Despite robust personalisation efforts, specific customer shopping goals may override the influence of personalisation, especially in environments where economic trends drive value-seeking behaviour (Pappas et al. 2017). Organisations must adapt their marketing and pricing strategies to address these unique conditions and continually refine their AI personalisation strategies to meet evolving customer expectations. Ultimately, e-commerce platforms that excel in personalisation will likely emerge as preferred destinations for consumers, driving revenue and market dominance.

Suggestions for further research

This research has contributed insights into South African consumers' perceptions of AI in e-commerce. Given Africa's underrepresentation in AI in e-commerce literature and its status with the lowest e-commerce revenue globally (Statista 2023), exploring customer perceptions across other African countries could offer valuable insights for fostering e-commerce success across the continent and enriching the existing literature base. Additionally, this study underscores the importance of striking a balance between functional and emotional attributes in personalisation design to evoke positive emotional responses from customers. Subsequent research could delve into the impact of anthropomorphic features on influencing customer purchase decisions. Moreover, the study highlights the significance of solution quality in shaping customers' perceptions of the usefulness and ease of use of AI personalisation. Future studies could empirically examine this aspect. Lastly, as AI continues to evolve, particularly with the emergence of generative AI capable of creating diverse digital content like text, images, audio, code and videos (Harreis et al. 2023), investigating emerging trends of generative AI in e-commerce and its impact on customer perceptions could be a promising avenue for research.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

K.M. contributed to the writing of the manuscript and presenting the findings. L.S. conceptualised and conducted the research for the report and findings as the foundation of the manuscript.

Ethical considerations

Ethical approval was granted by the Research Committee of the Wits Business School, University of the Witwatersrand (approval number WBS/DB2368773/452). Written consent was obtained from all human participants. Participation was voluntary and anonymous, with no requirement for participants to disclose their identities. Participants were also given the option to withdraw their feedback at any point. The survey collected no sensitive information, and all survey data were securely stored on a personal computer with restricted access.

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Data availability

The data that support the findings of this study are available from the corresponding author, K.M., upon reasonable request.

Disclaimer

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