Influence of AI Personalisation on E-commerce customer experience and purchase decisions in South Africa

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ABSTRACT

Covid-19 has underscored the importance of organisations to invest in E-commerce for sustainability and has accelerated E-commerce adoption globally and in South Africa. E-tailers need to look beyond product catalogues and competitive pricing and promotions for differentiation and look towards providing superior customer experience for competitive advantage. Artificial Intelligence is a transformational technology that can be harnessed for enhanced personalised interactions and customer experience in E-commerce.

The study investigates Artificial Intelligence (AI) capabilities that enable personalisation features in E-commerce, and examines how the Perceived Usefulness, Perceived Ease of Use, Relative Advantage and Voluntariness of Use of AI personalisation features in this medium influence Customer Experience, Purchase Intention, Repeat Purchases Intention and Loyalty.

An online survey was conducted with local online shoppers to gather their feedback on the use of AI-enabled personalisation features on E-Commerce. Factor analysis including Exploratory factor analysis (EFA), Confirmatory Factor analysis (CFA) and Structural Equation Modelling (SEM) was used to analyse the results. The results indicate that both Relative Advantage and Voluntariness of Use of AI personalisation in E-commerce, positively and significantly influence Customer Experience as well as customer Purchase Decisions. Perceived Ease of Use positively influences customer experience and negatively influences purchase decisions, although both effects are insignificant. Finally, Perceived Usefulness is found to have a negative, albeit insignificant influence on both Customer Experience and Purchase Decisions.

These findings contribute a South African perspective on understanding customer perceptions of AI personalisation applications in E-Commerce.

KEYWORDS: Artificial Intelligence, Customer experience, E-commerce, Loyalty, Personalisation, Purchase Intention, Repeat Purchase intention

DECLARATION

I, **Lavina Sookhdeo**, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Lavina Sookhdeo Signature:

Signed at …Midstream………………………………………………

On the 19 day of February 2024.

DEDICATION

This research report is dedicated to my husband Vijay and my children Kaedon and Milania who are my infinite source of strength and inspiration.

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I would like to acknowledge my supervisor Dr. Kebashnee Moodley for her commitment and support, and for consistently showing up for me throughout this journey. Thank you for being there when I needed you.

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- 4IR – Fourth industrial revolution
- AI - Artificial Intelligence
- ANN – artificial neural networks
- B2B – business to business
- B2C – business to consumer
- C2C – consumer to consumer
- COVID-19 – coronavirus pandemic of 2019
- ML – machine learning
- NLP – natural language processing
- TAM – technology acceptance model
- Wits – University of the Witwatersrand

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

The purpose of this study is to examine Artificial Intelligence (AI) capabilities that enable personalisation features in E-commerce, and investigate how these features influence Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty in a South African context, as depicted in Figure 1 below.

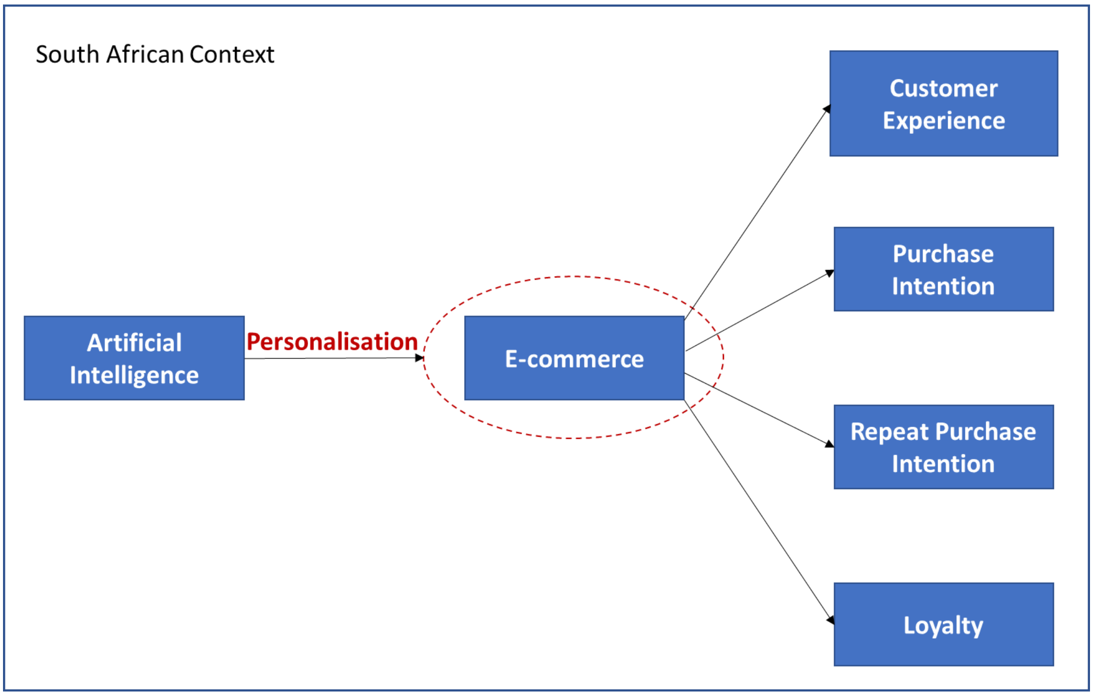

Figure 1 - High level conceptual framework

1.2 Background of the study

The current age of information with ubiquitous connectivity enables consumers to be constantly connected through multiple devices (e.g., wearables, mobile phones, laptops, cars, etc.), obtain comprehensive product and service information from multiple sources (Tyrväinen et al., 2020; Wu et al., 2017; Yoon et al., 2013), and transact anywhere at any time across multiple digital platforms (e.g., Web, Mobile applications, social media, etc). It is therefore vital for organisations to have a digital presence and invest in digital channels (Tyrväinen et al., 2020). Covid-19 has further underlined the importance for brick and mortar organisations to establish a digital presence and expand or transition to E-commerce channels (Chen et al., 2021; Torry, 2020).

E-commerce is increasing worldwide. According to Chevalier (2024), an estimated 5.8 trillion U.S. Dollars in retail E-commerce sales was realised globally in 2023 and this is projected to increase by 39%, to exceed 8 trillion U.S Dollars by 2027. Statista (2024b) reported that Asia lead the global retail E-commerce revenue ranking in 2023 with an estimated 1.7 trillion U.S. Dollars earned. This was mainly attributed to China which contributed an estimated 935 billion U.S. Dollars in revenue. The United States of America (USA) followed China from a country ranking perspective in 2023 (Statista, 2024a). Africa lagged, achieving the lowest E-commerce revenue worldwide at approximately 31 billion U.S. Dollars in 2023 (Statista, 2024b).

The most recent South African E-commerce statistics available rank South Africa as the 51st largest E-commerce market (ecommerceDB). The predicted E-commerce revenue for South Africa for 2023 was 7.22 billion U.S Dollars (Statista, 2022). A study conducted by Mastercard in 2020 found that the Covid-19 pandemic had accelerated South African consumer Online shopping by 68% (Mastercard, 2020). Due to increased Online shopping behaviour in 2020 as a result of the pandemic, the value of E-commerce transactions in South Africa was predicted to soar to R225 billion by 2025 and achieve a 150% increase (Thenga, 2020). In 2022, Online retail growth was 35% reaching a value of R55 billion (Mastercard, 2023). A 12.9% E-commerce revenue growth rate was anticipated for 2023 (ecommerceDB).

Despite the Covid-19 coronavirus pandemic serving as a catalyst for increased South African Online shopping behaviour, the E-commerce landscape remains underpenetrated (Reekie et al., 2022). South African user penetration was estimated at 49.4% in 2023 and expected to reach 59.7% in 2027 (Statista, 2022).

Pertinently, South African Online shopping does not appear to be limited to affluent segments of the population (Reekie et al., 2022). Research conducted by Reekie et al. (2022), in their 2022 South African Digital Customer Experience Report, found that over 50% of 2000 survey respondents had a monthly household income below R10 000. Thus, there is still an opportunity for further growth in this sector, and adopting an Online presence is essential for business growth and survival (NielsenIQ, 2023). However Online retailers will need to do more than rely on product offering, price, and promotion to remain competitive (Khrais, 2020; Lindecrantz et al., 2020; Sujata et al., 2019; Wang et al., 2023).

Global E-commerce giants like Amazon set the benchmark for high quality E-commerce customer experience, which consumers often use to draw comparisons (Edwards, 2023). E-commerce businesses therefore need to be competitive to attract customers and increase revenue, and a strategic focus on enhancing customer experience is crucial. Customers who enjoy a good experience with a brand are more likely to be loyal, advocate for the brand, and purchase more products and services (Kim & Baek, 2018; Mileva, 2023; Stanley, 2022; Sujata et al., 2019; Tyrväinen et al., 2020; Wu et al., 2017; Yoon et al., 2013).

One way in which E-commerce companies seek to enhance customer experience, is by personalising the experience for customers by using information available about them to meet their individual needs and preferences, and to make them feel more valued during their interaction on E-commerce platforms (Ameen et al., 2021; Kaptein & Parvinen, 2015; Wang et al., 2023).

The fourth industrial revolution (4IR) of greatly anticipated hyper automation and hyperconnectivity, enabled by technological capabilities like Artificial Intelligence (AI), Big Data, the Internet of things and Robots (Park, 2018), is anticipated to be an era where intelligence dominates. Companies that use this intelligence to provide superior customer experience will have a competitive advantage (Verma et al., 2021).

Artificial Intelligence is a disruptive technology that uses big data analytics to create enhanced personalised e-commerce experiences to meet customer needs and preferences (Ameen et al., 2021; Sujata et al., 2019; Verma et al., 2021; Wang et al., 2023). Organisations' survival and competitive advantage will depend on their ability to have awareness of, and harness disruptive technologies such as Artificial Intelligence to extract business value (Ameen et al., 2021; Chen et al., 2021; Wang et al., 2023).

1.3 Research problem

E-commerce businesses need to be competitive to be able to attract and retain customers for revenue generation and organisational sustainability (Wang et al., 2023). In the current highly competitive retail environment, with customers' effortless access to information, traditional pricing and promotion differentiation tactics or reliance on unique offerings, are not as effective because they can be replicated by competitors (Khrais, 2020; Lindecrantz et al., 2020; Sujata et al., 2019; Wang et al., 2023). Due to economic pressures and the motivation to reduce costs, consumers will often shop around on multiple Online sites to get the best deal (NielsenIQ, 2023).

As intense competition erodes margins, Online retailers will need to intensify their focus on differentiating themselves on customer experience to remain competitive (Chen et al., 2021). Customers who are accustomed to seamless experience and personalisation from global digital native E-commerce brands like Amazon, Netflix and Uber have a high benchmark of expectations to compare local Online businesses to (CMO Council, 2022; Reekie et al., 2022). Local Online retailers thus need to ensure that the customer experience they offer is seamless and on par or superior, to withstand competition from international E-commerce businesses (African Retail, 2023).

The imminent launch of Amazon in South Africa, expected in 2024 (Amazon, 2023), whilst beneficial for consumers, will likely exacerbate competition among incumbent e-tailers. It is the second largest E-commerce retailer worldwide after Alibaba (Statista, 2022) and tends to dominate in the E-commerce markets where it operates (African Retail, 2023). The phrase “Amazon effect” was coined to describe its dominance in Online sales and the enhanced customer expectations created as a result of the high quality experience provided on its Online platform (Edwards, 2023). Therefore, it is no longer an option for local Online businesses to lag when it comes to providing a seamless and enhanced personalised experience. Organisations can gain a competitive advantage by leveraging their customer data to create extremely personalised experiences, difficult for competitors to emulate (Ameen et al., 2021; Chen et al., 2021; Lindecrantz et al., 2020; Wang et al., 2023).

Artificial Intelligence is a key disruptive technology heralding the fourth industrial revolution. It has powerful capabilities that enable the enhanced personalisation of customer journeys (Ameen et al., 2021; Wang et al., 2023). Although it holds great promise for transforming business through its powerful capabilities, it is still in the early stages of application and there is limited awareness of how this technology can be applied in an E-commerce context for personalisation to enhance customer experience. (Kashyap et al., 2022; Rana et al., 2023). In an E-commerce context specifically, organisations need to understand how the technology may be leveraged for competitiveness by enabling personalised experience for customers who visit their sites, and the potential benefits to be delivered.

Thus, this study set out to investigate Artificial Intelligence (AI) capabilities that enable personalisation features in E-commerce, and examine how these features influence Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty in a South African context.

1.4 Research questions

The fundamental research questions to be answered include:

1. What are the Artificial Intelligence capabilities that can enable personalisation features in an E-commerce context?

2. What personalisation features do Artificial Intelligence capabilities enable in an E-commerce context?

3. How does AI personalisation in an E-commerce context influence Customer Experience?

4. How does AI personalisation in an E-commerce context influence Purchase Intention, Repeat Purchase Intention, and Loyalty?

1.5 Rationale

Previous studies of AI E-commerce personalisation in the literature tend to primarily fixate on the optimisation of recommendation engine performance, with the primary research approach being experimental rather than theory driven (Bawack et al., 2021). The AI research perspectives tend to be biased towards the technical or the organisational perspective (Ameen et al., 2021). Previous literature has highlighted the need for more empirical research into customer perceptions of AI-enabled Online shopping journeys and how it influences experience and shopping behaviour (Ameen et al., 2021; Sujata et al., 2019). This is needed to understand how these journeys can then be enhanced for a more positive experience that meets the needs of customers and enables organisations to build stronger relationships with customers.

This study sought to investigate customer perspectives of AI personalisation in E-commerce and contributed a theory driven approach with empirical research. It investigated customer perceptions of a broader set of AI personalisation features available in an E-commerce context that may include recommendation engines and also extend to chatbots, contentment curation, predictive analytics, and sentiment analysis.

It builds on previous empirical research, by attempting to additionally provide a high-level overview of the key Artificial Intelligence capabilities (technical underpinnings that power Artificial Intelligence) and indicate how these can be used to enable E-commerce personalisation features. A comprehensive search of the literature indicates this to be the first empirical study that evaluates the voluntariness of the use of AI personalisation in E-commerce.

Following a bibliometric review of literature in the Web of Science database relating to AI in E-commerce, Bawack et al. (2021) identified that the countries that dominate in investing in research and development towards AI in E-commerce, are China and the USA. These countries are also the market leaders in E-commerce (Bawack et al., 2021; Islam, 2023; Statista, 2022, 2024a). Rana et al. (2023) conducted a bibliometric review of AI in retail from the Scopus database and found that empirical studies on AI applications in Retail have predominantly been from the United States, United Kingdom, and India. Both Rana et al. (2023) and Bawack et al. (2021) identified a top ten list of country contributors to research on AI in retail E-commerce that did not feature African countries. This implies a need for more representation in the literature from an African perspective, and further from a South African perspective as a literature search for South African empirical studies on AI personalisation in E-commerce produced minimal results and only one study by Pillay (2022) could be found which pertained to the use of Online Apparel sites.

The case for more representation needed from Africa is supported by the fact that Statista (2022) found Africa to have achieved the lowest E-commerce revenue worldwide. Particularly, with the proliferation of and need for E-commerce triggered by the Covid-19 pandemic (Bawack et al., 2021; Mastercard, 2023; Reekie et al., 2022), African countries need to keep abreast of the latest AI developments in E-commerce, with due consideration of the African context, to remain competitive in the industry (Bawack et al., 2021). Thus, this study contributes an African perspective on the existing body of research, by investigating AI application in retail E-commerce, in a South African context.

It also offers insight to organisations contemplating investment in AI personalisation capabilities for E-commerce solutions, as to the potential customer experience benefits to be gained.

1.6 Delimitations of the study

The research study was limited to the AI capabilities applied in a Business to Customer (B2C) E-commerce context. Further, it did not focus on the full complement of AI capabilities that could be applied in an E-commerce context, but rather only those that lent themselves to the personalisation of the customer's experience.

The study did not seek to delve deep into the underlying technical aspects of AI capabilities but rather to provide an overview of these aspects and direct focus on the personalisation features enabled.

1.7 Definition of terms

a) Artificial Intelligence – This is the automation and continuous learning technology that executes data-driven analytics and decision-making (Kumar et al., 2019).

b) Customer experience – Customer experience is the holistic end to end interaction that a customer has with an organisation (Rahmawati & Arifin, 2022) and entails the combination of perceptions and emotions triggered by every interaction, across all its touchpoints (Wereda & Grzybowska, 2016)

c) E-commerce – E-commerce is defined as a digital business channel that enables the electronic trading of products and services via technology and the internet (Wang et al., 2023).

d) Loyalty – This is defined as a customer's inclination to seek out a shopping site for purchases, in preference over competitors, due to its personalisation features (Kim & Baek, 2018; Yoon et al., 2013).

e) Personalisation – Online personalisation entails the use of information technology to predict customer interest and intent in order to customise content and engagement to meet user needs (Zanker et al., 2019).

f) Purchase Intention - is defined as the customer's decision to make a purchase on an Online store based on the value they perceive, from personalised features offered (Pappas et al., 2016; Wu et al., 2017).

g) Repeat Purchase intention – is the customer's intention to purchase other products in the future, from the same Online store (Chiu et al., 2014; Rose et al., 2012).

h) Customer journey - A customer journey can be described as the interactions that a customer has with an organisation and typically entails company consideration, pre-purchase exploration of the organisations products and services, purchase of goods, post purchase engagement, use of goods, and repurchase (Lemon & Verhoef, 2016)

1.8 Assumptions

It was assumed that AI-enabled personalisation features were available to varying extents in utilised E-commerce sites that the survey population had access to, to enable respondents to evaluate various AI-enabled personalisation features that contributed to their experience and purchase decisions.

1.9 Chapter Outline

- Chapter 1: Introduces the purpose of the study, the research problem, research questions, rationale, and delimitations.
- Chapter 2: Provides background to the study, discusses the research questions, and theoretical and conceptual frameworks.
- Chapter 3: Describes the research approach, research instrument, data collection and quality assurance procedures to be employed.
- Chapter 4: Describes the findings from the survey feedback.
- Chapter 5: Discusses the survey findings in respect of the literature review.
- Chapter 6: Presents the conclusions, recommendations, and suggestions for future research.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

This chapter describes the key concepts of E-Commerce, Customer Experience, Artificial Intelligence, Personalisation, Purchase Intention, Repeat Purchase Intention, and Loyalty. It goes on to discuss each research question in detail before exploring a theoretical framework for the study and concluding with a proposed conceptual model.

2.2 Definition of topic or background discussion

Covid-19 has underscored the importance of organisations to invest in E-commerce sales channels for sustainability (Chen et al., 2021; Torry, 2020). It has further accelerated E-commerce adoption in South Africa (Mastercard, 2020, 2023; Reekie et al., 2022; Thenga, 2020). Wang et al. (2023) defined E-commerce as a digital business channel that enables the electronic trading of products and services via technology and the internet. Chawla and Kumar (2022) referred to it as a transaction facilitation mechanism for the electronic sale of products and services. E-commerce delivers convenience for consumers by enabling them to purchase desired goods/services, when they want to, usually at more competitive prices, using their preferred payment options (NielsenIQ, 2023). E-commerce transactions can take place between Business to Consumer (B2C), Business to Business (B2B) and Consumer to Consumer (C2C) (Budree, 2017). In this research, E-commerce is defined as the Online purchase or sale of products and services via the internet in a business to consumer context.

With local competition and the advent of global e-commerce giants like Amazon (African Retail, 2023; Amazon, 2023), e-tailers need to look beyond product and service catalogues and competitive pricing, to attract and retain customers (Khrais, 2020; Lindecrantz et al., 2020; Sujata et al., 2019). They need to focus on providing superior customer experience for competitive advantage (Ameen et al., 2021; Chen et al., 2021; Khrais, 2020; Wang et al., 2023; Wu et al., 2017). Customer experience is the holistic end to end interaction that a customer has with an organisation (Rahmawati & Arifin, 2022) and entails the combination of perceptions and emotions triggered by every interaction, across all its touchpoints (Wereda & Grzybowska, 2016). Lemon and Verhoef (2016, p71) further describe it as being multidimensional and encompassing a "customer's cognitive, emotional, behavioural, sensorial, and social responses" during engagement with the organisation, throughout the purchase journey. In this research context, customer experience refers to the combination of the customer's perceptions and emotions, experienced during the end-to-end E-commerce interaction.

In depth understanding of customers unique experience, can enable organisations to deliver personalised experiences for customers to earn their loyalty (Wereda & Grzybowska, 2016). Online personalisation entails the use of technology to predict customer interest and intent, and customising content and engagement to meet user needs (Zanker et al., 2019). In an E-commerce context, it entails the customisation of digital content to suit individual customer needs based on their unique attributes, to increase the likelihood of achieving business outcomes on the E-commerce platform (Kaptein & Parvinen, 2015).

The goal of personalisation in E-commerce is to enhance customer experience, customer purchase intention, repeat purchases and loyalty for organisation sustainability. According to Sujata et al. (2019), loyalty manifests as the likelihood of customers to recommend brands that they feel positively about to others and these customers are more likely to offer improvement suggestions to the brand. Yoon et al. (2013) define loyalty as a customer's inclination to return to an Online shopping site, with the intent of making repeat purchases and providing brand referrals to other potential customers. Kim and Baek (2018) view loyalty as a proclivity towards a long-term commitment to an entity. Loyalty in this study is defined as a customer's inclination to seek out a shopping site for purchases, in preference over competitors, due to its personalisation features.

Wu et al. (2017) viewed purchase intention as the customer's future intention to shop in an Online store. Pappas et al. (2016) defined it as a customer's preference to continue to purchase in an Online store due to the customised experience provided. Purchase intention in this research study is defined as the customer's decision to make a purchase on an Online store based on the value they perceive, from personalised features offered. Repeat purchase intention is the prospect of a customer continuing to purchase from a specific Online shop (Chiu et al., 2014; Rose et al., 2012). The definition of repeat purchase intention for this research study is aligned with Rose et al. (2012) and Chiu et al. (2014).

Artificial Intelligence is a transformational technology that can be harnessed to enhance personalised interactions in E-commerce channels through powerful capabilities, by analysing customer shopping behaviour, previous purchases, and preferences (Ameen et al., 2021; Khrais, 2020; Wang et al., 2023). It is an automation and continuous learning technology that executes data-driven analytics and decision-making (Kumar et al., 2019). The technology has evolved beyond algorithms defined by humans, to imitate human decision making and now aspires to emulate human learning (Borges et al., 2021). Kaplan and Haenlein (2019) define Artificial Intelligence (AI) as a technology with the ability to accurately decode and analyse external data, learn from it, and use the insights to accomplish specific outcomes via flexible adaptation. It consolidates information from big data sources and uses machine learning to determine pattern analysis on it. In this research context, the scope of AI capabilities and features pertinent to an E-commerce personalisation context will be discussed.

2.3 What are the Artificial Intelligence capabilities that can enable personalisation features in an E-Commerce context?

Great expectations have been set about the capabilities of Artificial Intelligence and its ability to revolutionise business and the delivery of customer experience. The concept of Artificial Intelligence is not new but convergence and maturity of augmented computational power, sophisticated algorithms, big data and cheaper data storage costs have dramatically increased its capability (Ergen, 2019). Business leaders and professionals need to understand what this technology encompasses to be able to harness and exploit its power. From an E-commerce context, research is fragmented on AI capabilities, and few endeavours have focussed on summarising key AI competencies that would be applicable (Kashyap et al., 2022). This section aims to provide insight into the core capabilities of AI that facilitate personalisation.

2.3.1 *Machine Learning*

Machine learning is a core component of AI that describes computer learning without specific human programming (Kaplan & Haenlein, 2019). It involves the training of machines using data and algorithms (Jakhar & Kaur, 2020). The algorithms enable the identification of patterns through the analysis of data and use these to make predictions (Ergen, 2019; Jakhar & Kaur, 2020).

Artificial Intelligence uses machine learning (ML) and predictive analytics capabilities to consolidate and process massive amounts of data (Ergen, 2019; Jakhar & Kaur, 2020). This facilitates the extraction of deep insights and the prediction and forecasting of outcomes to support retailers in making data evidenced business decisions (Rana et al., 2023). Machine learning algorithms require less data to be trained than Deep learning (Ergen, 2019).

2.3.2 *Artificial Neural Networks*

Artificial Neural Networks (ANNs) are a technical architecture inspired by the functioning of neurons in the human brain (Ergen, 2019; Jakhar & Kaur, 2020). The algorithms are applied to simulate the process of human neurons to enable the network to "learn" to problem solve (Pearson, 2019). The architecture comprises 3 layers: an input layer that accepts input data, a hidden layer that identifies patterns in the data and an output layer that generates outcome of data processing (Ergen, 2019; Jakhar & Kaur, 2020).

2.3.3 *Deep Learning*

Deep learning is a subgroup of Machine Learning that uses ANNs to simulate the neural network structure of the human brain. In deep learning, the term "deep" refers to the number of hidden layers in an ANN. Deep neural networks (deep learning) have multiple hidden layers (Ergen, 2019; Jakhar & Kaur, 2020).

Deep learning is effective at learning from unstructured or unlabelled data and tends to be more accurate than machine learning (Ergen, 2019; Jakhar & Kaur, 2020).

Goodfellow et al. (2016) described it as an adaptation of machine learning that entails the use of a hierarchy of concepts to enable computers to learn about the world. Computers can learn complex concepts by using the hierarchy of concepts to systematically develop understanding from simpler concepts in the hierarchy. Computers learn from experience through this process, negating the need for human intervention to specify rules to facilitate learning. Deep learning can also be described as using data representation learning techniques with numerous layers of representation. In this capability, the feature layers are learned from the data and not designed by humans (LeCun et al., 2015).

2.3.4 *Natural Language Processing*

Natural Language Processing (NLP) is a capability that enables human computer interaction by interpreting human language into computer executable commands (Kashyap et al., 2022). It uses machine learning algorithms, deep learning and NLP methods to create models for improved accuracy in analysing textual data (Kang et al., 2020). NLP enables sentiment analysis (Savci & Das, 2023; Sujata et al., 2019) which is the analysis of written or spoken language for specific attributes including content, positive or negative perceptions and emotion detection (Sujata et al., 2019).

2.3.5 *Expert Systems*

The aim of expert systems is the automated replication of human reasoning and decision making for optimal outcomes. It uses Machine Learning and Deep Learning to aggregate implicit expert knowledge through big data analysis (Matsuzaka & Yashiro, 2023). It's main components include a knowledge base with expert information, an inference engine and a user interface (Tan, 2017).

2.3.6 *Computer Vision*

Computer vision aspires to simulate how humans see and interpret what they view (Yang & Liu, 2021). It is enabled through sensing technology and uses image and object recognition powered by machine learning and deep learning (Matsuzaka & Yashiro, 2023). It is the technology that enables computers to see, through the application of algorithms that automatically analyse visual images, to identify objects and perceive and track their physical dimensions (Farinella et al., 2013; Yang & Liu, 2021).

The literature investigation has identified core capabilities of AI, that use sophisticated algorithms, and process vast quantities of data, to simulate human learning. These powerful capabilities can be employed in an E-commerce context, to enable personalisation features. Types of E-commerce personalisation features enabled by AI are discussed next.

2.4 What personalisation features do Artificial Intelligence capabilities enable in an E-commerce context?

In a competitive E-commerce industry, being able to differentiate your brand by offering personalised experiences that are difficult to emulate can be a competitive advantage (Chiu et al., 2014; Lindecrantz et al., 2020; Wang et al., 2023). AI elevates personalisation on E-commerce sites through the processing of big data for deeper insights and instantaneous, enhanced precision in customer journey personalisation (Ameen et al., 2021; Mileva, 2023; Necula & Păvăloaia, 2023; Pearson, 2019; Wang et al., 2023). AI can enable E-commerce providers to leverage their customer data and behavioural patterns into site features that can anticipate, predict, and fulfil individual customer needs (Ameen et al., 2021; Pearson, 2019; Sujata et al., 2019; Wang et al., 2023). This section discusses specific features powered by AI capabilities that are used for personalisation.

2.4.1 *Recommendation engines*

Recommendation systems are an established personalisation tool that helps to narrow down product selection options by offering unique product suggestions to each customer based on their determined preferences. As a result of this, it is possible to customise each customer's view of the web page with the products most likely to be of interest to them (Zanker et al., 2019).

AI-driven recommendation systems use machine learning and deep learning techniques and can also extend to augmented reality and virtual assistants (Necula & Păvăloaia, 2023). AI capabilities used, enhance the relevance and accuracy of the results thereby increasing the personalisation to an individual customer's preference (Necula & Păvăloaia, 2023). In addition to assisting customers with product selections at the pre-purchase stage, recommendation systems can also be used at the purchase stage to promote up selling and cross selling of products tailored to customers' interests (Moura et al., 2021).

2.4.2 *Chatbots and Virtual Assistants*

Chatbots are digital conversational solutions that employ machine learning and natural language processing to simulate human computer dialogue (Alnefaie et al., 2021; Reshmi & Balakrishnan, 2016). Two types of conversational agents are distinguished: Chatbots that interact via text or written phrases and voice-enabled chatbots that engage through auditory commands. Increased insight can be obtained to enhance customer support interactions as the chatbot, acting in a customer care capacity, progressively learns from conversations with customers (Sujata et al., 2019) .

Intelligent Virtual Assistants are an enhanced conversational agent that additionally uses natural language understanding and artificial emotional intelligence to resolve more complex customer queries. It can be applied in both a text and voice format (Dilmegani, 2023; Moussawi et al., 2021) These powerful virtual agents can function autonomously, emulating personalised human responses and learn and adapt, to action user requests (Moussawi et al., 2021)

A common application of virtual assistants is as a digital personal assistant that can execute tasks in real time for example meeting reminders and playing music. Apple's Siri, Alexa and Google Assistant are examples of this (Moussawi et al., 2021; Sujata et al., 2019)

2.4.3 *Content curation*

Content curation refers to how Artificial Intelligence can be applied in an E-commerce context to structure and tailor e-commerce content for individual customers.

AI can be used to create unique experiences for customers in multiple ways that includes customising video and image content for maximum appeal and relevance to customers (Pearson, 2019). It also includes adapting the E-commerce home page layout for new and existing customer by for example presenting new customers with the best-selling products and showing existing customers' previous purchases, items browsed and items still in cart (Chaudhuri et al., 2018; Mileva, 2023; Pearson, 2019; Sujata et al., 2019; Zanker et al., 2019). AI can customise content for customers in the end-to-end online purchase journey, from product discovery to order confirmation. During product discovery and on checkout, it can be used to indicate alternative product options and introduce customers to complementary products through "frequently bought together" suggestions, and at the order confirmation stage, it can remind customers of previous purchases, wish list items and related trending products should they wish to add these to their order (Mileva, 2023; Moura et al., 2021; Pearson, 2019; Sujata et al., 2019; Zanker et al., 2019).

2.4.4 *Predictive Analytics*

Predictive analytics is an enhanced analytical capability that uses methods such as machine learning, artificial neural networks, and predictive modelling, and analyses current and historical data, patterns, and trends, to anticipate an event taking place in the future (Gupta & Joshi, 2022). It can predict customer behaviour and purchase decisions and apply these insights for personalisation, to create a seamless journey and enhance customer experience. It's features include being able to evaluate the most appropriate marketing techniques relevant for an individual customer and when to implement them (Gupta & Joshi, 2022).

According to Gupta and Joshi (2022), predictive analytics make it possible to segment your customer base to identify and target prospective customers with personalised offers, discounts, promotion reminders etc. It can evaluate the most appropriate marketing techniques relevant for an individual customer and determine when to implement them. It can also be used to provide personalised recommended content e.g., recommended new music on Spotify, or recommended products and services e.g., clothing recommendations based on style preference. It makes it possible to create personalised experiences for anonymous visitors to the website even if you do not have their demographic information.

2.4.5 *Sentiment analysis*

Sentiment analysis is the automated analysis and dissection of customer statements, enabled through Natural Language Processing (NLP), that makes it possible to determine positive or negative sentiment expressed as well as emotion detection (Sujata et al., 2019). The algorithm becomes more accurate as it is exposed to more data and therefore is a powerful personalisation tool in terms of ascertaining customer needs. It enables the personalisation of customer messaging from macro campaigns to landing page wording (Sujata et al., 2019).

This concludes the review of various types of E-commerce personalisation features enabled by the AI capabilities discussed in section 2.3. The discussion will now move on to how personalisation features influence customer experience in an E-commerce context.

2.4.6 *Image search*

Commodity identification is an application of Computer Vision that enables image search in E-commerce (Yang & Liu, 2021). According to Yang and Liu (2021), this search overcomes the limitations of textual description searches for products and services as customers may not always have the correct descriptions and can instead upload a picture of a product for a more accurate search result. The content supervision component of computer vision plays an automated filtering and control role in identifying and blocking illegal or undesired image content (Yang & Liu, 2021).

2.5 How does AI personalisation in an E-commerce context influence Customer Experience?

AI personalisation can make it possible for E-commerce businesses to give every visitor to their site specialised, more accurate, real-time, relevant treatment tailored to their individual preferences and behavioural patterns. (Ameen et al., 2021; Chen et al., 2021; Gao et al., 2022) This is driven by data available about each individual (Ameen et al., 2021; Mileva, 2023). It can be a powerful tool to engage customers especially if the website targets multiple customer segments. It signals to customers that the Online retailer is invested in building a relationship with customer beyond the clinical focus of a purchase, makes them feel valued and special (Chen et al., 2021; Stanley, 2022) and can lead to a positive, enhanced customer experience (Ameen et al., 2021; Sujata et al., 2019; Tyrväinen et al., 2020). An earlier study by Liang et al. (2012) found that personalisation had a higher positive effect on the perceived economic and emotional benefits of Online shopping than E-commerce sites without personalisation. The emotional benefits in particular, which Liang et al. (2012) referred to as Perceived Care, and defined as an indication of the organisation's commitment to getting to know and build a relationship with customers, had a stronger effect than perceived economic benefits (such as cost savings as a result of promotional discounts offered), on the Perceived Usefulness of Online shopping.

The level of personalisation made possible by AI tools further enhances the quality of service, leading to greater satisfaction, and increased trust in the brand (Ameen et al., 2021; Sujata et al., 2019). As previously discussed, AI can enable robust personalisation features; however, the quality of the solution application will ultimately determine the experience of customers. Gao et al. (2022) identified both functional and enjoyment aspects (referred to as usability and passion respectively in their study) as important AI features in positively influencing customer experience. Their study revealed that if customers had very high expectations of the technology's usability and it fell short of the expectations, then their experience was diminished. Ameen et al. (2021) highlighted recognition attributes that made the customer feel important and welcome, as key to creating good AI personalised experiences. Ameen et al. (2021) further proposed that if the AI technology application was of high quality, and the personalisation features were holistically integrated into the user interface, content, and user interaction, then customer's perceived sacrifices (e.g. in terms of personal information relinquished, reduced control and absence of human interaction) to use the features, was reduced.

Shopping on Online sites with vast product or service catalogues can be overwhelming for customers who need a way to quickly narrow down options to their preferences. Some of the benefits personalisation can deliver to customers include reducing information fatigue, refining product selection, assisting them in picking up where they left off on their previous shopping and increasing purchasing intent by offering products or services applicable to their interests (Kashyap et al., 2022; Kumar et al., 2019; Moura et al., 2021; Rana et al., 2023).

AI-enabled image searches can help to increase customer shopping efficiency when customers do not have access to accurate textual product descriptions (Yang & Liu, 2021). AI powered recommender systems can overcome the limitations of traditional recommender systems by incorporating user purchase history, preferences, browsing behaviour, contextual information (e.g. locality, weather, and time) and unstructured data (e.g. user reviews) for deeper insights (Ameen et al., 2021; Necula & Păvăloaia, 2023). This enables more precise and relevant product recommendations and facilitates improved customer decision making, thereby reducing the time and effort required for Online shopping (Mileva, 2023; Necula & Păvăloaia, 2023). Increasing the accuracy of product recommendation options that are more relevant to customer needs is more likely to enhance user experience (Zanker et al., 2019). Necula and Păvăloaia (2023) highlight that the effectiveness of the tool will be determined by its contextual application.

Chatbots serve as digital sales support consultants on E-commerce websites, available 24X7, to engage and efficiently support customers with immediate responses to their product or purchase queries. This is done at their convenience thus saving customers time in finding pertinent information resulting in improved experience (Ameen et al., 2021; Chen et al., 2021; Moura et al., 2021; Rana et al., 2023). A study by Chen et al. (2021) demonstrated that chatbot usability positively influenced customer experience from an efficiency and functional perspective, while the chatbot responsiveness rate impacted their enjoyment of using the feature. Chen et al. (2021) also suggest that the extent of usability and responsiveness of the chatbot influenced customer perceptions of the level of company innovation, with a high responsiveness rate indicative of high company innovation. Chatbots that provided personalised experience were rated highly on usability and resulted in customers feeling valued, and at ease in their interactions (Chen et al., 2021).

Chatbots are also less susceptible to errors and can additionally assist customers with problem solving (Chen et al., 2021; Kashyap et al., 2022). They build social interaction with customers in an otherwise sterile environment (Alnefaie et al., 2021). Chatbots that integrate AI techniques like NLP and sentiment analysis can provide more human like responses as compared to clinical, scripted responses for enhanced support (Chen et al., 2021; Mileva, 2023). Intelligent Virtual Assistants can detect sentiment and emotions in human speech and respond appropriately (Chen et al., 2021; Dilmegani, 2023). Personalised chatbot engagements for problem solving enhances customer satisfaction and increases their perception of being valued by the company (Chen et al., 2021). Araujo (2018) found that anthropomorphic (human like features) integrated into a chatbot design had a positive influence on emotional connection and relationship building with customers.

Regarding E-commerce content curation, the quality of visual content such as product images on E-commerce sites determines the quality of the customer's Online shopping experience and plays a crucial role in influencing whether customers engage with the site and ultimately decide to purchase. (Chaudhuri et al., 2018). AI can customise image and video content presented to Online shoppers to suit their interests and preferences (Chaudhuri et al., 2018; Yang & Liu, 2021).

Introducing customers to alternative and complementary products and services, through customising content at various stages of the Online shopping journey (e.g. product detail page, order confirmation and checkout) facilitates product discovery, increased engagement and more informed decision making (Mileva, 2023; Moura et al., 2021).

The reviewed literature has discussed various applications of AI-enabled personalisation features that are indicated to enhance customer experience. Hence the following hypotheses are made:

2.5.1 *H1 Personalisation in an E-commerce context positively influences Customer Experience.*

2.6 How does AI personalisation in an E-commerce context influence Purchase Intention, Repeat Purchase Intention and Loyalty?

Provided that personalisation is well executed, it can potentially lead to customer loyalty, if customers feel that E-commerce providers have a good understanding of their preferences and can anticipate their needs (Kim & Baek, 2018; Mileva, 2023; Tyrväinen et al., 2020). This may lead to customers feeling more engaged and connected to the brand (Kim & Baek, 2018; Stanley, 2022; Tyrväinen et al., 2020). A positive attitude towards a brand can motivate customers to revisit a website and increase their purchase intentions (Wu et al., 2017).

Sujata et al. (2019) proposed a model to show how personalisation can be achieved through AI methods such as virtual assistants chatbots, content curation, sentiment analysis and emotion detection. Their model also proposes that personalisation can create superior service quality which in turn increases customer loyalty and positive sentiment towards a brand. Customers are then more likely to promote the brand and provide valueable feedback for service enhancement.

A study by Yoon et al. (2013) showed that customers judge the effectiveness of recommendation engines against previous Online shopping experience, and if the recommendations were deemed effective in comparison, were then perceived to be high quality and positively impacted customer satisfaction and loyalty.

These findings were supported by Rana et al. (2023), who found that AI personalistion techniques employed to facilitate customer decision making, can dramatically reduce the time and effort that the customer needs to invest in Online shopping, which can increase positive sentiment toward the brand. It can do this by immediately presenting options personalised to their requirements, or offering multiple formats for information search, including semantic, image and voice searches.

In terms of content curation, Chaudhuri et al. (2018) found that product visuals may play a more influential role in decision making during the customer's journey from exploration to purchase, than the product descriptions. Chaudhuri et al. (2018) showed how the creation of a visual content management system that uses machine learning could be used to aggregate images from multiple suppliers, ensure superior image selection and optimally sequence these according to customer preferences. The AI-enabled visual management system had a positive impact on consumer behaviour in terms of the add-to-cart and actual purchase measures.

Customer behaviour can be monitored by AI throughout their E-commerce journey and their positive and negative sentiments aggregated for insight (Moura et al., 2021). This can then be used to enhance the value offered to them which improves their experience and leads to increased sales and revenue (Even, 2019) as cited by (Moura et al., 2021). According to Pappas et al. (2016) good quality Online personalisation and its related benefits can lead to high purchase intentions. Pappas, Kourouthanassis, Giannakos and Chrissikopoulos (2017) found that quality of personalisation can increase customer persuasion (Online shopping site strategies to convince customers to buy a product or service), either directly, through customised messages or through anticipated benefits of personalisation, which in turn has a positive influence on customer purchase intention.

Mpinganjira (2014) identified personalisation as an important factor, together with information privacy protection and ease of communication with the e-tailer, that influenced Online customer satisfaction. Personalisation can increase Online customer satisfaction which in turn can lead to repeat purchase intention (Mpinganjira, 2014; Pappas et al., 2016). Tyrväinen et al. (2020) discovered that the positive experience created by personalisation positively influenced customers' repeat purchase intentions, and viewed repeat purchase intention as an indicator of loyalty. Rahmawati and Arifin (2022) found that personalisation's influence on cognitive and emotional aspects of customer experience in an Omni channel context, was most evident in Online shopping. Their findings supported that a positive Online shopping experience, enabled by personalisation, positively influenced repeat purchase intention. Interestingly, Pappas et al. (2016) discovered that positive emotion was so important in Online shopping that, even when the quality of personalisation features was low, faintly positive emotions would still influence customers to purchase.

Research by Pappas, Kourouthanassis, Giannakos and Lekakos (2017) offers a caveat to the influence of Online personalisation on purchase intention. According to Pappas, Kourouthanassis, Giannakos and Chrissikopoulos (2017), when customers are on a shopping mission with specific motivations, Online personalisation features may be insufficient to influence their purchase decisions. Shopping motivations can encompass multiple factors that include economic drivers (where price sensitive shoppers choose to shop Online for the best deals or promotions), brand image and brand loyalty (where customers have preferences for specific brands in a product range) , perception of service quality (that extends beyond the products and services, to entail the end to end journey including perceptions of Online or offline support, order fulfillment and delivery), and customer propensity to shop Online (Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2017).

Lindecrantz et al. (2020) however, argue that personalisation can be considered a hygiene factor as customers are accustomed to having it and its absence may result in the choice of competitors if it is not available. They suggest that successful personalisation initiatives significantly increase customer engagement, loyalty, and experience, and lead to increased sales and conversion rates.

The reviewed literature has discussed multiple perspectives on how AI-enabled personalisation features can influence customer purchase decisions, repeat purchases and loyalty. Hence the following hypotheses are made:

2.6.1 *H2 Personalisation in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.*

2.7 Limitations in the Literature Review

Although the literature review had provided insights that advocated the benefits of AI-enabled personalisation in positively influencing customer experience and purchase intentions in E-commerce, very few theory driven studies could be found that empirically tested customer perceptions related to these outcomes (Ameen et al., 2021; Bawack et al., 2021; Sujata et al., 2019).

Furthermore, the African context was underrepresented in the existing body of literature relating to AI in E-commerce and AI in retail (Bawack et al., 2021; Rana et al., 2023). Therefore, this study undertook to conduct a theory driven, empirical study of South African customer perceptions to contribute insights towards an African context. The study's theoretical and empirical concepts are discussed next.

2.8 ANALYTICAL FRAMEWORK

This section discusses the pertinent theoretical frameworks, and relevant constructs, that will be used to build a conceptual model for the study. The two theoretical frameworks drawn from, include the Technology Acceptance Model and the Diffusion of Innovation Theory.

2.8.1 *Theoretical Framework*

2.8.1.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) proposed by Davis (1989) was selected for the conceptual framework as it is a well proven model of technology adoption (Davis et al., 1989). It pinpoints two factors: Perceived Usefulness and Perceived Ease of Use as key for user adoption of technology. The TAM model (Davis et al., 1989) in Figure 2 below, posits that external variables (e.g. system characteristics, implementation quality), influence user perceptions of a system's Perceived Usefulness and Perceived Ease of Use, which then influence their overall attitude to use. The user's perception of the Perceived Usefulness of the system influences their behavioural intention to use. The combination of a user's attitude to use and behavioural intention to use, influences their system adoption.

According to Davis (1989), Perceived Usefulness refers to users' perception of the extent to which the technology usage is providing value to them in terms of helping them to accomplish their tasks e.g., helping them to be more effective and reducing the time taken to achieve their goals. Perceived Ease of Use refers to the level of difficulty and effort involved in accomplishing their goals.

Davis (1989) found both Perceived Usefulness and Perceived Ease of Use to be highly correlated to user present technology usage, as well as their predicted future technology usage. A key finding of the Davis (1989) study was that Perceived Usefulness was indicated as having a significantly stronger effect than Perceived Ease of Use, in determining innovation adoption, as users were prepared to tolerate some level of difficulty to benefit from the Perceived Usefulness of a technology.

In this research context, the innovation to be adopted is AI personalisation features implemented in an E-commerce site. The study investigated the influence of AI personalisation on the TAM constructs of Perceived Usefulness and Perceived Ease of Use, and how these influenced customer attitudes towards use in terms of Customer Experience, and actual usage, in terms of Purchase Intention, Repeat Purchase Intention and Loyalty.

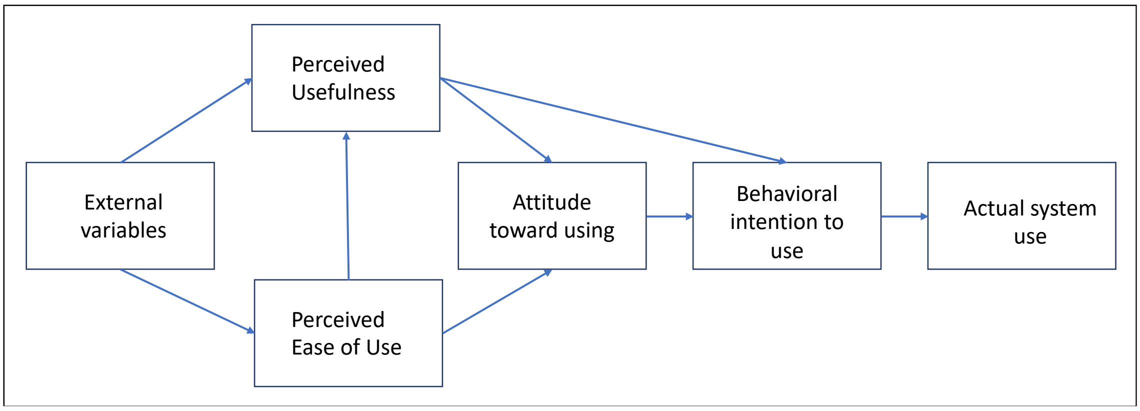

Figure 2 - Technology Acceptance Model (Davis et al., 1989)

2.8.1.2. Diffusion of Innovation Theory

Taherdoost (2018) explains Roger's (2003) Diffusion of Innovation Theory as being the process of how a new idea, behaviour or innovation is adopted over time, through various communication channels, via a social system. Figure 3 below depicts Roger's (1983) distribution framework of innovation adopter categories that includes Innovators, Early Adopters, Early Majority, Late Majority and Laggards. The framework depicts the estimated percentage of individuals in the respective adopter categories across the distribution.

Rogers (2003) identified 5 attributes that influence the adoption of new technology which include Relative Advantage, Complexity, Trialability, Compatibility and Observability. Relative Advantage is described as the extent to which an innovation is perceived as being superior to its predecessor and is proposed as a significant indicator of information technology adoption, Complexity assesses the extent to which users view an innovation as being difficult to use, Trialability determines the amount of experimentation possible with an innovation before adoption, Compatibility is the extent to which users perceive an innovation as being aligned with their values, needs, and previous experience, and Observability is the extent of the visibility of innovation outcomes to others (Agarwal & Prasad, 1998; Moore & Benbasat, 1991; Rogers, 1983). Although multiple attributes constitute the Diffusion of Innovation Theory, Relative advantage is one of the most prominently supported attributes in empirical studies, to predict system adoption (Agarwal & Prasad, 1998). The study set out to understand whether customers viewed AI personalisation as being an advantageous functionality in E-commerce sites compared to physical stores and Online shopping sites with no personalisation. Thus, Relative Advantage was selected as a pertinent construct for the conceptual model. The Complexity attribute was similar to the Perceived Ease of Use construct from TAM in measuring user effort to use and was therefore excluded. Observability was excluded because the study was concerned with individual customer perceptions of AI personalisation while shopping Online, therefore this attribute was viewed as irrelevant for the study. Trialability was not considered relevant for this study as customers have unlimited opportunities to test out personalisation features in an E-commerce context and the study was more concerned with how intentional use of the features influences Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty. The Compatibility attribute was viewed as being integrated into the Perceived Usefulness construct in measuring the fulfilment of customer's shopping needs, hence it was excluded as an explicit measure for the study.

Moore and Benbasat (1991) further built on the attributes defined by Rogers (1983) to include an attribute for Voluntariness of Use. They describe it as the extent to which an innovation is perceived as being voluntary or enables free will in use and view it as a pertinent consideration for individuals in deciding to adopt an innovation. With Voluntariness of Use, the study sought to understand how customers perceived the importance of being able to exercise control over their personal information for personalisation purposes. Thus, this study pinpointed the constructs of Relative Advantage and Voluntariness of Use to investigate their influence on Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty.

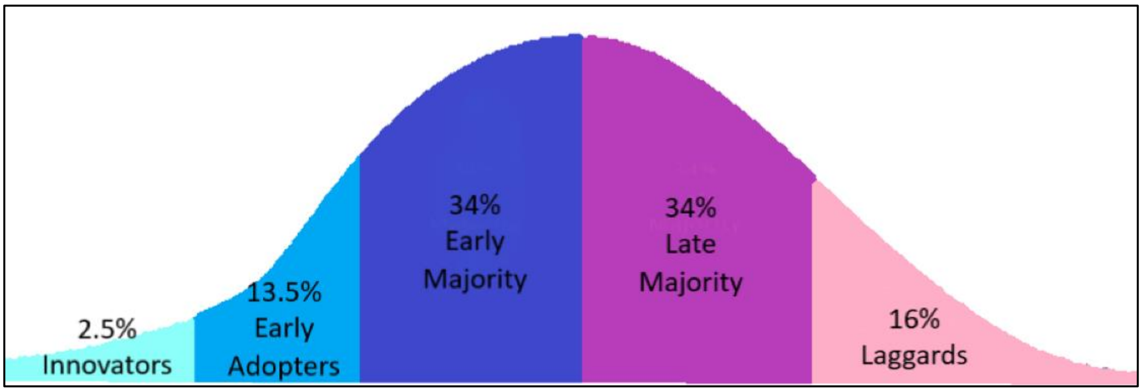

Figure 3 - Diffusion of Innovation Theory (Rogers, 1983)

2.8.2 *Conceptual Framework*

This section introduces the conceptual model that has been formulated using key constructs from the selected theoretical frameworks to propose a framework for the research.

Figure 4 below outlines the proposed conceptual model for the research investigation and the framework attributes are decomposed and explained below.

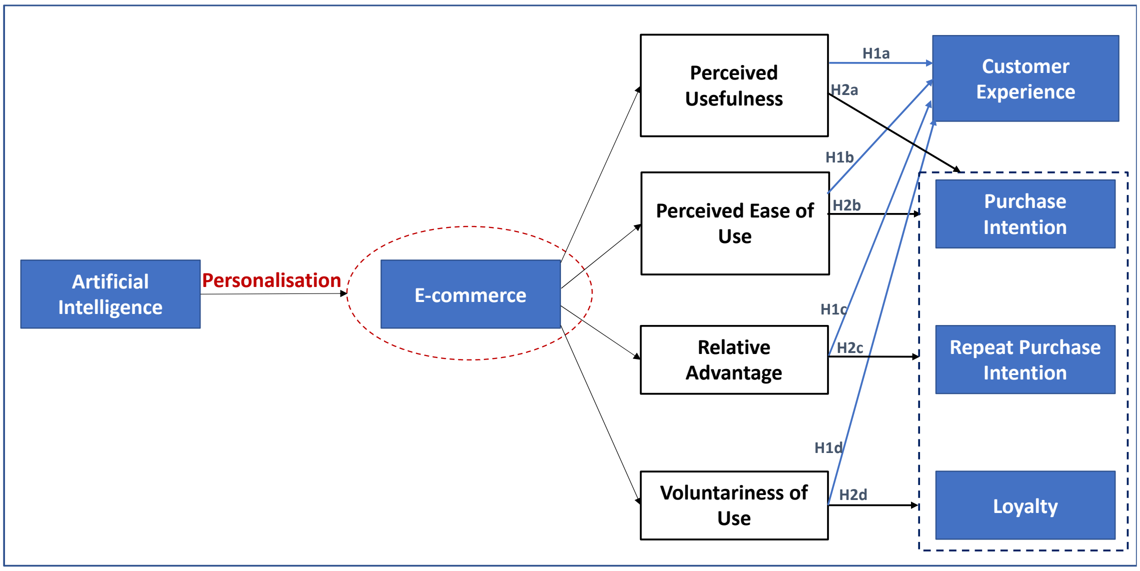

Figure 4: Conceptual Framework

2.8.2.1. Artificial Intelligence enabled personalisation

According to the Diffusion of Innovation Theory (Rogers, 2003), Artificial Intelligence enabled personalisation features is the *innovation* to be adopted on E-commerce platforms. In terms of TAM (Davis, 1989), it is the *technology* to be adopted. The conceptual model combined the relevant constructs of *Relative Advantage* and *Voluntariness of Use* from Diffusion of Innovation Theory, and *Perceived Usefulness* and *Perceived Ease of Use* from TAM to investigate how these factors influenced the adoption of the AI-enabled personalisation features and how this in turn influenced Customer Experience, Purchase Intention, Repeat Purchase Intention, and customer Loyalty.

2.8.2.2 E- commerce

E-commerce is the context within which AI-enabled personalisation features are being applied. Online shoppers' perceptions of the use of personalisation features in this context was investigated.

2.8.2.3 Perceived Usefulness

From the TAM model, Perceived Usefulness of AI personalisation in E-commerce would include the extent to which Online shoppers find that AI-enabled personalisation features make the tasks of finding information, preferred products, and services, and obtaining support, more effective, relevant, and suited to their needs. Liang et al. (2012) found that E-commerce personalisation resulted in higher customer perceptions of Perceived Usefulness than websites without personalisation features. Wang et al. (2023) also found Perceived Usefulness to positively influence the use of AI personalisation in E-commerce. Hence the following sub hypotheses were proposed for hypotheses H1 and H2 respectively:

- H1a - Perceived Usefulness in an E-commerce context positively influences Customer Experience.

- H2a - Perceived Usefulness in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.

2.8.2.4 Perceived Ease of Use

The Perceived Ease of Use construct in TAM, would encompass the extent to which Online shoppers perceive that AI-enabled personalisation features are easy to use and significantly reduce their time, physical effort, and consumption of mental resources during Online shopping. Wang et al. (2023) found the Perceived Ease of Use of AI personalisation in E-commerce to positively impact use, although in their study, this was subject to customer trust. Hence the following sub hypotheses were proposed for hypotheses H1 and H2 respectively:

- H1b - Perceived Ease of Use in an E-commerce context positively influences Customer Experience.

- H2b - Perceived Ease of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.

2.8.2.5 Relative Advantage

In this research context, when examining Relative Advantage as customer perception of an innovation being superior to its predecessor, consideration was given to the fact that the rate of E-commerce use in South Africa increased, despite the E-commerce landscape being underpenetrated (as discussed in section 2.2) The comparison therefore included Online shopping sites that offer personalisation compared to Online shopping sites that do not, as well as comparing Online shopping sites with AI personalisation, to shopping in physical stores.

In terms of Relative Advantage, the study aimed to understand whether the presence of AI-enabled personalisation features on E-commerce sites was perceived by users as being advantageous compared to physical stores and Online sites that did not offer these features. It further sought to understand whether this was a factor in Online shopping site selection and influenced Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty.

Hence the following sub hypotheses were proposed for hypotheses H1 and H2 respectively:

- H1c – Relative Advantage in an E-commerce context positively influences Customer Experience.

- H2c – Relative Advantage in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.

2.8.2.6 Voluntariness of Use

In the Diffusion of Innovation theory, Voluntariness of Use refers to the extent to which an innovation is perceived as being voluntary or enables free will in use (Moore & Benbasat, 1991; Rogers, 1983). In this study it referred to the extent to which customers believed that they could exercise control over whether their personal information was used to offer personalised services to them.

A study by Cecere and Rochelandet (2013) found that websites with easily accessible and transparent privacy policies tended to receive more customer traffic. However, they also suggested that in many cases, the presence of the privacy policy was an illusory signal of customer control over personal information, as the presence of a privacy policy did not necessarily guarantee compliance. The study further stated that the presence of a privacy policy tended to boost customer confidence excessively, into relinquishing control of their information.

Potoglou et al. (2015) found that concerns over personal information privacy, influenced customer decisions of whether to shop Online, with customers more likely to buy from Online retailers that required minimal personal information. This study sought to understand whether providing customers with a choice on whether their information was used to enhance their Online shopping experience through personalisation, influenced their Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty.

Hence the following sub hypotheses were proposed for hypotheses H1 and H2 respectively:

- H1d – Voluntariness of Use in an E-commerce context positively influences Customer Experience.

- H2d – Voluntariness of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.

2.8.2.7 Customer Experience

Good customer experience is the desired outcome of the adoption of AI-enabled personalisation features. Thus, the research investigation aimed to understand the influence of Perceived Usefulness, Perceived Ease of Use, Relative Advantage, and Voluntariness of Use on Online shoppers' experience in an E-commerce platform.

2.8.2.8 Purchase Intention

One of the end goals of AI-enabled personalisation is to positively influence customer purchase decisions. Therefore, the research investigation sought to understand the influence of Perceived Usefulness, Perceived Ease of Use, Relative Advantage and Voluntariness influence on Online shoppers' Purchase Intention on E-commerce platforms.

2.8.2.9 Repeat Purchase Intention

AI-enabled personalisation seeks to attract Online shoppers back to the E-commerce platform for repeat purchases. Thus, the research investigation aimed to understand the influence of Perceived Usefulness, Perceived Ease of Use, Relative Advantage and Voluntariness influence on Online shoppers' repeat purchase decisions on E-commerce platforms.

2.8.2.10 Loyalty

With AI-enabled personalisation, the goal is to make an emotional connection with Online shoppers by recognising their unique attributes and interests and curating their journey in line with that, so that they feel seen and valued as individuals by the business. The research investigation therefore sought to understand the influence of Perceived Usefulness, Perceived Ease of Use, Relative Advantage, and Voluntariness of Use on Online shoppers' Loyalty in E-commerce platforms.

2.9 Conclusion of Literature Review

The literature review highlighted the need to focus on customer experience as a differentiator in E-commerce and made the case for using AI-driven personalisation for competitive advantage. It then unpacked the key AI capabilities used for personalisation in an E-commerce context and went on to describe the E-commerce personalisation features enabled by the AI capabilities. It discussed the various perspectives from relevant literature on personalisation influence on Customer Experience as well as Purchase Intention, Repeat Purchase Intention and Loyalty. Finally, it discussed a theoretical framework and formulated a conceptual model for the research investigation. All hypotheses are summarised below. The next section will cover the research methodology and design.

2.9.1 *H1 Personalisation in an E-commerce context positively influences Customer Experience.*

Sub hypotheses:

- H1a - Perceived Usefulness in an E-commerce context positively influences Customer Experience.

- H1b - Perceived Ease of Use in an E-commerce context positively influences Customer Experience.

- H1c – Relative Advantage in an E-commerce context positively influences Customer Experience.

- H1d – Voluntariness of Use in an E-commerce context positively influences Customer Experience.

2.9.2 *H2 Personalisation in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.*

Sub hypotheses:

- H2a - Perceived Usefulness in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty

- H2b - Perceived Ease of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty

- H2c – Relative Advantage in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty

- H2d – Voluntariness of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty

CHAPTER 3. RESEARCH METHODOLOGY

This section describes the research approach used to obtain insight into customer perceptions of AI personalisation in an E-commerce context. It unpacks the design, population, sampling method, and the research instrument employed. It further outlines the data collection procedure and the strategies used to analyse and interpret the results. It concludes with the ethical considerations.

3.1 Research approach

A quantitative research approach was used in the study with a post positivist paradigm. This paradigm adopts the view that there can be multiple perceptions of reality and it is not possible to know or measure all variables (Krauss, 2015). A quantitative approach was selected to understand the relationships between the variables of Perceived Usefulness, Perceived Ease of Use, Relative Advantage and Voluntariness of Use and their influence on the variables of Customer Experience, Purchase Intention, Repeat Purchase Intention and Loyalty.

A post-positivist paradigm was used, as the study obtained feedback on participants' subjective experience in using E-commerce sites and their perception of the personalisation features available. The quantitative approach aimed to infer objective relationships between the variables investigated. Limitations encountered in relation to the generalisability of the findings are detailed in section 3.8.

3.2 Research design

The research study undertook to obtain comprehensive insight into multiple aspects of participants' experience, with E-commerce platform personalisation features. Hence a cross sectional survey with standardised questions, using a 5-point Likert scale (Dawes, 2008) was used to obtain feedback from participants.

The 5-point scale was selected to strike a balance between simplicity for participants and offering sufficient alternative response options for research insight. This design enabled varied participant feedback on the multiple variables under investigation. Participants were not compelled to answer all survey questions, with the result that some gaps in data were encountered and had to be addressed. The survey was cross sectional in nature in that the results were a snapshot of user perspectives at a particular point in time.

3.3 Data collection methods

A digital survey was selected as the method for data collection. This method was chosen as it was estimated to be the most effective way to quickly and easily reach a large number of respondents for sufficient and varied feedback in terms of demographic, and to increase the likelihood of meeting the requisite sample size for the study.

3.4 Population and sample

This section details the attributes of the population sampled as well as the sampling method that was used.

3.4.1 *Population*

The population consisted of South African participants who use E-commerce platforms to purchase goods and services, to determine their perceptions of personalisation features available on these platforms.

3.4.2 *Sample and Sampling Method*

The sample size was based on the Kass and Tinsley’s (1979) respondent per variable ratio, where they proposed that for each variable studied, between 5 and 10 participants needed to be surveyed up to a maximum of 300. There were 35 variable measures defined in total in the research instrument which therefore required a minimum sample size of 175 participants.

A non-probability sampling method was applied as it was not possible or practical to identify upfront, and narrow down with certainty, a sample of individuals who had used E-commerce platforms to survey. Non-probability sampling refers to the fact that the sampling was completely random, and a specific target sample group could not be pinned down. Only participants who had been included in the survey distribution or received awareness of the survey via the social media posts, and had the stipulated E-commerce shopping experience, were able to participate. Convenience sampling was used as the survey relied on voluntary participation. Convenience sampling does not restrict participation to a particular group and hence any individual who had access to the survey, and the relevant E-commerce experience, could participate.

3.5 The research instrument

The research instrument that was used to obtain feedback from participants was an Online survey. It consisted of 4 key sections. The first section described the objectives of the research. Feedback was required from participants who had had exposure to E-commerce platforms utilising personalisation features. To ensure that survey participants had clear understanding of the E-commerce features to be evaluated, the survey had defined Artificial Intelligence and elaborated on the concept of AI personalisation. Participants were also assured of the anonymity of their feedback.

The second section requested participant permission to opt into the survey and to use their feedback for the study. The third section requested demographic information. Participants were not required to identify themselves, however the survey did require some demographic information that included gender and age group, which was used to contextualise the investigation outcomes.

The prelude to the fourth section was a description of AI-enabled personalisation features found on E-commerce sites, with examples. The purpose of this was to provide participants with clarity on the type of features to be evaluated. This section covered the 8 latent variables outlined in the conceptual framework (in Section 2.7.2) and the respective measurements. The variables included Perceived Usefulness, Perceived Ease of Use, Relative Advantage, Voluntariness of Use, Customer Experience, Loyalty, Purchase Intention and Repeat Purchase Intention. Measures for the variables were adapted from scales from the respective sources listed in Table 1 below.

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)
Customer experience	Bawack et al. (2021); Carlson and O'Cass (2010); Yang et al. (2004)
Loyalty	Srinivasan et al. (2002)
Purchase intention	Putrevu and Lord (1994)
Repeat purchase intention	Loiacono et al. (2007)

The survey was designed to include a 5-point Likert scale (Likert, 1932) as this allowed the participants to rate their views of the AI personalisation features.

3.6 Procedure for data collection

The survey was designed using the Qualtrics survey software supplied by The University of the Witwatersrand (Wits). All data provided by participants was stored in this repository. Qualtrics was utilised as it is endorsed and licensed for student use by the university. Three avenues of soliciting participant feedback were used to increase likelihood of meeting the minimum acceptable sample size required to enhance the confidence level in the investigation outcomes. The first included obtaining permission to distribute the survey to Wits students. The second entailed obtaining permission from a Cellular Network Provider to distribute the survey to employees. The final method of distribution was via social media. The survey was distributed to 39132 Wits students and 1060 employees of the Cellular Network Provider. 284 survey responses were received back.

3.7 Data analysis strategies and interpretation

In this quantitative study, the IBM SPSS statistical analysis software version 28 was used for descriptive data analysis and Exploratory Factor analysis. IBM SPSS Amos version 28 was utilised for Confirmatory Factor analysis (CFA) and Structural Equation Modelling (SEM).

As per Field (2018) and Hair (2019), Exploratory Factor analysis (EFA) can be used to analyse the relationships and structure between multiple variables to determine if they can be consolidated into a smaller set of fundamental factors. The variables and related measurements items identified in the research model was extensive and the aim of using EFA was to validate the scales and rationalise these into key factors or dimensions to be analysed. Following the completion of EFA, Confirmatory Factor Analysis (CFA) was conducted to test the extent to which the conceptual model was represented by the data and to assess validity and reliability of the constructs (Hair, 2019).

Finally, to test the structural model relationship between the independent variables of Perceived Ease of Use, Perceived Usefulness, Relative Advantage and Voluntariness of Use, on Customer Experience, Purchase intention, Repeat Purchase intention and Loyalty, Structural Equation Modelling (SEM) was conducted. SEM was selected as a multivariate analysis technique based on the decision flow for multivariate techniques outlined by Hair (2019). Hair (2019) highlights that this technique enables simultaneous analysis of interdependent relationships among measurement items and constructs, and between constructs, by consolidating factor analysis and multiple regression features.

3.8 Limitations and challenges of the study

Limitations included:

- The study was limited to participants in South Africa and the results are not generalisable to other country contexts.
- The study relied on participant's individual shopping experience on E-commerce sites and the personalisation features available there. To ensure that participants had a good understanding of features to be evaluated, examples of AI personalisation features were provided in the survey.

3.9 Quality Assurance

Quality assurance procedures needed to be complied with to ensure credibility in the study and its outcomes. The section below details how external validity, internal validity and reliability were integrated into the study.

3.9.1 *External validity*

External validity describes the extent to which the study and its findings can be generalised to other contexts (Drost, 2011) This study is not generalisable to other contexts as it relied on non-probability convenience sampling. As a result, a controlled group of characteristics representative of the entire population could not be specified and controlled for. Furthermore, the study was specific to a South African context and dependent on the local Online shopping experience. This could vary in other contexts, particularly in a very technology savvy market. Hence the findings were deemed to be unique to the study.

3.9.2 *Internal validity*

Internal validity is an indication of whether the research study delivers the desired investigation outcomes in a credible approach (Andrade, 2018). This research study attempted to maintain internal validity through compliance with ethical governance procedures, using empirically validated variable measures, objective statistical analysis methods by best practice software (IBM SPSS Statistical analysis software and IBM SPSS AMOS software) and not attempting to influence participant feedback or data in any way. As outlined in the data analysis strategy, Confirmatory Factor Analysis (CFA) was conducted to test the extent to which the conceptual model was represented by the data and to assess validity and reliability of the constructs (Hair, 2019). The combination of CFA model fit results with construct validity tests, enables insight into the quality of the measurement model (Hair, 2019). Convergent and discriminant validity of the latent variables (or factors) in the conceptual model were evaluated. Convergent validity measures the extent to which the variable items or measures of a factor are correlated, and discriminant validity measures the level of distinction between concepts (Hair, 2019).

3.9.3 *Reliability*

According to Drost (2011), reliability is an indication of whether the measurements can consistently measure what they were designed to. This study aimed to increase reliability by using standardised surveys and following standardised statistical procedures to measure relationships between the variables. The survey was first piloted to evaluate and refine its effectiveness and ease of understanding with users before it could be implemented.

The Cronbach Alpha test was applied to all variable scales in the survey to test for reliability of the research instrument (Field, 2018; Hair, 2019).

3.10 Ethical considerations

The following ethical considerations were addressed:

- Participant permission was requested to opt them into the survey and to use their data in the study
- Participation was voluntary
- Participation was anonymous, and participants were not required to identify themselves
- Participants were provided with the option of retracting their feedback at any time
- Participants were not paid or incentivised for participating
- No sensitive information was required of participants
- The survey data was stored on a secure personal computer with restricted access.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This chapter outlines the statistical analysis procedures conducted on the survey response data using IBM SPSS Software version 28 and IBM SPSS AMOS software. Descriptive and Inferential analysis was carried out on the data and the results are discussed in the subsequent sections.

4.2 Pilot Survey

Before commencing the research survey, a pilot survey was conducted with 20 participants to assess the user-friendliness of the survey in terms of ease of use and comprehensibility of the questions. Feedback from participants was then used to enhance the clarity of the objectives of the survey and the understandability of the survey questions. Observations of the pilot feedback were also used to enhance the efficiency of the instrument for better quality feedback. Improvements included, for example, the removal of duplicate questions and making questions mandatory to encourage more complete feedback.

4.3 Pre - Analysis

4.3.1 *Data Clean up*

On conclusion of data collection, the survey results were first reviewed for missing data. A total of 284 survey responses were received. Following the removal of incomplete responses with more than 10% of missing feedback, 218 usable survey data records remained.

4.3.2 *Outliers*

Outliers are generally identified as survey responses that differ significantly from the rest of the sample population on one or more variables (Field, 2018; Hair, 2019). In pre-analysis, the objective was to ensure the representativeness of the sample population (Hair, 2019) therefore the data was first examined to root out very unique results that would potentially introduce bias into the statistical analysis. Standardised scores were employed as a method to identify outliers. With standardised scores, a value outside of +- 3,29 is identified as an outlier (Field, 2018). Therefore the acceptance level of +- 3,29, as recommended by Field (2018), was used as the criteria to remove identified outliers. Following outlier removal, the survey response sample size decreased from 218 to 204.

4.4 Descriptive Analysis

Descriptive analysis was conducted next on the data to understand frequency patterns in data obtained, shape of the data distribution through normality tests and reliability testing of the survey instrument.

4.4.1 *Frequency Analysis*

Frequency analysis was conducted on participant gender, age, E-commerce site selections (from survey options provided) and the E-commerce sites listed by participants (when asked to provide their own examples of Online shopping sites used).

- **Participant Gender Frequency Analysis**

Survey responses comprised approximately 59% of female participants and 41% of male participants as indicated in Table 2 and in Figure 5 below. It is interesting to observe that more females have responded to the survey than males, as in South Africa, males tend to outstrip females in Online shopping according to The Online Retail in South Africa 2023 report (Swanepoel, 2023).

The gender response trend does however, align with other larger scale surveys conducted on South African consumer E-commerce perceptions like the South African Digital Customer Experience Report (Reekie et al., 2022), where the majority of the 2000 respondents (73%) were also female.

Table 2: Frequency of Survey Participant Gender

Participant gender

Gender		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	83	40.7	40.7	40.7
	Female	121	59.3	59.3	100.0
	Total	204	100.0	100.0	

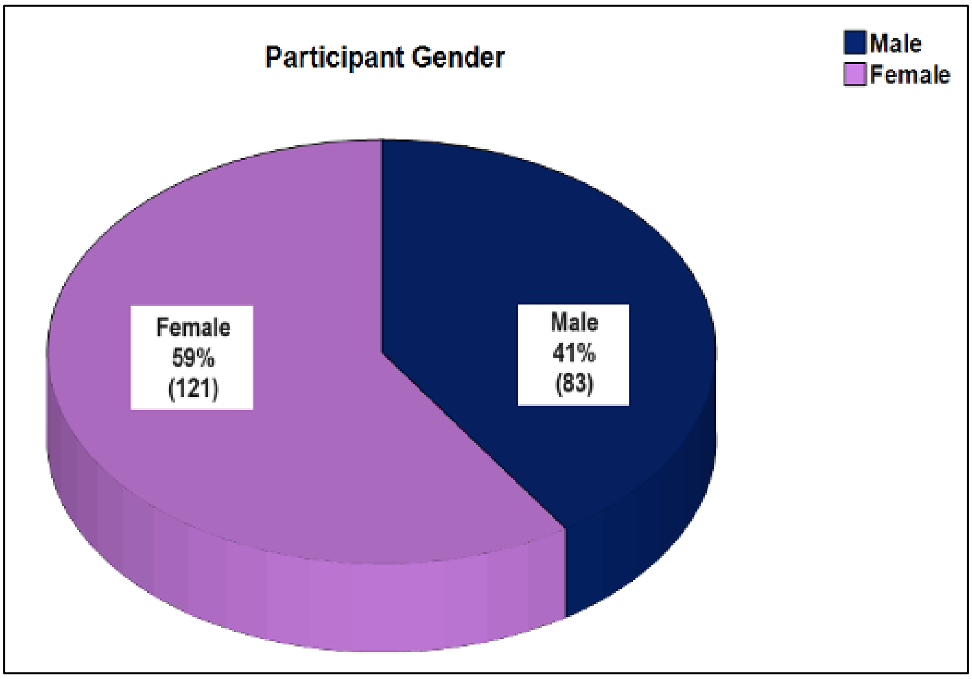

Figure 5: Pie Chart of Survey Participant Gender Frequency

- **Participant Age Group Frequency analysis**

In terms of age breakdown, most responses were from participants in the 35 to 44-year age grouping, with 32% of respondents falling into this category. It was closely followed by the 45 to 54-year age grouping with 28% of respondents. The age grouping figure breakdown is indicated in Table 3 below and depicted in Figure 6 below. The lowest response rate was received from the 55 to 64-year age grouping, with approximately 4% of respondents making up this category. The survey did include a category for over 64, but no responses were received from this age group. 18- to 24-year-old participants made up 15% of responses and 25- to 34-year-old respondents made up 21% of responses.

Table 3: Frequency of Survey Participant Age Group

Participant age group

Age Groupings		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 - 24 years	31	15.2	15.2	15.2
	25 - 34 years	43	21.1	21.1	36.3
	35 - 44 years	66	32.4	32.4	68.6
	45 - 54 years	56	27.5	27.5	96.1
	55 - 64 years	8	3.9	3.9	100.0
	Total	204	100.0	100.0	

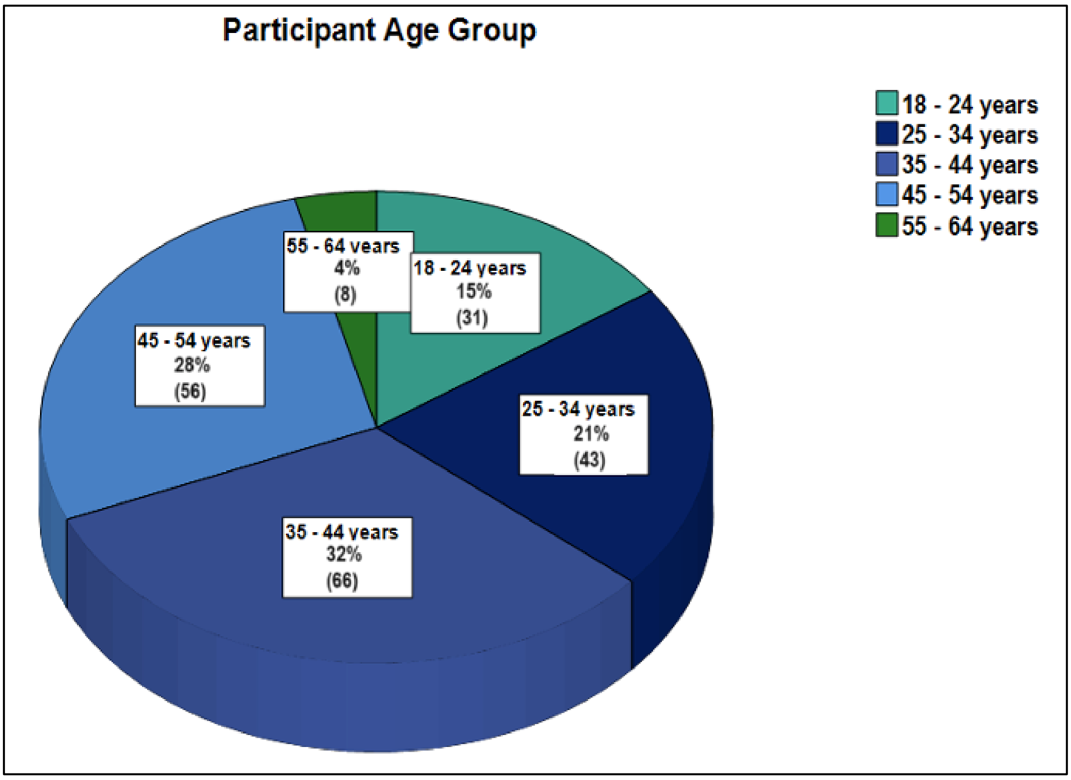

Figure 6 : Pie Chart of frequency of Survey Participant Age Group

- **Frequency of E-commerce Sites Selected**

The survey provided participants with a list of South African E-commerce sites and asked them to indicate through multiple selection, which sites they used. The objective of this question early in the survey was mainly to trigger participant memory of E-commerce sites they were familiar with, and the personalisation features available on these sites, so that they could better contextualise the survey questions.

If participants were not familiar with the suggested Online shopping website selections, they were also provided with the option of listing their own E-commerce sites, not mentioned in the list. The objective of this was a further measure to help them recall Online shopping sites used, to respond meaningfully in the survey.

Table 4 and Figure 7 below depict the participant responses for online shopping sites used. From the suggested Online shopping sites selection, the most visited site by participants was Takealot, followed by Checkers 6060. Takealot is an e-commerce platform that sells a wide range of products and services and Checkers 6060 is a 60-minute online grocery delivery service. Woolworths (an online clothing and grocery retailer) was the least frequently selected option. These results align closely with the Statista (2023) report which ranked Takealot as the largest online marketplace in South Africa in 2023. Superbalist (an online retail fashion site) and Woolworths took third and fourth place respectively, in the Statista (2023) report.

Table 4 : Frequency of E-Commerce Sites Selected by Participants

E-Commerce Site	Frequency	Percentage
Takealot	182	30
Checkers 6060	108	18
Booking.com	98	16
Superbalist	78	13
Woolworths	77	13
Other	54	9

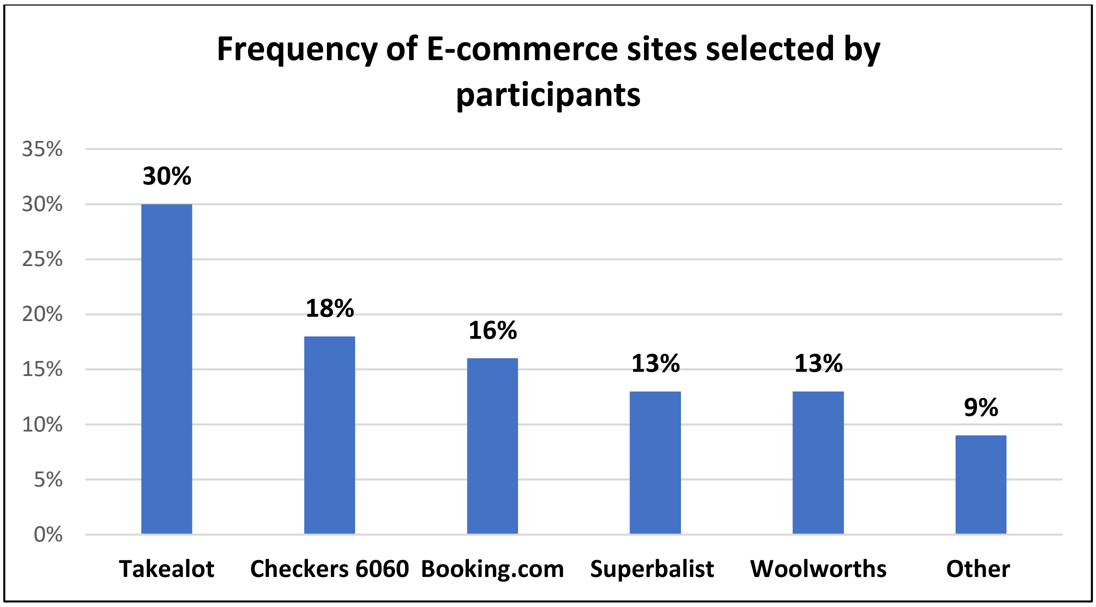

Figure 7: Frequency of E-Commerce Sites Selected by Participants

- **Frequency of E-Commerce Sites Listed by Participants**

The “Other” option in the survey consisted of online shopping websites listed by participants and these are displayed in Figure 8 below. Shein, a global Chinese Online fashion retailer, was the most listed alternative E-commerce site option indicated by participants. Shein launched in South Africa in 2020 during the Covid-19 pandemic and quickly gained popularity with local consumers leading to it becoming the most downloaded shopping app on the Google Play store and the third most downloaded app in the Apple app store in 2023 (Kew et al., 2023; Labuschagne, 2023).

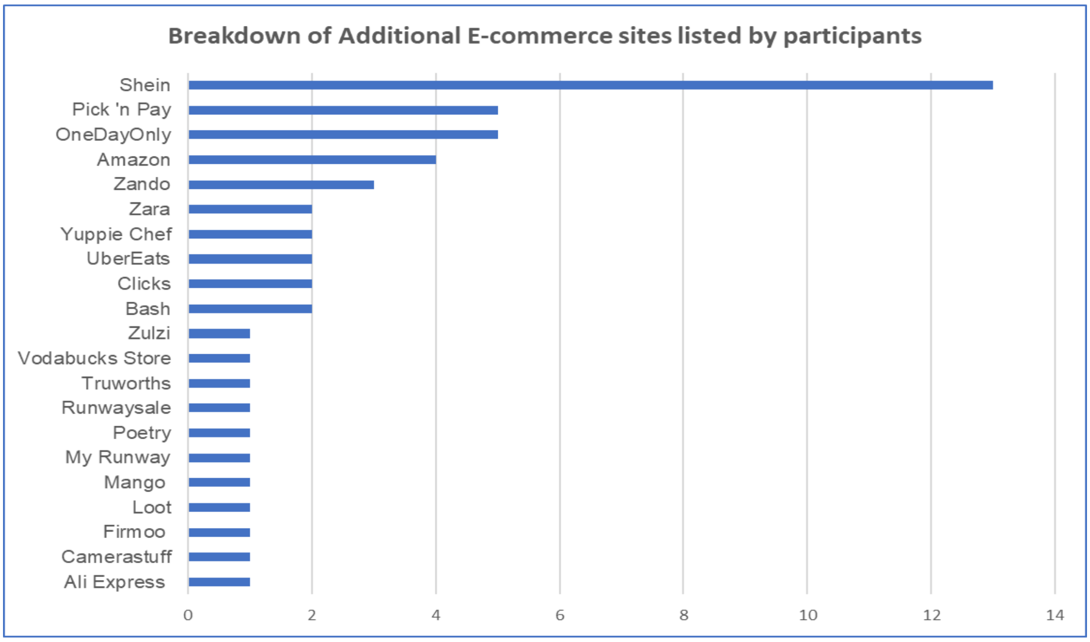

Figure 8: Breakdown of Additional E-commerce Sites

4.4.2 *Variable Name Coding*

To simplify the readability and presentation of statistical results in relation to the conceptual framework variables, all research variables have been coded to shorter variable labels and will be referenced as such going forward in the report. The shortened variable coding used is indicated in Table 5 below.

Table 5: Variable Name Coding

Variable	**Item code**	**Variable item**
Perceived Usefulness	PU41	4.1. Personalised Online shopping would enable me to accomplish my shopping goals more quickly e.g. I can quickly find items I am interested in from a large catalogue.
	PU42	4.2. Personalised Online shopping would enhance my success in achieving my shopping goals on the site. e.g., I can obtain relevant recommendations quickly to make a decision.

	PU43	4.3. Personalised Online shopping would enhance my shopping outcomes e.g. I may find additional useful products and services that I was not aware of.
	PU44	4.4. Personalised Online shopping would make it easier to shop i.e., being presented with items that are relevant to me reduces my shopping efforts Online.
	PU45	4.5. Personalised Online shopping would be useful.
Perceived Ease of Use	PEU51	5.1. Adapting to the use of Online shopping personalisation features is easy for me. e.g., using Search functions and chatbot assistants.
	PEU52	5.2. My interaction with Online shopping personalisation features is clear and understandable. e.g., I know how to search for products I need, utilise recommendations and raise my queries with a chatbot.
	PEU53	5.3. I find Online shopping personalisation tools flexible to interact with e.g. I know how to refine my chatbot queries to get information I need, or I know how to refine my product/service search to get more relevant results.
	PEU54	5.4. It is easy for me to become competent at using Online shopping personalisation features.
	PEU55	5.5. I find Online shopping personalisation tools easy to use.
Relative Advantage	RA61	6.1. It is easier to shop on websites/apps that provide personalisation than those that do not.
	RA62	6.2. It is easier to shop on websites/apps that provide personalisation than to shop in store.
	RA63	6.3. Personalised Online shopping provides me with greater control in achieving my shopping goals e.g. I can find discover multiple options and obtain more information to make an informed purchase.
	RA64	6.4. Overall, I find personalised Online shopping advantageous.
Voluntariness of Use	VOU71	7.1. My use of personalisation features is voluntary on Online shopping sites that provide them.
	VOU72	7.2. Online shopping sites that provide personalisation, allow me to opt in to having my personal data used to personalise my shopping experience.
Customer Experience	CE81	8.1. My decision to use Online shopping sites that offer personalisation features, is a wise one as it provides me with a more engaging, relevant experience.
	CE82	8.2. I am very satisfied with personalised Online shopping.
	CE83	8.3. I am very satisfied with the recommended products/services offered on personalised Online shopping sites.

	CE84	8.4. Overall, I am very satisfied with my last personalised Online shopping experience.
	CE85	8.5. Personalised Online shopping helps me to save money when it comes to shopping tasks e.g., through providing relevant recommendations and/or promotional discounts/offers.
	CE86	8.6. Personalised Online shopping helps me acquire new shopping knowledge e.g., receiving recommendations that provide me with new information.
	CE87	8.7. Personalised Online shopping helps me acquire new shopping skills e.g., the ability to refine my product searches and find relevant recommendations.
	CE88	8.8. Personalised Online shopping helps me to come up with innovative shopping ideas e.g., recommendations may introduce me to new products or complementary products.
Loyalty	LO91	9.1. When I need to make a purchase, Online shopping sites that provide personalisation are my first choice.
	LO92	9.2. I like using Online shopping sites that provide personalisation.
	LO93	9.3. I prefer to shop on Online shopping sites that provide personalisation.
	LO94	9.4. My favourite Online shopping sites provide personalisation.
	LO95	9.5. I seldom consider switching to Online shopping sites that do not provide personalisation.
	LO96	9.6. I try to use Online shopping sites that provide personalisation whenever I need to make a purchase.
Purchase Intention	PI101	10.1. It is very likely that I will buy from Online shopping sites that provide personalised shopping experiences.
	PI102	10.2. I will purchase from Online shopping sites that provide personalised experience next time I need a product/service.
	PI103	10.3. I will try shopping on Online shopping sites that provide a personalised experience.
Repeat Purchase Intention	RPI111	11.1. If I need a product or service in the future, I would be likely to buy it from an Online shopping site that provides personalisation.
	RP112	11.2. If I need a product or service in the future, I will probably revisit an Online shopping site that provides personalisation.

4.4.3 *Normality Assessment*

Normality tests were conducted to evaluate the shape of the data distribution of the individual variables in the research model. A bell-shaped curve or "normal" distribution is desired to reduce bias in parameter estimates and increase accuracy in confidence intervals and accuracy in significant testing of models (Field, 2018). Field (2018) states that according to the central limit theorem, the size of the research sample size may negate the need for normality tests, as in the case of larger sample sizes (sample sizes larger than 30), parameter estimates will have a normal distribution, irrespective of the shape of the population. In larger sample sizes, tests of normality are of little concern as they will have minimal effect on confidence intervals and significance tests (Field, 2018; Hair, 2019). Field (2018) advises not to use significance tests if the data sample is large and to not be too concerned with normality.

The research study participant sample size of 204, was considered large by the benchmarks indicated by Field (2018) and Hair (2019). Tests of normality were still conducted to provide an indication of the results for reference,

Following the removal of the outliers from the survey data, two commonly used statistical test methods were selected to evaluate the distribution of the data: skewness and kurtosis and the Kolmogorov – Smirnov test. This will be discussed in the following sections.

4.4.3.1. Skewness and Kurtosis

Kurtosis describes the "peakedness" or "flatness" of the distribution, while skewness measures the symmetry of the distribution (Hair, 2019). The acceptance criteria used for this evaluation was a maximum skewness range of between ± 1 (Hair, 2019) and a maximum Kurtosis range of between ± 3 (Kallner, 2018) for an indication of normal distribution. The test results for all survey variables fell within the Skewness and Kurtosis ranges for normal data as indicated in Table 6 below.

Table 6 :Skewness and Kurtosis Test Results

Variables	Items	N		Mean	Median	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Range	Min	Max
		Valid	Missing										
Perceived Usefulness	PU41	204	0	1,47	1,00	0,582	0,796	0,170	-0,347	0,339	2	1	3
	PU42	204	0	1,56	1,00	0,621	0,647	0,170	-0,528	0,339	2	1	3
	PU43	204	0	1,57	1,50	0,636	0,901	0,170	0,859	0,339	3	1	4
	PU44	204	0	1,55	1,00	0,667	0,905	0,170	0,115	0,339	3	1	4
	PU45	204	0	1,52	1,00	0,615	0,995	0,170	1,233	0,339	3	1	4
Perceived Ease of Use	PEU51	204	0	1,64	2,00	0,698	0,973	0,170	0,994	0,339	3	1	4
	PEU52	204	0	1,62	2,00	0,666	0,921	0,170	0,977	0,339	3	1	4
	PEU53	204	0	2,06	2,00	0,942	0,729	0,170	0,056	0,339	4	1	5
	PEU54	204	0	1,71	2,00	0,689	0,733	0,170	0,450	0,339	3	1	4
	PEU55	204	0	1,75	2,00	0,729	0,878	0,170	0,905	0,339	3	1	4
Relative Advantage	RA61	204	0	2,04	2,00	0,930	0,626	0,170	-0,427	0,339	3	1	4
	RA62	204	0	2,09	2,00	0,940	0,568	0,170	-0,361	0,339	4	1	5
	RA63	204	0	1,90	2,00	0,736	0,605	0,170	0,351	0,339	3	1	4
	RA64	204	0	1,80	2,00	0,705	0,817	0,170	1,618	0,339	4	1	5
Voluntariness of Use	VOU71	204	0	2,25	2,00	1,068	0,769	0,170	-0,153	0,339	4	1	5
	VOU72	204	0	2,32	2,00	1,052	0,551	0,170	-0,527	0,339	4	1	5
Customer Experience	CE81	204	0	1,98	2,00	0,775	0,803	0,170	1,451	0,339	4	1	5
	CE82	204	0	2,02	2,00	0,836	0,627	0,170	0,234	0,339	4	1	5
	CE83	204	0	2,12	2,00	0,876	0,778	0,170	0,543	0,339	4	1	5
	CE84	204	0	1,96	2,00	0,735	0,888	0,170	1,754	0,339	4	1	5

	CE85	204	0	2,18	2,00	1,082	0,915	0,170	0,194	0,339	4	1	5
	CE86	204	0	2,02	2,00	0,873	0,848	0,170	0,715	0,339	4	1	5
	CE87	204	0	2,07	2,00	0,907	0,703	0,170	0,030	0,339	4	1	5
	CE88	204	0	2,02	2,00	0,871	0,821	0,170	0,460	0,339	4	1	5
Loyalty	LO91	204	0	2,54	3,00	1,061	0,171	0,170	-0,773	0,339	4	1	5
	LO92	204	0	2,15	2,00	0,823	0,630	0,170	0,650	0,339	4	1	5
	LO93	204	0	2,30	2,00	0,950	0,402	0,170	-0,262	0,339	4	1	5
	LO94	204	0	2,14	2,00	0,849	0,711	0,170	0,611	0,339	4	1	5
	LO95	204	0	2,73	3,00	1,066	0,001	0,170	-0,558	0,339	4	1	5
	LO96	204	0	2,57	2,50	1,110	0,175	0,170	-0,916	0,339	4	1	5
Purchase Intention	PI101	204	0	2,09	2,00	0,924	0,533	0,170	-0,519	0,339	3	1	4
	PI102	204	0	2,17	2,00	0,868	0,389	0,170	-0,466	0,339	3	1	4
	PI103	204	0	2,01	2,00	0,803	0,492	0,170	-0,170	0,339	3	1	4
Repeat Purchase Intention	RPI111	204	0	2,11	2,00	0,870	0,378	0,170	-0,355	0,339	4	1	5
	RP112	204	0	2,05	2,00	0,861	0,598	0,170	0,059	0,339	4	1	5

4.4.3.2. Kolmogorov – Smirnov test

The Kolmogorov – Smirnov test was also used for empirical analysis of the distribution of variable data. This test was selected as it is more effective for sample sizes of 100 participants and above.

The normality criteria used to assess the test results was as per Field (2018), who indicates that if $p > 0.05$, results are not significant, and the distribution can be considered normal. If $p<0.05$ then the data distribution can be considered non-normal. The test results for all variables (in Table 7) were significant with $p<0.05$.

Field (2018) suggests that in larger samples, tests for normality should be of low concern as the results are more likely to be significant, even when the scores are marginally different from the normal distribution, as was observed with the Kolmogorov – Smirnov test results in Table 7 below. He cautions against unnecessary concern for these results and attempting corrections where they may not be required. Thus, the assessment of the data distribution, according to the principle of normality advocated by Field (2018) using the central limit theorem and sample size, was to classify the distribution as normal. The skewness and kurtosis test results further support this assessment.

Table 7 :Kolmogorov - Smirnov Normality Test Results

Tests of Normality							
		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Variables	Items	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Usefulness	PU41	0,364	204	0,000	0,698	204	0,000
	PU42	0,326	204	0,000	0,735	204	0,000
	PU43	0,314	204	0,000	0,732	204	0,000
	PU44	0,336	204	0,000	0,737	204	0,000
	PU45	0,332	204	0,000	0,711	204	0,000
Perceived Ease of Use	PEU51	0,287	204	0,000	0,756	204	0,000
	PEU52	0,294	204	0,000	0,747	204	0,000

	PEU53	0,257	204	0,000	0,850	204	0,000
	PEU54	0,259	204	0,000	0,777	204	0,000
	PEU55	0,256	204	0,000	0,779	204	0,000
Relative Advantage	RA61	0,252	204	0,000	0,840	204	0,000
	RA62	0,240	204	0,000	0,859	204	0,000
	RA63	0,280	204	0,000	0,811	204	0,000
	RA64	0,269	204	0,000	0,785	204	0,000
Voluntariness of Use	VOU71	0,292	204	0,000	0,848	204	0,000
	VOU72	0,268	204	0,000	0,870	204	0,000
Customer Experience	CE81	0,289	204	0,000	0,816	204	0,000
	CE82	0,264	204	0,000	0,845	204	0,000
	CE83	0,301	204	0,000	0,839	204	0,000
	CE84	0,322	204	0,000	0,787	204	0,000
	CE85	0,290	204	0,000	0,837	204	0,000
	CE86	0,286	204	0,000	0,833	204	0,000
	CE87	0,275	204	0,000	0,845	204	0,000
	CE88	0,293	204	0,000	0,827	204	0,000
Loyalty	LO91	0,191	204	0,000	0,902	204	0,000
	LO92	0,287	204	0,000	0,847	204	0,000
	LO93	0,228	204	0,000	0,884	204	0,000
	LO94	0,295	204	0,000	0,845	204	0,000
	LO95	0,219	204	0,000	0,905	204	0,000
	LO96	0,196	204	0,000	0,899	204	0,000
Purchase Intention	PI101	0,251	204	0,000	0,851	204	0,000
	PI102	0,260	204	0,000	0,861	204	0,000
	PI103	0,267	204	0,000	0,841	204	0,000
Repeat Purchase Intention	RPI111	0,226	204	0,000	0,862	204	0,000
	RP112	0,260	204	0,000	0,852	204	0,000
a. Lilliefors Significance Correction							

4.4.4 *Reliability Analysis*

To test the reliability of the survey instrument in being able to accurately measure the scale variables, the Cronbach Alpha test was applied to all scales in the survey. An acceptance level of > 0.7 is an indication of good reliability (George & Mallery, 2011). All scale items received a test result >0.7 in Table 8 below, indicating strong reliability of the research instrument.

Table 8: Cronbach Alpha Test Results

Reliability Statistics			
Scale Items	**Cronbach's Alpha**	**Cronbach's Alpha Based on Standardized Items**	**N of Items**
Perceived Usefulness	0,863	0,864	5
Perceived Ease of Use	0,859	0,866	5
Relative Advantage	0,773	0,785	4
Voluntariness of Use	0,760	0,760	2
Customer Experience	0,896	0,899	8
Loyalty	0,905	0,906	6
Purchase Intention	0,882	0,884	3
Repeat Purchase Intention	0,910	0,910	2

4.5 Inferential Analysis

Inferential analysis was conducted next and included tests to determine any significant differences in participant gender or age categories, tests to detect for Common Method Bias in the instrument and Factor Analysis, including Exploratory Factor Analysis (CFA), Confirmatory Factor Analysis, and Structural Equation Modelling (SEM), to analyse the conceptual model and its constructs.

4.5.1 *Influence of Gender Differences in Survey Responses*

An independent Sample T–test was conducted on gender against all survey variables to determine if significant differences could be detected in survey responses between males and females. First the means of the test results for the respective variables were examined to identify any obvious differences, this was followed by a review of the respective Levene's Test result for Equality of Variances to determine if any equal variances could not be assumed (Field, 2018). As per Field (2018), a result of $p<0.05$ indicates that equal variances cannot be assumed. A total of 6 cases where equal variance could not be assumed were identified, which included PEU54, VOU72, and CE85, CE86, CE87 and CE88. On subsequent examination of the 2 tailed significance test results for these variables, significant differences were ruled out with $p>0.05$. Thus, no significant differences were detected in responses between male and female respondents.

4.5.2 *Influence of Age Differences in Survey Responses*

To determine if any significant differences in participant perspectives existed across age groups, in responding to the survey, a One-Way ANOVA test was performed. The means between age groups for all survey variables were examined, followed by the respective significance scores in the ANOVA table. A significant score is denoted by $p<0.05$ (Field, 2018). The significance score for variable CE87 was identified as being significant. The Homogeneity of Variances table was then reviewed to determine if the variance between respective age groups was homogenous.

A significance score of $p<0.05$ in this table is an indication that variance is not homogenous (Field, 2018). The p-value for CE87 indicated that the variance between the age groups was not homogenous. A post hoc test was then performed for CE87 using Tamhane's T2 test (as equal variances were not assumed) and the significance results for each age group were assessed for significance. The p value results for all groups examined were $p>0.05$ which indicated no significant differences. Thus, no significant differences in survey feedback was identified between participant age groups.

4.5.3 *Common Method Bias Test*

Common method bias can occur when participant feedback is influenced by the design of the survey instrument rather than the actual perspectives being sought. This bias may consequently influence the data (Jakobsen & Jensen, 2015; Podsakoff et al., 2012). Non-probability convenience sampling was employed in this study which served as a measure against common method bias. Further measures utilized to counteract bias were the anonymity offered by the survey during data collection, and the randomization of the independent and dependent variables for feedback. Nevertheless, because a single survey was used with a consistent 5-point Likert scale across all questions, a post hoc Harman single-factor test was used to check for common method bias.

The post hoc Harman Single Factor test is a method to detect common method bias by determining whether the variance in the data can be attributed to a single factor alone. If a single factor can account for more than 50% of the variance then common method bias is indicated in the data (Chang et al., 2010; Harman, 1960). The test was conducted in SPSS on all variables, using principal component analysis and constraining the factors to 1. The results indicated that the percentage of variance explained by the single factor was 41.14% which was below the 50% threshold, thus no bias was present in the data.

4.5.4 *Exploratory Factor Analysis*

EFA was conducted on all conceptual model variables (independent and dependent) using the Principal Component analysis method and Varimax rotation to validate the scales and rationalise these into key factors or dimensions to be analysed. Varimax Rotation was used as it is the most widely used orthogonal rotation method and is known to provide a clearer distinction between the factors (Hair, 2019). The factor loading criteria was set to a minimum of 0.5 as per the guidelines of Hair (2019).

4.5.4.1. Determining suitability of EFA Application

To determine the suitability of applying EFA to the research model, the Kaiser-Mayer-Olkin Measure of Sampling Adequacy (KMO MSA) and Bartletts Test of Sphericity were conducted (Field, 2018; Hair, 2019).

According to Hair (2019), a KMO MSA value of >0.5 should be achieved before proceeding with factor analysis. The KMO MSA score obtained (in Table 8) was 0.925 which met the sampling adequacy requirement. Bartlett's test evaluates the existence of correlations among the variables (Hair, 2019). A statistically significant score of p<0.50 is an indication that it is permissible to continue with the EFA. The results (in Table 9 below) were significant x^2 (n=204) = 5060.229 (p<0.001) which satisfied the conditions to proceed with factor analysis.

Table 9: KMO and Bartlett Test Results (Initial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.925
Bartlett's Test of Sphericity	Approx. Chi-Square	5060.229
	df	595
	Sig.	.000

4.5.4.2. Communality Assessment

Communality is an indication of the strength of the variable items in explaining each variable, by depicting the amount of variance accounted for by the variable item (Hair, 2019). Hair (2019) provides the guideline of checking for communality >0.50 as an indication of significant contribution by variable items.

Variable communalities were assessed, and all variables (depicted in Table 10 below) achieved a score over 0.5 except for variable RA61 which earned a score of 0.488 that narrowly missed the contribution cut off threshold.

Table 10: Communalities Results EFA Test (Initial)

Communalities		
Variables	Initial	Extraction
PU41	1,000	0,716
PU42	1,000	0,675
PU43	1,000	0,585
PU44	1,000	0,679
PU45	1,000	0,683
PEU51	1,000	0,717
PEU52	1,000	0,594
PEU53	1,000	0,667
PEU54	1,000	0,690
PEU55	1,000	0,753
RA61	1,000	0,488
RA62	1,000	0,667
RA63	1,000	0,643
RA64	1,000	0,557
VOU71	1,000	0,615
VOU72	1,000	0,728
CE81	1,000	0,600
CE82	1,000	0,636
CE83	1,000	0,596
CE84	1,000	0,635
CE85	1,000	0,656
CE86	1,000	0,678
CE87	1,000	0,718
CE88	1,000	0,712
LO91	1,000	0,684
LO92	1,000	0,676
LO93	1,000	0,736
LO94	1,000	0,614
LO95	1,000	0,559
LO96	1,000	0,777
PI101	1,000	0,691
PI102	1,000	0,794
PI103	1,000	0,668

RPI111	1,000	0,778
RPI112	1,000	0,784
Extraction Method: Principal Component Analysis.		

4.5.4.3. Factor Extraction

To determine the number of factors to extract, the Kaiser rule was used and only factors with an eigenvalue greater than 1 were considered significant (Hair, 2019). The cumulative percentage of variance for factors with eigenvalues greater than 1, was also assessed for a value that explained a significant amount of the variance. According to Hair (2019), no specific benchmarks have been specified for all applications, although he suggests that Social Sciences consider at least 60% of total variance satisfactory. For this research, a threshold of 60% of the total cumulative variance percentage was also applied. The initial results of the analysis yielded 6 factors (indicated in Table 11 below) with eigenvalues over 1, which accounted for a cumulative 66.993% of the variation in the data.

Table 11: Total Variances Explained Results (Initial)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.399	41.140	41.140	14.399	41.140	41.140	7.285	20.814	20.814
2	3.055	8.729	49.869	3.055	8.729	49.869	3.922	11.206	32.020
3	2.006	5.730	55.600	2.006	5.730	55.600	3.889	11.112	43.132
4	1.727	4.935	60.535	1.727	4.935	60.535	3.730	10.658	53.790
5	1.206	3.445	63.980	1.206	3.445	63.980	2.471	7.060	60.850
6	1.055	3.013	66.993	1.055	3.013	66.993	2.150	6.144	66.993
7	.955	2.729	69.723						
8	.885	2.530	72.252						
9	.810	2.313	74.566						
10	.724	2.070	76.636						
11	.670	1.914	78.550						
12	.641	1.832	80.382						
13	.620	1.770	82.152						
14	.565	1.615	83.767						
15	.466	1.333	85.100						
16	.426	1.218	86.317						
17	.409	1.167	87.485						
18	.400	1.142	88.627						
19	.391	1.116	89.743						
20	.353	1.010	90.752						
21	.331	.946	91.699						
22	.315	.899	92.597						
23	.299	.854	93.452						
24	.281	.803	94.254						
25	.251	.716	94.970						
26	.246	.701	95.672						
27	.234	.670	96.341						
28	.212	.606	96.947						
29	.198	.565	97.511						
30	.188	.537	98.048						
31	.163	.465	98.513						
32	.150	.428	98.941						
33	.141	.403	99.344						
34	.119	.341	99.685						
35	.110	.315	100.000						

Extraction Method: Principal Component Analysis.

A review of the rotated component matrix indicated that 5 out of 8 variables were loaded on a factor with their original scales. This included Perceived Usefulness (PU41 to PU45), Perceived Ease of Use (PEU51 to PEU55), Voluntariness of Use (VOU71 and VOU72), Purchase Intention (PI101 to PI103) and Repeat Purchase Intention (RPI111 and RPI112).

The process followed to rationalise the remaining factor loadings was to first remove variables that did not load against a factor. This was followed by the removal of items which did not load together with their scales or that presented with comparatively low scores against other factors. The process of elimination was done systematically, removing one variable at a time to observe resulting changes on the remaining factor loadings. Following this process, variables RA61, CE81, CE82, CE83, CE84, CE85 and LO94 were removed.

The Exploratory Factor Analysis was then re-run with the remaining variables, and the original dimension reduction criteria, to determine any changes to the Bartletts Test of Sphericity results and the total variance explained.

The results of the revised Bartletts Test of Sphericity (depicted in Table 12 below) achieved a Kaiser – Meyer Olkin measure of sampling adequacy (MSA) of 0.916. This was marginally lower than the original result but still quite high. The results remained significant x^2 (n=204) = 3912.086 ($p<0.001$) which indicated that it remained suitable for factor analysis.

Table 12: KMO and Bartlett's Test Result (Revised)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.916
Bartlett's Test of Sphericity	Approx. Chi-Square	3912.086
	df	378
	Sig.	.000

The revised communalities in Table 13 below, all achieved an extraction score above 0.50.

Table 13: Communalities Results (Revised)

Communalities		
Variables	**Initial**	**Extraction**
PU41	1,000	0,740
PU42	1,000	0,697
PU43	1,000	0,592
PU44	1,000	0,699
PU45	1,000	0,708
PEU51	1,000	0,697
PEU52	1,000	0,588
PEU53	1,000	0,629
PEU54	1,000	0,706
PEU55	1,000	0,752
RA62	1,000	0,697
RA63	1,000	0,747
RA64	1,000	0,611
VOU71	1,000	0,763
VOU72	1,000	0,821
CE86	1,000	0,709
CE87	1,000	0,742
CE88	1,000	0,770
LO91	1,000	0,686
LO92	1,000	0,630
LO93	1,000	0,727
LO95	1,000	0,541
LO96	1,000	0,783
PI101	1,000	0,684
PI102	1,000	0,812
PI103	1,000	0,682
RPI111	1,000	0,791
RPI112	1,000	0,792
Extraction Method: Principal Component Analysis.		

The revised analysis (indicated in Table 14 below) yielded 6 factors with eigenvalues over 1, which accounted for a cumulative 70.708% of the total variance in the data. This was an improvement on the initial results, as the cumulative percentage contribution of the 6 factors increased by approximately 6%.

Table 14: Total Variance Explained Results (Revised)

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.371	40.612	40.612	11.371	40.612	40.612	6.688	23.884	23.884
2	2.948	10.527	51.139	2.948	10.527	51.139	3.584	12.798	36.682
3	1.993	7.117	58.255	1.993	7.117	58.255	3.470	12.392	49.074
4	1.374	4.909	63.164	1.374	4.909	63.164	2.471	8.827	57.901
5	1.105	3.948	67.112	1.105	3.948	67.112	1.934	6.907	64.808
6	1.007	3.595	70.708	1.007	3.595	70.708	1.652	5.900	70.708
7	.873	3.117	73.824						
8	.747	2.669	76.493						
9	.655	2.341	78.834						
10	.623	2.224	81.058						
11	.556	1.984	83.042						
12	.471	1.683	84.725						
13	.421	1.504	86.229						
14	.402	1.437	87.666						
15	.393	1.402	89.069						
16	.372	1.328	90.397						
17	.345	1.232	91.629						
18	.327	1.169	92.798						
19	.294	1.051	93.849						
20	.260	.927	94.776						
21	.251	.896	95.673						
22	.216	.770	96.443						
23	.210	.749	97.192						
24	.195	.697	97.890						
25	.173	.619	98.508						
26	.161	.575	99.083						
27	.133	.477	99.559						
28	.123	.441	100.000						

Extraction Method: Principal Component Analysis.

4.5.4.4. Scree Plot

The scree plot of the revised results (depicted in Figure 9 below) was also examined to determine the optimal number of factors to extract. It plots the eigenvalues against the number of factors, in order of extraction (Field, 2018; Hair, 2019). As per Hair (2019), the scree plot must be examined to identify the inflection point or “elbow” before the plot begins to resemble a horizontal line. The number of factors before the inflection point are considered to have unique variance and is an indication of the number of factors to extract. The scree plot for the revised variables did not indicate a clear inflection point for factor extraction so the decision was based solely on the eigenvalue threshold of >1.

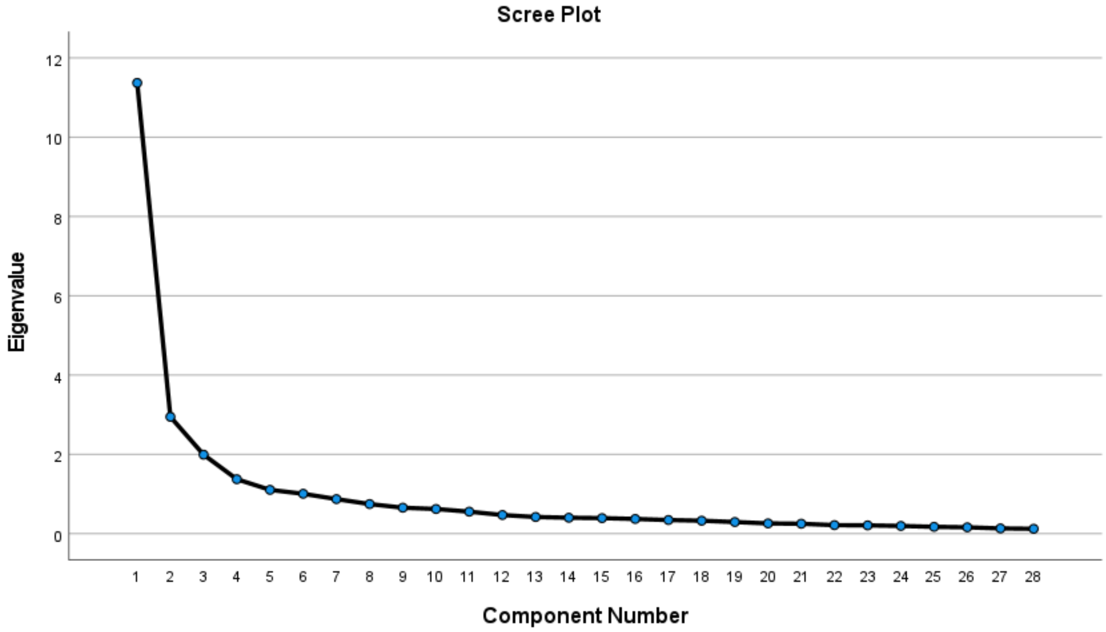

Figure 9: Scree Plot for Revised Variables

4.5.4.5. Rotated Component Matrix

The Rotated Component Matrix depicts the factor loadings of each variable on the respective factors, calculated after rotation (Field, 2018). The revised Rotated Component Matrix contained unique loadings against factors and grouped remaining items with their scale items as depicted in Table 15 below.

Table 15: Rotated Component Matrix (revised variables)

Rotated Component Matrix[a]						
	Component					
Variables	Purchase Decision	Perceived Ease of Use	Perceived Usefulness	Customer Experience	Relative Advantage	Voluntariness of Use
PU41			0,765			
PU42			0,753			
PU43			0,653			
PU44			0,779			
PU45			0,780			
PEU51		0,787				
PEU52		0,707				
PEU53		0,714				
PEU54		0,794				
PEU55		0,828				
RA62					0,684	
RA63					0,778	
RA64					0,506	
VOU71						0,776
VOU72						0,806
CE86				0,706		
CE87				0,713		
CE88				0,749		
LO91	0,736					
LO92	0,579					
LO93	0,754					
LO95	0,611					
LO96	0,772					
PI101	0,773					
PI102	0,878					
PI103	0,722					
RPI111	0,856					
RPI112	0,856					
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.						
a. Rotation converged in 6 iterations.						

Factors were classified according to the variable items that loaded highly against them. While the remaining variable items for Customer Experience, Relative Advantage, Perceived Usefulness, Perceived Ease of Use and Voluntariness of Use, grouped on respective factors against their original scale items, the variable items for Loyalty, Purchase Intention and Repeat Purchase Intention converged under a single factor. Thus CE86, CE87 and CE88 were grouped under Customer Experience, RA62, RA63 and RA64 were grouped under Relative Advantage, PU41 to PU45 were grouped under Perceived Usefulness, PEU51 to PEU55 were grouped under Perceived Ease of Use, VOU71 and VOU72 were grouped under Voluntariness of Use, and LO91 to LO96 (excluding LO94), PI101 to PI103, and RPI111 to RPI112 were grouped under a new factor called Purchase Decision. The plotted components are depicted in Figure 10 below.

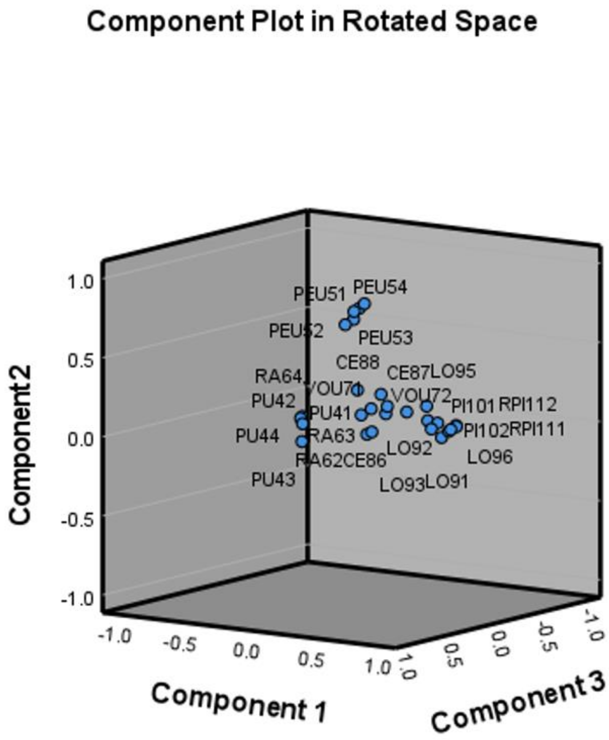

Figure 10: Component Plot of revised variables

Following the EFA analysis and rationalisation of the factors, the conceptual model was revised for further analysis as depicted in Figure 11 below.

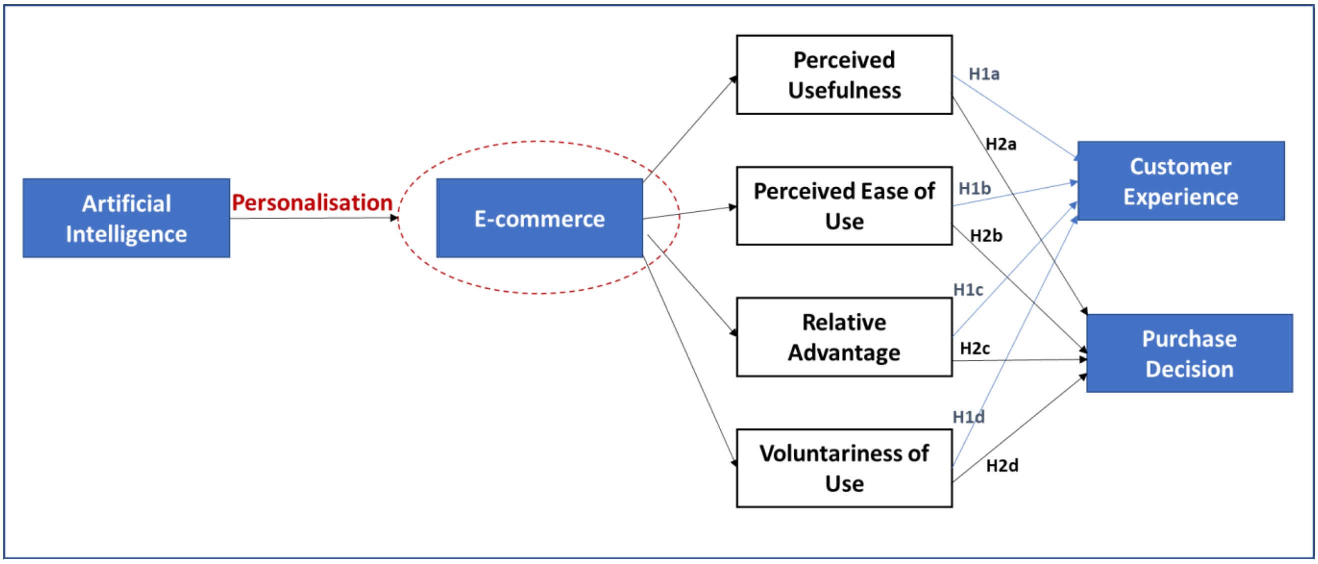

Figure 11: Revised Conceptual Model

4.5.5 *Confirmatory Factor Analysis*

Following the completion of EFA, Confirmatory Factor Analysis (CFA) was conducted to test the extent to which the conceptual model was represented by the data and to assess the validity and reliability of the constructs (Hair, 2019). IBM SPSS AMOS version 28 was used for the analysis.

The measurement model was first specified to conduct CFA. In alignment with Hair (2019), it contained 6 fundamental elements: the latent constructs (Perceived Usefulness, Perceived Ease of Use, Relative Advantage, Voluntariness of Use, Customer Experience and Purchase Decision), the measurement items for each construct (as specified in section 4.5.4.5), the relationship between the latent constructs and the measured variables (denoted by a single-headed arrow from the construct to the measured variable), Covariance relationships among constructs (represented by curved 2 headed arrows), and the error variance and covariance terms for each measured variable. Error variance was depicted by ovals prefixed with the letter “e”. The initial CFA model before scoring is depicted in Figure 12 below. Figure 13 below depicts the model after scoring with unstandardised scores and Figure 14 below depicts the model after scoring with standardised scores.

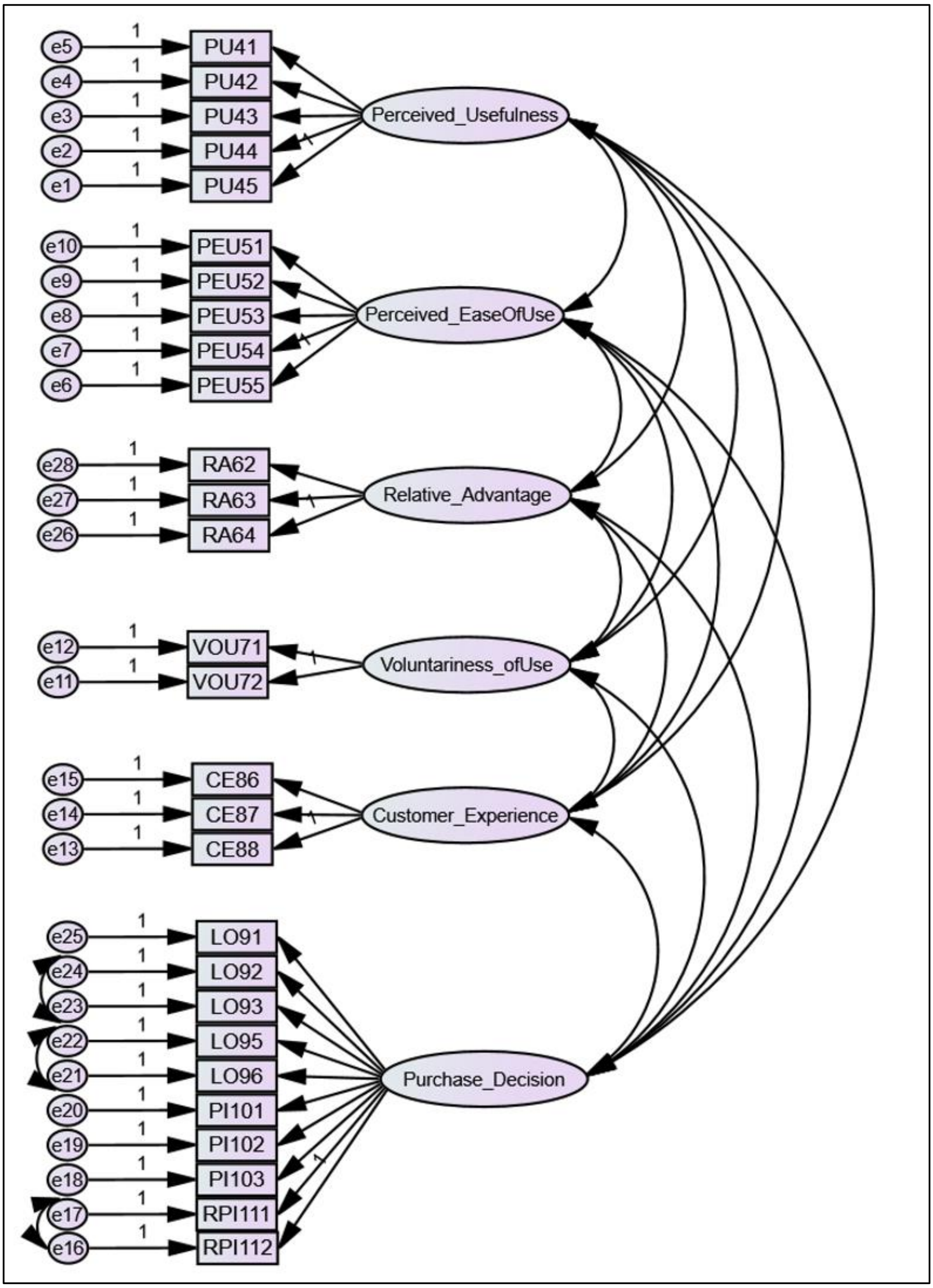

Figure 12: Initial CFA Model Before Scoring

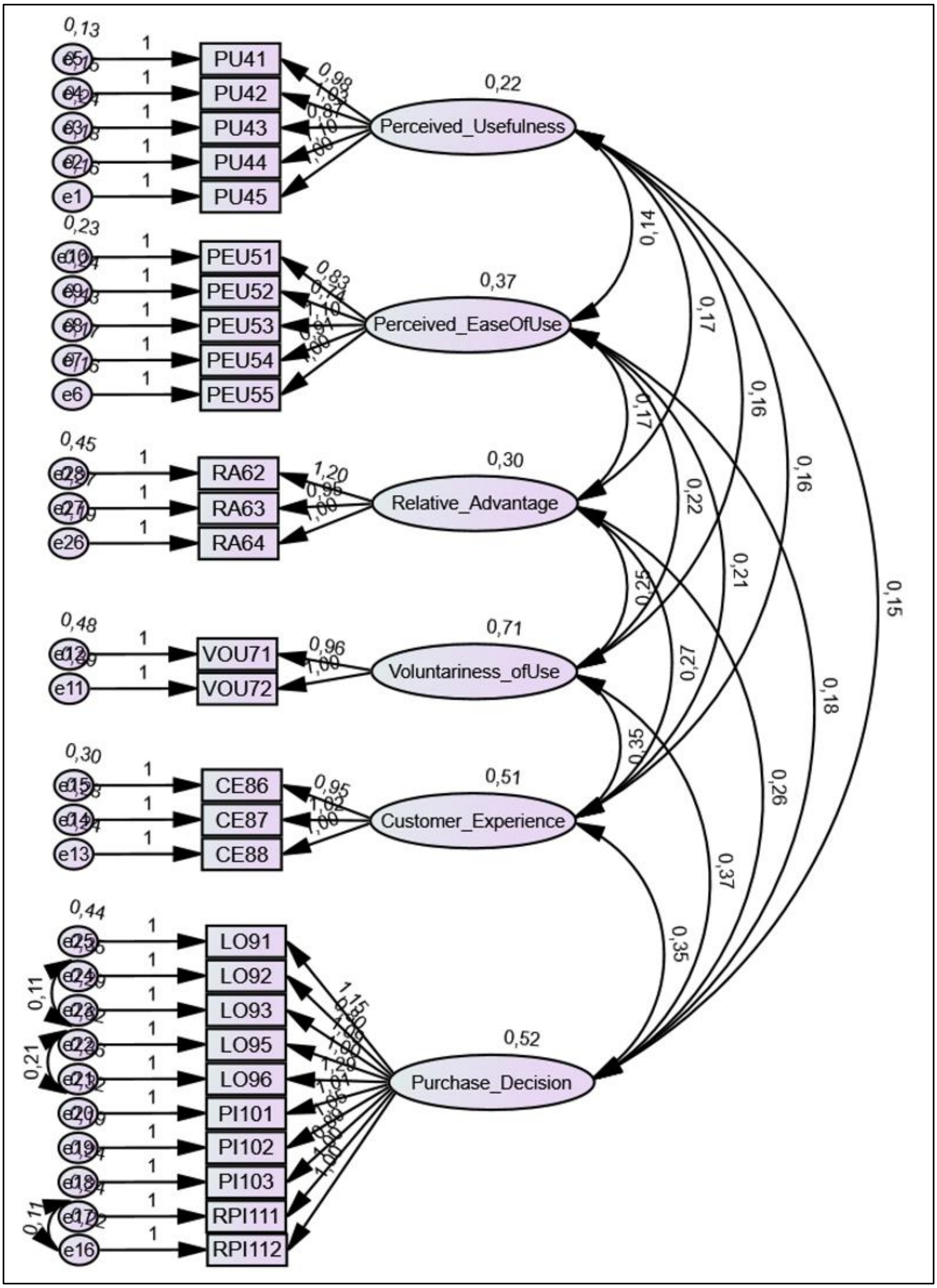

Figure 13: CFA Model with Unstandardised Scores

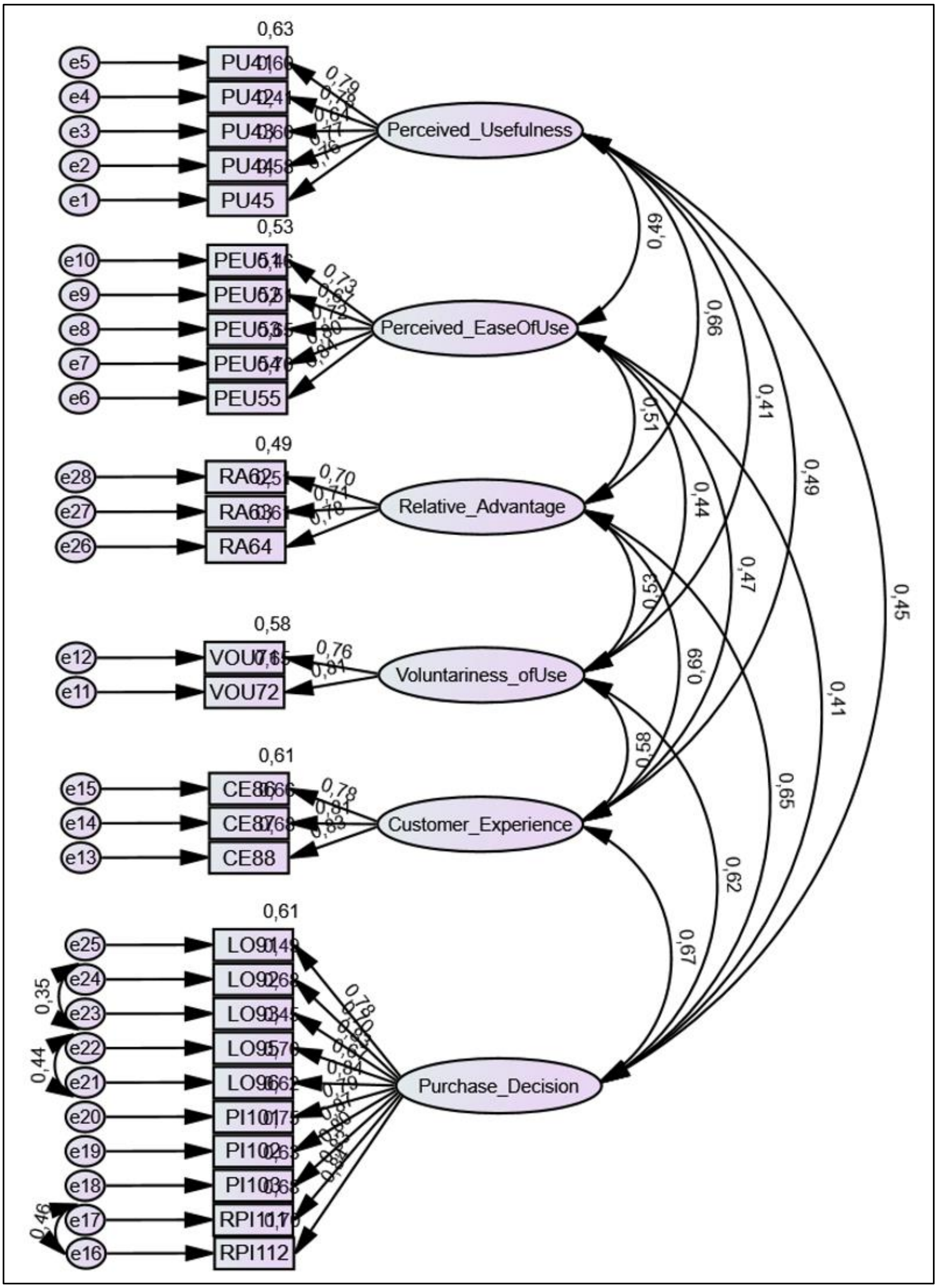

Figure 14: CFA Model with Standardised Scores

4.5.5.1. Model Fit

Following generation of the initial CFA results, the model fit was evaluated first. Modification indices were then reviewed for opportunities to enhance the model fit. Three error term covariances were created on the largest modification indices found and the enhanced fit statistics were then assessed.

The acceptance level of the CFA output scores was assessed on the recommended guidelines of Browne and Cudeck (1992) and Hu and Bentler (1999) who proposed the following thresholds: RMSEA<0.08, RMR<0.05, and CFI>0.90. Compared to this, the CFA model achieved an overall good fit on statistical scores (depicted in Table 16 below) that included X2/df = 1.988, RMSEA =0.70, RMR =0,038, and at least 3 incremental fit scores meeting acceptance level of > 90. (TLI = 0.900, CFI = 0,912, and IFI = 0.913). The results were thus considered acceptable to continue with further assessment of the model.

Table 16: CFA Model Fit Statistics

Model Fitness Indicators			
Category	**Indicator**	**Acceptance Level**	**Model score**
Chi-square (X^{2})	P-value	>0.05	0.000
	X^2	Not applicable	660.022
	Degrees of Freedom (df)	Not applicable	332
Absolute Fit	RMSEA	<0.08	0.70
	GFI	>0.90	0.812
	RMR	<0.05	0.038
	Chi-square/df	<3.0	1.988
Incremental Fit	TLI	>0.90	0.900
	CFI	>0.90	0.912
	IFI	>0.90	0.913
	NFI	>0.90	0.840

4.5.5.2. Reliability and Validity

Next the model was assessed for reliability and validity. The combination of CFA model fit results with construct validity tests, enables insight into the quality of the measurement model (Hair, 2019). In addition to reliability, convergent and discriminant validity was assessed for the model. The results are presented in Tables 17 and 18 below, respectively.

Convergent validity measures the extent to which the variable items or measures of a factor are correlated, and discriminant validity measures the level of distinction between concepts. All factors (or scales) in the model need to have discriminant validity from each other (Hair, 2019).

All items achieved standardised factor loadings above 0.60 and average variance extract (AVE) above 0.50 which was a strong indication of convergent validity (Hair et al., 2017). The reliability of variables was measured using the Cronbach Alpha and Composite Reliability scores as indicators. An acceptance level of > 0.7 is an indication of reliability for these statistics, and all variables achieved scores > 0.7 indicating acceptable reliability.

Table 17: Reliability and Convergent Validity

Factors	Items	Standardised Factor Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted	Maximum Shared Variance
Perceived Usefulness	PU45	0,760	0.863	0,865	0,564	0,441
	PU44	0,774				
	PU43	0,642				
	PU42	0,777				
	PU41	0,791				
Perceived Ease of Use	PEU55	0,839	0.859	0,868	0,569	0,256
	PEU54	0,805				
	PEU53	0,715				
	PEU52	0,675				
	PEU51	0,727				

Voluntariness of Use	VOU72	0,805	0.760	0,760	0,614	0,382
	VOU71	0,761				
Customer Experience	CE88	0,826	0.847	0,847	0,649	0,471
	CE87	0,810				
	CE86	0,781				
Purchase Decision	RPI112	0,836	0.944	0,945	0,632	0,456
	RPI111	0,825				
	PI103	0,796				
	PI102	0,868				
	PI101	0,789				
	LO96	0,838				
	LO95	0,673				
	LO93	0,826				
	LO92	0,697				
	LO91	0,780				
Relative Advantage	RA64	0,780	0.766	0,775	0,536	0,471
	RA63	0,711				
	RA62	0,702				

The Fornell and Larcker (1981) criteria were used to determine discriminant validity for the model. The square root of AVE values is depicted in bold font, running diagonally in the Table 18 below. 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. In Table 17 above, the Maximum Shared Variance (MSV) scores were lower than the corresponding AVE scores for all variables which further supported evidence of Discriminant validity.

Table 18: Discriminant Validity Results

	Voluntariness of Use	Perceived Usefulness	Perceived Ease of Use	Relative Advantage	Customer Experience	Purchase Decision
Voluntariness of Use	**0,783**					
Perceived Usefulness	0,407	**0,751**				
Perceived Ease of Use	0,436	0,487	**0,755**			
Relative Advantage	0,531	0,664	0,506	**0,732**		
Customer Experience	0,578	0,492	0,469	0,686	**0,806**	
Purchase Decision	0,618	0,454	0,408	0,653	0,675	**0,795**

4.5.6 *Hypothesis Testing (Conceptual Model)*

Following CFA analysis, Structural Equation Modelling was conducted to test the structural model relationship between the independent variables of Perceived Ease of Use, Perceived Usefulness, Relative Advantage and Voluntariness of Use, on Customer Experience and Purchase Decision

SEM analysis entailed first imputing the CFA results in AMOS, using regression imputation, to create new variables (named after the latent constructs from CFA) with a computed latent variable score based on the CFA results. A path diagram representative of the revised conceptual model was then constructed using the imputed latent variables. It depicted dependence relationships between the variables, with arrows originating from the independent variable, linking the arrowhead to the dependent variables. Double-sided, curved arrows were used to depict correlations between factors (Hair, 2019). Path analysis was then used to assess the strength of the paths depicted in the diagram. This was executed in AMOS through the imputation of Factor scores from CFA. Hypothesis testing entailed evaluating the influence of Perceived Ease of Use, Perceived Usefulness, Relative Advantage and Voluntariness of Use on Customer Experience and Purchase Intention.

The AMOS path diagram before scoring is depicted in Figure 15 below. After scoring, the unstandardized scores are presented in Figure 16 below and depicted with standardised scores in Figure 17 below. This is followed by discussion of the SEM analysis results.

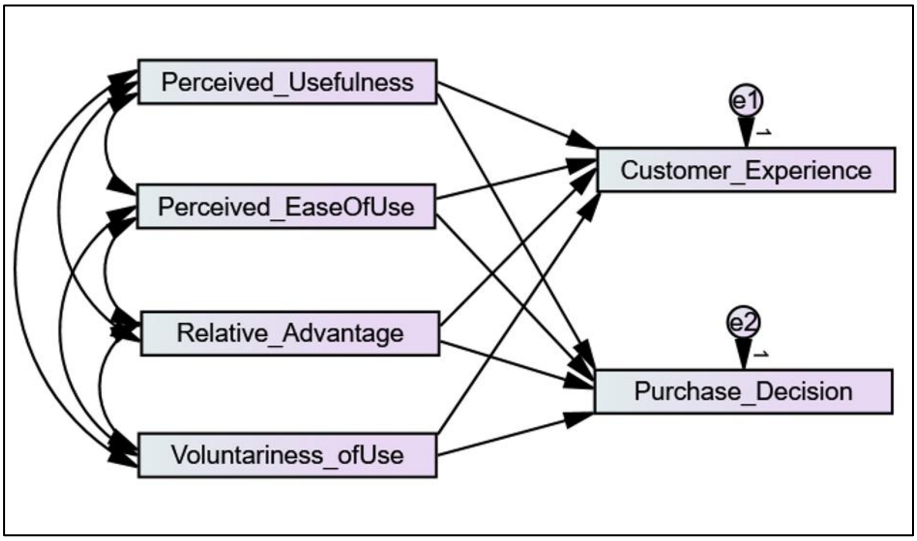

Figure 15: Path Diagram for Hypotheses Testing Before Scoring.

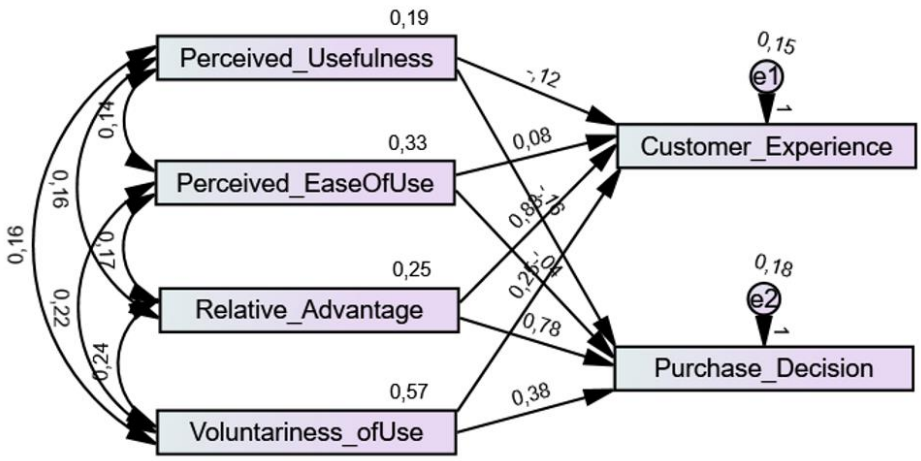

Figure 16: Measurement Model Results - Unstandardised Values

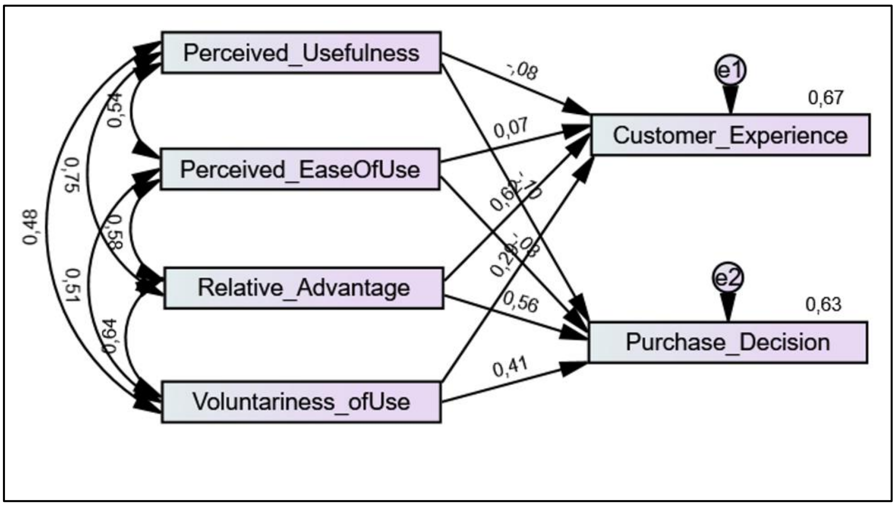

Figure 17: Measurement Model Results: Standardised Values

4.5.6.1. SEM Model Fit

The SEM Model fit statistics were first evaluated and indicated a good fit overall for the conceptual model. The recommended guidelines of Browne and Cudeck (1992) and Hu and Bentler (1999), which are described in section 4.5.5.1 for CFA Model fit, were also used to evaluate acceptable SEM model fit. Statistical results are depicted in Table 19 below, and included RMR = 0.010, GFI = 0.976, and CFI = 0.982. RMSEA did not meet the acceptable threshold level of <0.08 with a score of 0.269.

Table 19: Structural Model Fit Statistics

Model Fitness Indicators			
Category	**Indicator**	**Acceptance Level**	**Model score**
Chi-square (X^2)	P-value	>0.05	0.000
	X^2	Not applicable	15.734
	Degrees of Freedom (df)	Not applicable	1
Absolute Fit	RMSEA	<0.08	0.269
	GFI	>0.90	0.976
	RMR	<0.05	0.010
	Chi-square/df	<3.0	15.734

Incremental Fit	CFI	>0.90	0.982
	NFI	>0.90	0.981
	IFI	>0.90	0.982

The estimate of regression weights was examined next for path analysis results. The outcomes and discussion follow in chapter 5.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

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.

5.2 Path Analysis Results

The estimated path coefficients of the structural model (in Table 20 below) were analysed to evaluate alignment with the hypotheses.

Table 20: Regression Weights

Hypothesis	Path Analysis	Estimate	S.E.	C.R.	P	Outcome
H1a	Perceived Usefulness--> Customer Experience	-0,124	0,095	-1,301	0,193	Rejected
H1b	Perceived Ease of Use--> Customer Experience	0,079	0,061	1,3	0,194	Rejected
H1c	Relative Advantage--> Customer Experience	0,826	0,095	8,737	***	Accepted
H1d	Voluntariness of Use--> Customer Experience	0,254	0,048	5,298	***	Accepted
H2a	Perceived Usefulness--> Purchase Decision	-0,162	0,105	-1,543	0,123	Rejected
H2b	Perceived Ease of Use--> Purchase Decision	-0,040	0,067	-0,589	0,556	Rejected
H2c	Relative Advantage--> Purchase Decision	0,778	0,104	7,455	***	Accepted
H2d	Voluntariness of Use--> Purchase Decision	0,377	0,053	7,133	***	Accepted

Estimate: Estimate of regression weights

S.E.: standard error of regression weights,

C.R.: critical ratio for regression weight = regression weight estimate/estimated standard error

P: significance value

5.3 Discussion of H1 Personalisation in an E-commerce context positively influences Customer Experience

Hypothesis H1 aimed to understand how AI personalisation in an E-commerce context influenced Customer Experience and was measured through the independent latent variables of Perceived Usefulness, Perceived Ease of Use, Relative Advantage, and Voluntariness of Use.

5.3.1 *H1a Perceived Usefulness in an E-commerce context positively influences Customer Experience.*

In terms of Perceived Usefulness, sub-hypothesis H1a had investigated whether customers felt that they had gained value through, for example, enhanced product and service searches, chatbot assistance, or were introduced to new or complementary products through AI personalisation. The outcomes indicated that for hypothesis H1a, the Perceived Usefulness of AI personalisation was negatively and insignificantly associated with Customer Experience ($\beta = -0.124$, $P > 0.05$). Thus, hypothesis H1a was rejected. This outcome deviates from the findings of Liang et al. (2012), Wang et al. (2023) and others (Kashyap et al., 2022; Kumar et al., 2019; Moura et al., 2021; Rana et al., 2023) who propose positive influence on Perceived Usefulness and Customer Experience through the benefits of personalisation However, there are a few possible explanations for this outcome.

The extent and quality of personalisation features available to customers on frequented Online shopping sites can play a role. AI can deliver robust personalisation features however the quality of the solution will determine the experience of customers (Ameen et al., 2021; Gao et al., 2022; Necula & Păvăloaia, 2023). Necula and Păvăloaia (2023) highlighted that the effectiveness of the tool will depend on its appropriate application. Gao et al. (2022) stressed that if the technology fell short of customer’s expectations, then their experience would be diminished. Gao et al. (2022) also indicated that both functional and enjoyment features were important in positively influencing Customer Experience.

According to Ameen et al. (2021), there are perceived sacrifices for customers who shop Online. In addition to the lack of privacy, this also includes a lack of human contact that personalisation features need to compensate for (Ameen et al., 2021). It needs to trigger a positive emotional response in customers that forges a connection and relationship with the brand (Alnefaie et al., 2021; Ameen et al., 2021; Gao et al., 2022; Liang et al., 2012). Araujo (2018) found that when chatbot design integrated anthropomorphic (human like) features, it positively influenced emotional connection and relationship-building with customers. Customers additionally need to feel recognised, welcomed, and valued when they visit the site (Ameen et al., 2021; Liang et al., 2012; Rahmawati & Arifin, 2022), experience sensory enjoyment (Ameen et al., 2021; Chaudhuri et al., 2018; Gao et al., 2022), and be able to obtain useful information (Ameen et al., 2021; Rahmawati & Arifin, 2022) e.g. product specifications, support, digital content etc. Many local E-commerce sites visited are in the early application stage of AI personalisation, leaning more towards functional aspects and an economical focus e.g., promotional pricing and discounts. This might be perceived as clinical and lacking opportunity to provide enjoyment aspects or to engage customers emotionally e.g., no personalised welcome messaging, poor imagery, lack of sufficient product information or digital content, and chatbots with emotionless scripted responses.

In the research data, local E-commerce platform Takealot was the top selected online shopping site, and Shein was the most frequently user-suggested shopping site option. Both these E-commerce sites invest extensively in AI personalisation (Axel Tidemann, 2022; KrASIA, 2023). However, the fact that there is still scope for E-commerce development in South Africa (NielsenIQ, 2023; Reekie et al., 2022), combined with the reality of AI being in the early stages of application (Kashyap et al., 2022; Rana et al., 2023), may mean that many local sites still have room to enhance existing personalisation features to make them more effective, expand on features offered, and holistically integrate these into the user interface, content, and interaction as highlighted by Ameen et al. (2021). Good execution has been indicated to enhance customer engagement and connection to the brand (Kim & Baek, 2018; Stanley, 2022; Tyrväinen et al., 2020).

Another explanation for reduced experience, as Perceived Usefulness increases, are customer concerns around information privacy and the perceived sacrifice of having to relinquish more personal information to benefit from personalisation. This was a pertinent factor underscored in the studies of Potoglou et al. (2015) and Mpinganjira (2014).

5.3.2 *H1b Perceived Ease of Use in an E-commerce context positively influences Customer Experience.*

Perceived Ease of Use was found to be positively but insignificantly associated with Customer Experience ($\beta = 0.079$, $P>0.05$), indicating that hypothesis H1b was not supported. Interestingly, this result counters the earlier findings by Davis (1989) that Perceived Usefulness has a stronger effect than Perceived Ease of Use, as in this case, Perceive Ease of Use has relatively outperformed Perceived Usefulness in positive association with Customer Experience, albeit insignificantly. The case has already been made as to why Perceived Usefulness has underperformed in positively influencing Customer Experience. The positive association with Customer Experience is in line with the literature (Ameen et al., 2021; Chen et al., 2021; Gao et al., 2022; Kumar et al., 2019; Moura et al., 2021; Rana et al., 2023; Wang et al., 2023; Zanker et al., 2019) on the convenience, time savings and improved decision-making benefits to be gained by customers with AI personalisation. Even though positive influence is indicated, the fact that it is insignificant may be an indication that low effort to use the features is insufficient to influence experience if the outcomes are not effectively meeting customer needs.

5.3.3 *H1c Relative Advantage in an E-commerce context positively influences Customer Experience.*

Relative Advantage was positively and significantly associated with Customer Experience (β = 0. 0,826, P<0.05) and had the strongest overall positive influence on this variable. Thus, hypothesis H1c was accepted. This indicated that as customers' perceptions of the Relative Advantage of E-commerce AI personalisation, over physical stores, and E-commerce sites without personalisation increased, so did their experience. Perceived advantages surveyed included AI personalisation helping to increase their control over the shopping process and reducing their shopping effort. The literature has identified the powerful key AI capabilities of machine learning, deep learning, artificial neural networks (Ergen, 2019; Jakhar & Kaur, 2020; Kaplan & Haenlein, 2019), natural language processing (Kang et al., 2020; Kashyap et al., 2022; Savci & Das, 2023; Sujata et al., 2019), expert systems (Matsuzaka & Yashiro, 2023; Tan, 2017) and computer vision (Farinella et al., 2013; Matsuzaka & Yashiro, 2023), that are enabled through the processing of Big Data. It has further elaborated on how these capabilities enable enhanced and sophisticated personalisation features such as recommendation engines (Moura et al., 2021; Necula & Păvăloaia, 2023; Zanker et al., 2019), chatbots (Alnefaie et al., 2021; Reshmi & Balakrishnan, 2016; Sujata et al., 2019), virtual assistants (Moussawi et al., 2021; Sujata et al., 2019), content curation (Chaudhuri et al., 2018; Mileva, 2023), predictive analytics (Gupta & Joshi, 2022), sentiment analysis (Sujata et al., 2019) and image search (Yang & Liu, 2021), that can enhance engagement and shopping benefits offered to E-commerce shoppers.

5.3.4 *H1d Voluntariness of Use in an E-commerce context positively influences Customer Experience.*

Voluntariness of Use related to customers' perceived choice in having their personal information utilized to provide them with personalized services. Voluntariness of Use was positively and significantly associated with Customer

Experience (β =0,254, P<0.05), resulting in the acceptance of hypothesis H1d. The results indicated that increased perception of choice in opting for personalisation, positively influenced customer experience. This result is aligned with the research findings of Cecere and Rochelandet (2013) to the extent that customers appear to be assured by the presence of a privacy policy to opt in to and view it as a sign of choice of control over their personal information.

5.4 Discussion of H2 Personalisation in an E-commerce context positively influences Purchase Decision

Hypothesis H2 aimed to understand how AI personalisation in an E-commerce context influenced Purchase Intention, Repeat Purchase Intention and Loyalty, collectively grouped under Purchase Decision. It was measured through the independent latent variables of Perceived Usefulness, Perceived Ease of Use, Relative Advantage, and Voluntariness of Use.

5.4.1 *H2a Perceived Usefulness in an E-commerce context positively influences Purchase Decision*

The hypotheses result outcomes for hypothesis H2a indicated that Perceived Usefulness was negatively and insignificantly associated with Purchase Decision (β = -0,162, P>0.05). Thus, H2a was rejected. This result differentiates from prior research findings (Even, 2019; Kim & Baek, 2018; Moura et al., 2021; Pappas et al., 2016; Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2017; Rahmawati & Arifin, 2022; Rana et al., 2023; Stanley, 2022; Sujata et al., 2019; Tyrväinen et al., 2020; Wu et al., 2017; Yoon et al., 2013) that personalisation benefits can increase customer satisfaction thus leading to positive purchase decisions.

As in the case of the Customer Experience discussion, this result can be related to the quality of execution. Quality of personalisation must meet customer expectations (Gao et al., 2022) so that customers can feel that e-tailers have a sound understanding of their preferences and can anticipate their needs (Kim &

Baek, 2018; Mileva, 2023; Tyrväinen et al., 2020) This can increase customer engagement and inspire a connection to the brand (Kim & Baek, 2018; Stanley, 2022). Wu et al. (2017) accentuated that when customers develop a positive attitude towards a brand, it could motivate them to revisit and repurchase. Rahmawati and Arifin (2022) added that positive emotions like feeling welcome and enjoyment, in addition to pricing strategy and product quality, played a role in influencing customers to future purchases and customer advocacy. Pappas et al. (2016) found that positive emotion was significant in Online shopping because even when the quality of personalisation was low, it could still influence a customer to purchase. This implies that organisations may need to consider balancing personalisation efforts to integrate both functional and emotional aspects to inspire positive emotions towards the brand from customers.

The negative association of Perceived Usefulness with a purchase decision, finds support with the research by Pappas, Kourouthanassis, Giannakos and Lekakos (2017) which indicated that the influence of personalisation may be diminished if customers had specific shopping goals. Customers may only choose to shop Online in search of the lowest prices or the best deals. This is plausible in the South African context where the increasing cost of living as a result of the weak economy, and increasing food, electricity, and fuel costs, can potentially put customers under financial pressure (Lechman, 2024; Roets, 2024), leading to value-seeking, economic purchase decisions. Alternatively, customers may be in search of specific product brands or service quality e.g., information privacy, security, support, or delivery policies that meet their needs. Service quality needs are supported by Mpinganjira (2014) who also found information privacy protection and ease of communication with the e-tailer to be important influencers of customer satisfaction and purchase decisions. If the conditions of the shopping need are not met, then customers will not purchase regardless of the level of personalisation offered (Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017).

5.4.2 *H2b Perceived Ease of Use in an E-commerce context positively influences Purchase Decision*

Perceived Ease of Use was negatively but insignificantly associated with Purchase Decision (β = -0,040, P>0.05), leading to H2b being rejected. These results can be explained by specific shopper goals (Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017) as in the case of Perceived Usefulness. Research by Wang et al. (2023) found that trust positively influences Perceived Ease of Use. This provides an alternate reason as to why customers are not persuaded to purchase even when there is low effort to use. There may be other factors hindering customer trust to purchase. This finding is supported by the *service quality* shopping goals identified by Pappas, Kourouthanassis, Giannakos and Lekakos (2017), which found that if customers' have concerns about service elements like security, privacy, support etc., this impacts the decision to purchase.

Another explanation for this result relates to the quality of the solution that customers have been exposed to, as has been indicated for Perceived Usefulness. The need for high quality personalisation solutions has been emphasized by Kim and Baek (2018); Mileva (2023); Pappas et al. (2016); Pappas, Kourouthanassis, Giannakos and Chrissikopoulos (2017); Tyrväinen et al. (2020); Yoon et al. (2013), as key in influencing purchasing decisions and loyalty. Therefore, if the features are easy to use but do not generate satisfactory results in terms of relevant recommendations, useful content, or support, then this potentially negatively affects intention to purchase and leads to customers relying on their emotions for purchase decision (Pappas et al., 2016).

5.4.3 *H2c Relative Advantage in an E-commerce context positively influences Purchase Decision.*

Relative Advantage was positively and significantly associated with Purchase Decision (β = 0,778, P<0.05). It also had the highest positive influence on this variable. Thus, hypothesis H2c was accepted. This finding indicated that as customers' perceptions of the Relative Advantage offered by AI personalisation in E-commerce sites increased in comparison to physical stores, and Online shopping sites that did not offer these features, it positively influenced purchase decisions and loyalty towards the website. This aligns with findings by Yoon et al. (2013) which highlighted that customers compared personalisation features across sites based on the shopping experience, and their Purchase Decisions were positively influenced by the perceived superior features offered. It also supports studies that emphasize the advantages of AI E-commerce personalisation features that positively influence customer Purchase Decisions, including enhancing engagement and making customers feel valued (Kim & Baek, 2018; Mileva, 2023; Stanley, 2022; Sujata et al., 2019; Tyrväinen et al., 2020; Wu et al., 2017), helping customers to find better, or new products and services (Pappas et al., 2016; Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2017; Yoon et al., 2013), reducing shopping time and effort (Rana et al., 2023), and enhancing customer satisfaction (Mpinganjira, 2014; Yoon et al., 2013).

5.4.4 *H2d Voluntariness of Use in an E-commerce context positively influences Purchase Decision.*

Finally, Voluntariness of Use was positively and significantly associated with Purchase Decision (β =0. 0,377, $P<0.05$), resulting in hypothesis H2d being accepted. It implied that customers valued control over how their information was used for AI personalisation purposes in Online shopping, and as the perception of control over privacy increases, this gave them more confidence to shop on a site without fear of violation of their information privacy. This result supported the research findings of Cecere and Rochelandet (2013). In addition to finding that customers were assured by the visibility of a website privacy policy and the perception of control that it offered, Cecere and Rochelandet (2013) also discovered that Online sites with transparent information privacy conditions, tended to attract larger audiences ultimately leading to higher revenues for these sites.

5.5 Conclusion

This section discussed the outcomes of the hypothesis testing and evaluated the results with the findings from the literature review.

The research study results have found that both Relative Advantage and Voluntariness of Use of AI personalisation in E-commerce, positively and significantly influenced Customer Experience as well as customer Purchase Decisions.

While Perceived Ease of Use was seen to positively influence Customer Experience, the effect was insignificant. Alternatively, Perceived Ease of Use was found to have a negative and insignificant influence on Purchase Decisions. Hence both hypotheses related to Perceived Ease of Use were rejected. The most surprising results of the study related to Perceived Usefulness. It was found to have a negative, albeit insignificant influence on both Customer Experience and Purchase Decisions. Thus, both hypotheses related to Perceived Usefulness were rejected.

In summary, the supported sub hypotheses H1c, H1d, H2c and H2d were accepted. Sub hypotheses H1a, H1b, H2a and H2b were rejected.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This section revisits the research questions that initiated the study and combines them with concluding remarks about the results. It then provides recommendations based on the outcomes, for identified stakeholders, and concludes with suggestions for future research.

The research study set out to investigate the Artificial Intelligence (AI) capabilities that enable personalisation features in E-commerce, and investigate how these features influence Customer Experience, Purchase Decisions, Repeat Purchases and Loyalty in a South African context.

A conceptual model was formulated on the integrated theoretical framework elements of TAM and Diffusion of Innovation theory to investigate whether AI personalisation in E-commerce, evaluated through the independent latent variables of Perceived Usefulness, Perceived Ease of Use, Relative Advantage, and Voluntariness of Use, influenced customer’s Online shopping experience, Purchase Intention, Repeat Purchase Intention and Loyalty.

6.2 Conclusions regarding Artificial Intelligence capabilities that can enable personalisation features in an E-commerce context

Artificial Intelligence is a new technology with powerful capabilities that have the potential to transform business performance and augment customer experience in E-commerce. An understanding of the key capabilities that underpin the technology is vital to realise the potential opportunities to be harnessed with it. The key Artificial Intelligence capabilities identified in the study, were decomposed into machine learning, deep learning, artificial neural networks, natural language processing, expert systems, and computer vision. Following an extensive review of the literature, this was identified to be the first empirical theory-based study, relating to AI personalisation in E-commerce, that also attempted to include a comprehensive overview of the core AI capabilities relevant for E-commerce.

6.3 Conclusions regarding personalisation features enabled by Artificial Intelligence capabilities in an E-commerce context

Artificial Intelligence is still in the early stages of application and there is limited awareness of how this technology can enable personalisation in an E-commerce context to enhance Customer Experience (Kashyap et al., 2022; Rana et al., 2023). Organisations need to understand the personalisation applications of the technology, to realise competitiveness though tailoring experience for E-commerce customers. The E-commerce AI personalisation features identified by the study were recommendation engines, chatbots, virtual assistants, content curation, sentiment analysis, predictive analytics, and image search. A comprehensive review of the literature indicated this to be the first empirical theory-based study, relating to AI personalisation in E-commerce, that attempted to relate the core AI capabilities to a portfolio of personalisation features enabled in E-commerce.

6.4 Conclusions regarding how AI personalisation in an E-commerce context influences Customer Experience

E-tailers need to look beyond price and promotion alone for competitive advantage, as this can easily be replicated by rivals, and margins can be eroded as customers effortlessly access information from multiple Online competitors for comparison. With the impending arrival of global E-commerce giants like Amazon, who set the standard for E-commerce personalisation and customer experience (African Retail, 2023; Amazon, 2023; Statista, 2022), it has become imperative for local organisations to not lag. Thus, online retailers need to differentiate themselves on superior customer experience. Artificial Intelligence is a technology that has the potential to enhance customer experience by facilitating tailored service for individual customers.

The study found that as customer perceptions of the Relative Advantage of Artificial Intelligence applications in E-commerce increased, so did their positive experience. This indicated that customers did believe that it was advantageous to shop on E-commerce sites that utilise AI personalisation compared to sites that did not offer these features and physical stores. This variable was found to have the strongest positive influence on Customer Experience. A thorough review of the literature pointed to this as being the first empirical theory-based study, relating to AI personalisation in E-commerce, that has measured customer perceptions of the Relative Advantage of AI personalisation in E-commerce, on Customer Experience.

Voluntariness of the Use of AI personalisation followed Relative Advantage in terms of strength of positive influence on Customer Experience. This indicated that customers valued control over their personal information in the enablement of AI personalisation features in E-commerce, and it had a significant influence on their experience. Following the literature review, this was identified as the first empirical theory-based study relating to AI personalisation in E-commerce, that has measured customer perceptions of Voluntariness of Use of AI personalisation in E-commerce, on Customer Experience.

Perceived Ease of Use was seen to positively influence Customer Experience, suggesting that if the personalisation features presented to customers are easy and intuitive to use, then it did provide a positive experience, however, the effect was found to be insignificant in this study. Finally, Perceived Usefulness was found to have a negative, albeit insignificant influence on Customer Experience. The potential reasons attributed to this outcome included quality of execution, customer concerns about information privacy, and a lack of personalisation features to trigger emotional connection with customers in the absence of human contact.

6.5 Conclusions regarding how AI personalisation in an E-commerce context influences Purchase Decision.

E-commerce businesses need to be competitive to be able to attract and retain customers for revenue generation and for organisational sustainability. Artificial Intelligence enables tailoring of the customer's end-to-end E-commerce journey with features that can reduce their shopping time and effort and optimise meeting their shopping goals.

The study found that in terms of Relative Advantage, customers perceived shopping on Online sites with AI personalisation as more advantageous than shopping on websites that did not offer personalisation or physical stores. This positively and significantly influenced their decision to purchase on the online store, revisit for future purchases and develop a preference to shop on sites that offer AI personalisation. An expansive literature review has found this to be the first empirical theory-based study relating to AI personalisation in E-commerce, that has measured customer perceptions of the Relative Advantage of AI personalisation in E-commerce on Purchase Decision.

In terms of Voluntariness of Use, sites that provided customers with perceived control over their personal information by offering an opt-in into their privacy policy, positively and significantly influenced the decision to purchase. This implied that perceived control was important to reassure customers that it was safe to shop on the E-commerce site. Substantial review of the literature determined this to be the first empirical theory-based study, relating to AI personalisation in E-commerce, that has measured customer perceptions of Voluntariness of Use of AI personalisation in E-commerce, on Purchase Decision.

Perceived Ease of Use was unexpectedly found to negatively influence customer Purchase Decisions, indicating that the easier customers found personalisation features to use, the more unlikely they were to purchase from the website. However, the effect was insignificant. The possible reasons attributed to this outcome included specific shopper goals that could override the influence of personalisation, factors that impeded trust to purchase, and quality of execution of the personalisation features, that although simple to use, did not deliver useful results.

Perceived Usefulness was negatively and insignificantly associated with Purchase Decisions. This was also ascribed to specific shopper goals which could diminish the effect of personalisation, as well as the quality of the solution that needs to balance the functional and emotional aspects in personalisation design to inspire positive emotions and a connection with the brand.

6.6 Recommendations

With the accelerating growth of E-commerce in South Africa, personalisation for enhancement of customer experience and achievement of competitive advantage can be viewed as a hygiene factor (Lindecrantz et al., 2020), meaning if E-commerce sites do not have it, their customers may likely seek out competitors. This is compounded by the imminent arrival in the country of E-commerce industry giants like Amazon who are the leaders in E-commerce personalisation and customer experience (African Retail, 2023; Amazon, 2023; Statista, 2022)

The study has found that although personalisation is imperative for the survival and success of online shopping sites, and Artificial Intelligence technology has powerful capability to deliver enhanced personalisation features, attention and care must be given to the solution execution to ensure a positive influence on customer experience and purchase decisions.

E-commerce AI personalisation features must be easy to use, with accessibility factored into design, to enable customers to benefit from their use with low effort and help to reduce their shopping time and effort. For example, providing multiple formats for information search, including text, image and voice searches, can help reduce the time invested by customers and increase their positive sentiment toward the brand (Rana et al., 2023; Yang & Liu, 2021). Use content curation functionality to customise the experience for new or existing customers by adapting the website layout (Gupta & Joshi, 2022; Mileva, 2023) New customers can be provided with information on best-selling products, and existing customers can be reminded of previous purchases, items browsed and items still in the cart (Ameen et al., 2021; Mileva, 2023; Yoon et al., 2013).

Personalisation features must not only be effortless for customers to use but need to deliver value to customers in return for the cost of personal information traded. Customers need to have confidence that the e-tailer is appropriately using their personal information to thoroughly understand their preferences and anticipate their needs (Kim & Baek, 2018; Mileva, 2023; Tyrväinen et al., 2020). In terms of feature attributes, this should translate into high accuracy and relevance of recommendation options that are more likely to enhance user experience (Zanker et al., 2019). AI-driven recommendations can provide deeper insights by integrating user purchase history, preferences, browsing behaviour, contextual information (e.g. weather and time) and unstructured data (e.g. user reviews) (Ameen et al., 2021; Necula & Păvăloaia, 2023). These must be capitalised to refine the recommendation results to be highly adaptive and relevant to customers' interests and needs. In addition, the recommendations must be integrated seamlessly through all stages of the customers' Online shopping journey, from product discovery to order confirmation and checkout, to facilitate the customer's discovery of new and complementary products, increased engagement and enhanced decision making (Mileva, 2023; Moura et al., 2021). At the order confirmation stage, AI content curation can remind customers of previous purchases, wish list items and related trending products should they wish to add these to their order (Ameen et al., 2021; Mileva, 2023; Pearson, 2019).

Predictive analytics techniques can be applied to identify and target prospective customers at the optimal time in the shopping journey with personalised offers, discounts, and promotion reminders to encourage purchase conversions (Gupta

& Joshi, 2022). Chatbot agents used for online customer support must be efficient, with a high responsiveness rate and effective problem solving to positively influence customer experience and customer perceptions of the level of the organisations innovation (Chen et al., 2021). Insights from the chatbot customer care interactions must be used to enhance the chatbot performance as it learns from customer problem solving engagements (Sujata et al., 2019).

Highly functional and efficient features are the minimum standard for the implementation of personalisation solutions, but on their own, they may still be insufficient to trigger positive influence on customer experience and purchase decisions. When selecting to shop on a digital channel, customers incur the perceived sacrifice of loss of human contact (Ameen et al., 2021). Functional features alone may be too clinical and sterile to trigger a positive emotional response in customers. Features that cater to customer enjoyment and inspire an emotional connection to the brand increase customer engagement, and build the relationship between the customer and the brand (Alnefaie et al., 2021; Ameen et al., 2021; Gao et al., 2022; Liang et al., 2012; Rahmawati & Arifin, 2022). A positive attitude to the brand can increase customer purchase intentions, revisits to the site and loyalty (Wu et al., 2017). Thus, functional, and emotional aspects must be factored into personalisation solution design. Enjoyment features provide customers with entertainment, excitement, escapism and positive emotions (Pappas et al., 2016; Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017). Integrate recognition attributes that make the customer feel important, welcome and valued by the organisation on the website (Ameen et al., 2021; Liang et al., 2012; Rahmawati & Arifin, 2022). Implement AI personalisation features that create sensory enjoyment (Ameen et al., 2021; Chaudhuri et al., 2018; Gao et al., 2022). Use AI to customise and optimise the image and video content presented to customers to meet their interests and preferences and increase their engagement (Chaudhuri et al., 2018; Pearson, 2019).

Consider AI-driven recommendation systems that extend to augmented reality and virtual assistants (Necula & Păvăloaia, 2023) for a more immersive and engaging experience. Integrate anthropomorphic features into the chatbot and virtual assistant design e.g. use NLP and sentiment analysis for more human like, personalised responses that foster emotional connection, engagement and perception of being valued (Araujo, 2018; Chen et al., 2021; Mileva, 2023; Moussawi et al., 2021). Intelligent virtual assistants are enhanced conversational agents that can use natural language understanding and artificial emotional intelligence to resolve more complex customer queries, in a more human like way, through both text and voice format (Dilmegani, 2023; Moussawi et al., 2021). These features can provide the opportunity for the organisation to integrate their brand values and tone into the interaction to build the relationship with customers.

Even with a robust personalisation solution in place, the study has identified that specific customer shopping goals may take precedence and render E-commerce personalisation efforts redundant in positively influencing customer experience and purchase decisions (Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017). Organisations must be aware of unique environmental conditions or trends that could influence specific shopping goals e.g., economic trends that can lead to value-seeking behaviour and customers in search of the lowest prices or best deals, so that they can adapt personalised marketing and pricing strategies accordingly. This is particularly relevant in the current South African economic context where the increasing cost of living as a result of the weak economy, and increasing food, electricity, and fuel costs places customers under financial pressure (Lechman, 2024; Roets, 2024).

Organisations need to utilise insights from customer search trends to enhance their product and service catalogue to anticipate evolving customer needs and interests and cater to these. Customer shopping goals can also include specific service quality needs like security, support, or delivery policies, that may impact their trust of the e-tailer or decision to purchase. Organisations must ensure that they understand these needs to enhance the relevant service features to seamlessly integrate with and complement personalisation efforts for positive experience and purchase decisions.

The study has revealed that customers value being able to exercise control over how their personal information is used for E-commerce personalisation purposes and the perception of control positively influences their customer experience and purchase decision. Thus, organisations should prominently bring their information privacy policy to customers' attention on the website, ensure that their privacy conditions are transparent, and provide customers with the option to opt for personalisation. The visibility of a privacy policy does tend to reassure customers about the safety of shopping on a website without fear of personal information violations (Cecere & Rochelandet, 2013), and the organisation's compliance with the privacy policy will increase credibility and trust with customers. Policy makers therefore have a role to play in ensuring that E-commerce businesses comply with implementing rigorous consumer privacy controls to protect consumers. As AI additionally requires large amounts of data to train models on consumer behaviour for personalisation purposes, they will also need to ensure that ethical considerations are catered for in designing solutions to guard against consumers being adversely impacted by biased data.

Finally, e-tailers must constantly look for opportunities to refine their AI personalisation strategies in E-commerce, as customers will compare their experience to the best in class. The best-performing E-commerce sites will be viewed as advantageous to shop on and likely to attract the most consumers and revenue.

6.7 Suggestions for further research

This study provided a South African context of consumer perceptions of AI in E-commerce. As Africa tends to be underrepresented in AI in E-commerce literature in addition to having the lowest E-commerce revenue worldwide (Statista, 2022), it would be beneficial to understand customer perceptions in other African country contexts, to leverage insights for the success of E-commerce throughout the continent and to build on the body of literature represented by Africa. This study has further identified that a balance of functional and emotional attributes must be integrated into personalisation design to trigger a positive emotional response from customers. Future studies can investigate the influence of anthropomorphic features in influencing customer experience and purchase decisions. Quality of solution has been identified as a factor that potentially influences customers' Perceived Usefulness and Perceived Ease of Use of AI personalisation. Future studies can empirically test this.

Finally with the evolution of AI, and the advent of generative AI, capable of generating new digital content in the form of text, images, audio, code and videos (Harreis et al., 2023), future studies could investigate emerging trends of generative AI in E-commerce and customer perceptions related to it.

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APPENDIX A Consistency table

This table lists the research questions and links them to the hypotheses, data collection detail and data analysis methods.

RQ #	Research Question	Hyp #	Hypothesis	Data collection detail	Data analysis method
2.5	How does personalisation in an E-commerce context influence Customer Experience?	H1	Null Hypothesis: Personalisation in an E-commerce context does not affect Customer Experience. Alternative Hypothesis: Personalisation in an E-commerce context positively influences Customer Experience.	Questionnaire Likert statements (5-point Likert scale)	Factor analysis using EFA, CFA & SEM
		H1a	Null Hypothesis: Perceived Usefulness in an E-commerce context does not affect Customer Experience. Alternative Hypothesis: Perceived Usefulness in an E-commerce context positively influences Customer Experience.		

RQ #	Research Question	Hyp #	Hypothesis	Data collection detail	Data analysis method
		H1b	Null Hypothesis: Perceived Ease of Use in an E-commerce context does not affect Customer Experience. Alternative Hypothesis: Perceived Ease of Use in an E-commerce context positively influences Customer Experience.		
		H1c	Null Hypothesis: Relative Advantage in an E-commerce context does not affect Customer Experience. Alternative Hypothesis: Relative Advantage in an E-commerce context positively influences Customer Experience.		
		H1d	Null Hypothesis: Voluntariness of Use in an E-commerce context does not affect Customer Experience.		

RQ #	Research Question	Hyp #	Hypothesis	Data collection detail	Data analysis method
			Alternative Hypothesis: Voluntariness of Use in an E-commerce context positively influences Customer Experience.		
2.6	How does personalisation in an E-commerce context influence Purchase Intention, Repeat Purchase Intention and Loyalty	H2	Null hypothesis: Personalisation in an E-commerce context does not affect Purchase Intention, Repeat Purchase Intention and Loyalty. Alternative Hypothesis: Personalisation in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.	Questionnaire Likert statements (5-point Likert scale)	Factor analysis using EFA, CFA & SEM
		H2a	Null Hypothesis: Perceived Usefulness in an E-commerce context does not affect Purchase Intention, Repeat Purchase Intention and Loyalty. Alternative Hypothesis: Perceived Usefulness in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.		

RQ #	Research Question	Hyp #	Hypothesis	Data collection detail	Data analysis method
		H2b	Null Hypothesis: Perceived Ease of Use in an E-commerce context does not affect Purchase Intention, Repeat Purchase Intention and Loyalty. Alternative Hypothesis: Perceived Ease of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.		
		H2c	Null Hypothesis: Relative Advantage in an E-commerce context does not affect Purchase Intention, Repeat Purchase Intention and Loyalty. Alternative Hypothesis: Relative Advantage in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.		
		H2d	Null Hypothesis: Voluntariness of Use in an E-commerce context does not affect Purchase Intention, Repeat Purchase Intention and Loyalty.		

RQ #	Research Question	Hyp #	Hypothesis	Data collection detail	Data analysis method
			Alternative Hypothesis: Voluntariness of Use in an E-commerce context positively influences Purchase Intention, Repeat Purchase Intention and Loyalty.		

APPENDIX B Research Instrument

Section 1 – Demographic Information Some demographic information will first be required from you. This information is needed to understand the demographic makeup of overall research feedback received however it is generic and anonymous. Please select from the drop-down list, the response that is most applicable to you.	
Q1. Please confirm your gender	• Male • Female • Non-binary/third gender • Prefer not to say
Q2. Please select your age group	• 18 - 24 years • 25 - 34 years • 35 - 44 years • 45 - 54 years • 55 - 64 years • over 64 years
Section 2 - Context When shopping Online, some shopping sites use Artificial Intelligence (AI) technology to personalise your shopping experience. Examples of personalisation features in Online shopping include: • Optimisation of search results to present the most relevant options to help you quickly find products or services you are interested in e.g., search function on Takealot, Superbalist.	

• Provide you with product or service recommendations that you might be interested in based on your personal information and shopping history e.g., the Recommended for You section on Takealot, Recommended section in Woolworths. • Provide you with discounts or promotional offers based on your purchase/browsing history e.g., checkers 6060 Xtra saving discounts, Woolworths WRewards vouchers, pop-up promotional discount codes on Superbalist, and accommodation discounts in destinations you search on in Booking.com. • Arrange the layout of the website/ app to show you products/services that you previously viewed, and/or recommended products that you might be interested in, based on your customer profile or shopping history e.g., Booking.com will recommend accommodation offers based on your previous search, Takealot will show you recently browsed and recommended products. • Provide you with a chatbot/ virtual assistant that can provide information on product or service queries or assist with support queries e.g., Telkom's Thuso chatbot, Vodacom's Tobi chatbot, Mercedes Benz's Mercedes chatbot. On a scale from 1 to 5 - with 1 meaning to strongly agree, 3 meaning neutral (neither agree nor disagree), and 5 meaning to strongly disagree - please indicate your view of personalisation features, available on Online shopping platforms, by rating the statements in the questions that follow. NB: All questions need to be answered to proceed.

Q3. Please select Online shopping sites that you use from the list below:	• Takealot • Checkers 6060 • Booking.com • Woolworths • Superbalist

		• Other – Please specify
4. Perceived Usefulness		
Q4. The following statements refer to how useful you find personalisation features while shopping Online. Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
PU41	4.1. Personalised Online shopping would enable me to accomplish my shopping goals more quickly e.g. I can quickly find items I am interested in from a large catalogue.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
PU42	4.2. Personalised Online shopping would enhance my success in achieving my shopping goals on the site. e.g., I can obtain relevant recommendations quickly to make a decision.	
PU43	4.3. Personalised Online shopping would enhance my shopping outcomes e.g., I may find additional useful products and services that I was not aware of.	
PU44	4.4. Personalised Online shopping would make it easier to shop i.e., being presented with items that are relevant to me reduces my shopping efforts Online.	
PU45	4.5. Personalised Online shopping would be useful.	
5. Perceived Ease of Use		
Q5. The following statements refer to how easy you find personalisation features to use while shopping Online.		

Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
PEU51	5.1. Adapting to the use of Online shopping personalisation features is easy for me. e.g., using Search functions and chatbot assistants.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
PEU52	5.2. My interaction with Online shopping personalisation features is clear and understandable. e.g., I know how to search for products I need, utilise recommendations and raise my queries with a chatbot.	
PEU53	5.3. I find Online shopping personalisation tools flexible to interact with e.g. I know how to refine my chatbot queries to get the information I need, or I know how to refine my product/service search to get more relevant results.	
PEU54	5.4. It is easy for me to become competent at using Online shopping personalisation features.	
PEU55	5.5. I find Online shopping personalisation tools easy to use.	
6. Relative Advantage		
Q6. The following statements relate to whether you find Online shopping sites that offer personalisation features more appealing than those that do not. Examples of Online shopping sites that DO NOT provide personalisation include: https://mutlefurnitures.co.za/shop-2/ http://le-chateau.co.za https://millersonsiemert.com/?s=mirrors		

Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
RA61	6.1. It is easier to shop on websites/apps that provide personalisation than those that do not.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
RA62	6.2. It is easier to shop on websites/apps that provide personalisation than to shop in store.	
RA63	6.3. Personalised Online shopping provides me with greater control in achieving my shopping goals e.g. I can discover multiple options and obtain more information to make an informed purchase.	
RA64	6.4. Overall, I find personalised Online shopping advantageous.	
7. Voluntariness of Use		
Q7. The following statements relate to the extent to which you believe you have control over the use of your personal information for personalisation purposes on Online shopping sites. Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
VOU71	7.1. My use of personalisation features is voluntary on Online shopping sites that provide them.	1. Strongly agree 2. Agree

VOU72	7.2. Online shopping sites that provide personalisation, allow me to opt into having my personal data used to personalise my shopping experience.	3. Neutral 4. Disagree 5. Strongly disagree

8. Customer Experience

Q8. The following statements relate to the type of customer experience you have on Online shopping sites that offer personalisation features.

Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.

CE81	8.1. My decision to use Online shopping sites that offer personalisation features, is a wise one as it provides me with a more engaging, relevant experience.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
CE82	8.2. I am very satisfied with personalised Online shopping.	
CE83	8.3. I am very satisfied with the recommended products/services offered on personalised Online shopping sites.	
CE84	8.4. Overall, I am very satisfied with my last personalised Online shopping experience.	
CE85	8.5. Personalised Online shopping helps me to save money when it comes to shopping tasks e.g., through providing relevant recommendations and/or promotional discounts/offers.	
CE86	8.6. Personalised Online shopping helps me acquire new shopping knowledge e.g., receiving recommendations that provide me with new information.	

CE87	8.7. Personalised Online shopping helps me acquire new shopping skills e.g., the ability to refine my product searches and find relevant recommendations.	
CE88	8.8. Personalised Online shopping helps me to come up with innovative shopping ideas e.g., recommendations may introduce me to new products or complementary products	

9. Loyalty

Q9. The following statements relate to whether personalisation features play a role in Online shopping site preference.

Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.

LO91	9.1. When I need to make a purchase, Online shopping sites that provide personalisation are my first choice.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
LO92	9.2. I like using Online shopping sites that provide personalisation.	
LO93	9.3. I prefer to shop on Online shopping sites that provide personalisation.	
LO94	9.4. My favourite Online shopping sites provide personalisation.	
LO95	9.5. I seldom consider switching to Online shopping sites that do not provide personalisation.	
LO96	9.6. I try to use Online shopping sites that provide personalisation whenever I need to make a purchase.	

10. Purchase intention		
Q10. The following statements relate to whether personalisation features on Online shopping sites play a role in determining whether you purchase a product or service. Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
PI101	10.1. It is very likely that I will buy from Online shopping sites that provide personalised shopping experiences.	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree
PI102	10.2. I will purchase from Online shopping sites that provide personalised experience next time I need a product/service.	
PI103	10.3. I will try shopping on Online shopping sites that provide a personalised experience.	
11. Repeat purchase intention		
Q11. The following statements relate to whether personalisation in Online shopping sites plays a role in your return to make subsequent purchases. Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, and arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.		
RPI111	11.1. If I need a product or service in the future, I would be likely to buy it from an Online shopping site that provides personalisation.	1. Strongly agree 2. Agree 3. Neutral

RPI112	11.2. If I need a product or service in the future, I will probably revisit an Online shopping site that provides personalisation.	4. Disagree 5. Strongly disagree

APPENDIX C Consent Letter

Project Title: Influence of AI personalization on E-commerce customer experience and purchase decisions in South Africa

Researcher: Lavina Sookhdeo

Please select a YES or NO response to the following statements relating to your consent to participate in the above-mentioned survey:

The research study was explained to me, and I understand what it is about.	YES	NO
I agree to participate in the above-mentioned project research survey.	YES	NO
I agree that participation is voluntary, and I may withdraw my feedback at any time.	YES	NO
I agree that the survey is anonymous and private, and I do not need to provide my name or any identification information.	YES	NO
I agree that other researchers may use my survey feedback (dependent on obtaining their own ethics approval), but my feedback remains anonymous.	YES	NO

APPENDIX D Participant Information Sheet

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Dear Participant

My name is Lavina Sookhdeo, and I am completing a Master of Management in Digital Business at Wits. Do you enjoy Online shopping? I am looking for Online shoppers to assist me with input into my research on *The Influence of AI personalisation on E-commerce customer experience and purchase decisions in South Africa*.

AI personalisation is the use of your unique personal attributes and shopping history to tailor digital content to you and to make your online shopping experience more relevant and engaging. Examples of AI personalisation features in Online shopping would include optimisation of your search results, providing you with product/service recommendations, providing promotional discounts/offers on products you are interested in, arranging the layout of the site to show you content that you are most interested in, and providing a chatbot/virtual assistant to assist you with your queries.

The objective of the study is to investigate how AI personalisation influences the following in an E-commerce context:

1. Customer experience
2. Purchase decisions, repeat purchases and loyalty

I would appreciate your time and valuable feedback in taking this survey. It should not take longer than 15 minutes to complete. Participation is voluntary, anonymous, and private and you are free to withdraw your feedback at any point. Demographic information such as age and gender will be requested but no personal identification information will be required. The data will be used for academic research purposes only.

If you would like to participate, please click on the on the link below:

[Link to be confirmed]

If you have any questions during or afterward about this research study, feel free to contact me or my supervisor at the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), by telephone at +27(0) 11 717 1408, or email hrecnon-medical@wits.ac.za.

Thank you in advance for your time and effort, should you decide to participate.

Researcher:

Lavina Sookhdeo

Cell number: 071 612 1001/ E-mail: 2368773@students.wits.ac.za

Supervisor:

Rd. Kebashnee Moodley

Cell number: 073 217 8503/ E-mail: kebashnee.moodley@wits.ac.za

APPENDIX E Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB2368773/452

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).
This certificate is only valid if permission has been granted by the Registrar's Office of Wits University.
This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	The influence of AI personalisation on e-commerce customer experience and purchase decisions in South Africa
Investigator / Researcher	Mrs Lavina Sookhdeo
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	9/11/2023
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Et Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research a guarantee to ensure compliance with these conditions. Should any departure to be contemplated from th research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

11.09.23
Date: