Factors influencing online shopping in South Africa – a post-lockdown context

Raeesa Mohamed

Student number: 318982

Student email: 318982@students.wits.ac.za

Mobile: 082 404 0424

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ABSTRACT

Purpose – To evaluate the factors that have influenced the use of online shopping in South Africa during the COVID-19 lockdowns, the role of perceived risk and trust in online shopping and how customers' online shopping behaviour has changed since the start of the pandemic.

Design/methodology/approach – A total of 381 South African consumers responded to an online survey based on the UTAUT2 model, which was extended to include perceived risk and trust as factors. A confirmatory factor analysis was conducted to validate the measurement model followed by a structural equation model to identify the significance of the factors and the strength of the relationship to the dependent variable, behavioural intention.

Findings – The research shows that consumers have changed their online shopping behaviour, they have increased their usage of online shopping since COVID-19 and plan to continue to shop online. Additionally, all nine variables are significant to varying extents and the hypothesis is supported for each of them. The strongest correlations were found to be with effort expectancy, performance expectancy, hedonic motivation and habit.

Research limitations/implications – The research provides an overall view of eCommerce in South Africa during the COVID-19 lockdown period. To provide further insight, age and gender could be tested as moderators. Moreover, the use of stratified random sampling could create a more generalised view in future studies.

Practical implications – The insights from this research can help SMME businesses understand which elements are most important to customers when shopping online and where they should prioritise their limited resources to better serve their clients.

Originality/value – This study provides valuable insights into South African consumers' behaviour as a result of the COVID-19 pandemic. Since this topic has not been extensively researched as yet, this study can benefit SMME businesses to understand the influences that drive consumer adoption of online shopping to enable them to be on a digital transformation journey.

Keywords Adoption, Online Shopping, UTAUT2, South Africa, SEM

DECLARATION

I, Raeesa Mohamed, 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: Raeesa Mohamed **Signature:**

Signed at Johannesburg

On the 28th **day of** February 2023

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Table 1: List of Acronyms

Acronym	Description
3Rs	Recommendations, ratings and reviews
AVE	Average variance extracted
BI	Behavioural Intention
CFA	Confirmatory Factor Analysis
CT	Consumer trust
DT	Disposition to trust
ECM	Expectation Confirmation Model
EE	Effort expectancy
eWOM	e-Word of Mouth
FC	Facilitating conditions
H	Habit
HM	Hedonic motivation
PE	Performance expectancy
PR	Perceived risk
PV	Price value
R^2	R-squared
SCT	Social Cognitive Theory
SEM	Structural Equation Modelling
SI	Social influence
SMME	Small, Medium and Micro Enterprises
SRW	Standard regression weight
TAM	Technology Acceptance Model
TPS	Third-Party Signals
TRA	Theory of Reasoned Action
TTF	Task-Technology Fit Model
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Extended Unified Theory of Acceptance and Use of Technology

1 INTRODUCTION

1.1 Purpose of the Study

The purpose of this research was to determine key factors that influenced the adoption of retail online shopping, during the COVID-19 lockdown restrictions. Using a quantitative method, the Unified Theory of Acceptance and Use of Technology (UTAUT2) model was extended to include trust and risk and examined in the South African market. The study also determined how consumers' online shopping behaviour has changed since the COVID-19 lockdown restrictions. The model was tested using primary data collection through an online questionnaire to respondents in South Africa, who are over 18 and have shopped online.

1.2 Context of the Study

The following section provides background into online shopping. Section 1.2.1. provides an overview of eCommerce globally and Section 1.2.2 provides an overview of the South African online shopping environment, with factors that have contributed to online shopping adoption.

1.2.1 eCommerce Globally

eCommerce can be defined as "the ability for consumers to purchase products and services on-line using Internet technologies and associated infrastructure" (Pavlou, 2003, p. 102) and has been gaining popularity in the last decade. In 2022, the global eCommerce market was estimated to be $5.7 trillion and is expected to grow to $6.51 trillion in 2023. It is estimated to contribute 22% of the retail shopping market share in 2023 and is expected to continue to enjoy double-digit growth (Keenan, 2022). One of the drivers of eCommerce is the pervasiveness of technology and mobile phones in consumers' day-to-day activities. However, many physical stores were forced to close during the COVID-19 pandemic to deter the virus from spreading. This forced consumers online and accelerated the shift to online shopping by as much as five years (Bernhardt, 2022; Perez, 2020).

Developed markets such as the United Kingdom and the United States of America (U.S.) have displayed a faster adoption of online shopping compared to developing countries such as South Africa and India (Makhitha et al., 2019; Tandon & Kiran, 2019); however, many of the challenges faced in terms of online shopping adoption are universal. Only a small percentage of internet users are willing to shop online as consumers still perceive online shopping to be a higher risk than shopping in-store, which creates a lack of inherent trust in the process (Tandon & Kiran, 2019). The potential causes of this include; consumers relying on recommendations, prior experience or the tactile experience for completing a purchase in-store and they find it hard to trust eCommerce as it cannot provide these factors and it has a time and distance gap in fulfilling the purchase (Chatterjee, 2015; Mou et al., 2017). To build trust, online sellers need to find signals to serve as trust-building mechanisms for the in-store experience (Mavlanova et al., 2012).

1.2.2 South African Online Shopping

South Africa has a diverse economy with a mix between emerging and developed market characteristics. The retail industry is critical since it contributes to approximately 20% of gross domestic product (GDP), employs over a million people, is the third largest sector and serves as an indicator for consumer spending which determines economic growth. The sector has been growing at 5% year-on-year and is the most evolved Sub-Saharan country (Monzon, 2022; Pentz et al., 2020a).

While most retail transactions still happen in physical stores, retailers need to shift to consumer demands. There has been a shifting trend towards online and social media sales, especially when it comes to large businesses that have a physical presence from which trust transference can occur between the physical and online presence.
In South Africa, 98.5% of all registered businesses are SMMEs (small, micro, and medium enterprises). These businesses contribute to GDP, drive job creation and serve their communities (Small Business Institute, 2016). However, SMMEs have yet

to establish their foothold in the virtual space which creates an opportunity for the eCommerce growth in South Africa (Menon, 2018; Pentz et al., 2020a).

Building trust is a critical component of both sales and technology adoption. This is harder to achieve for SMMEs as they do not convey the same level of trust signals as established brands (Mavlanova et al., 2012). Online shopping makes trust even harder to establish as there is a level of anonymity with the sellers and a high percentage of buyers will abandon their cart if they do not trust the transaction (Thompson et al., 2019). SMME businesses need to understand which signals consumers look for that build trust so that they are able to overcome the perceived risk and drive adoption (Featherman & Pavlou, 2003).

The biggest challenges faced by SMME businesses when establishing an online presence are the high set-up costs, consumers' lack of trust in payments being secure online, and the lack of knowledge of where to start or how to run an online store. To overcome the barrier of trust in online payments, SMMEs should use card acceptance solutions as well as payment providers need to provide more low-cost and easy-to-use payment solutions for SMMEs to offer to their customers (iKhokha, 2023). Further, by adopting online solutions SMMEs can stabilise their financial performance, enabling them to achieve a competitive advantage in their niche (Ur Rahman et al., 2020).

The South African eCommerce landscape has been evolving over the last decade and there has been a shift towards online shopping. The COVID-19 lockdown restrictions helped consumers overcome some of the online shopping barriers and accelerated the adoption of online shopping by forcing consumers to rely more on digital solutions; however, online shopping is still a fraction of the total retail shopping. Arthur Goldstuck, the MD of World Wide Worx, calls the growth in retail commerce in the last couple of years, the "pandemic dividend". Prior to the pandemic, eCommerce sales were 1.4% of total retail sales in 2019 and were estimated to contribute 2% by 2022. However, it surpassed those forecasts and more than doubled to 5% in 2022, due to the pandemic (World Wide Worx, 2018, 2022). This was due to impressive growth over the last two years with 2021 achieving 40% growth, followed by 30% in 2022. Ultimately, online retail contributed R 55 billion by the end of 2022. While this growth is impressive, the contribution is still minute relative to total South African retail sales for 2022 amounting to R 1.2 trillion (World Wide Worx, 2022). eCommerce card purchases show similar trends comprising only 8% of total card payments currently and are expected to grow to 20% in the next 5 years (Thenga, 2020). Compared to the global estimate of eCommerce market share, which tracks closer to 20% (Keenan, 2022), South Africa's adoption of online shopping still has a lot of opportunity to grow and contribute to the South African economy - an opportunity that can also benefit SMMEs.

SMMEs bore the brunt of lockdown restrictions as they were forced to close for an extended period and needed to shift their business models to preserve their business' future. Online shopping created an opportunity for small businesses to evolve and continue to sell without a physical presence and within the restrictions. Expanding into the virtual space enables them to grow their market share and fulfil sales beyond their geographic limitations. It is estimated that there are approximately 5 000 businesses online with a turnover great than R 100 000 (Thenga, 2020). Additionally, the adoption of online shopping has been a bigger barrier for SMMEs as consumers perceive online shopping to be riskier due to the information asymmetry. Consumers look for signals to help them build trust in an interaction and online shopping, especially for SMMEs, has fewer signals (Mavlanova et al., 2012). This study can help SMMEs develop a strategic approach to their online presence and better understand what consumers prioritised when adopting online shopping during the pandemic.

The lockdown restrictions forced late-adopter consumers to overcome the learning cost of using online shopping due to necessity (Kim, 2020). World Wide Worx (2021) suggests that 68% of South African consumers switched to online shopping due to it being a positive learning experience. Consumers stated that they shifted to online shopping because they're able to deal with trustworthy businesses and enjoy convenience and personalisation (iKhokha, 2022; Kim, 2020). Additionally, Deloitte Digital (2021) indicates that South African consumers prioritise ease of use, delivery options, customer service, data protection, easy return and refund policies, and brand trust when shopping online (Deloitte Digital, 2021). The growing online shopping usage trend is expected to continue once the COVID-19 pandemic passes due to the convenience, variety available and lowered search costs (Heyns & Kilbourn, 2022; Kim, 2020).

1.3 Research Problem

COVID-19 had many negative impacts on the global community, however one of the shining beacons of the pandemic was the acceleration of eCommerce adoption. eCommerce has been extensively studied pre-COVID-19 lockdowns, however, there has been little research on the lockdowns' impact on consumer behaviour.

Understanding which factors helped propel consumers to shop online during the lockdown restrictions will provide insight into the South African eCommerce landscape as well as help businesses, especially SMMEs, prioritise the most important factors in driving the adoption of eCommerce. Since perceived risk and trust are critical factors in online shopping adoption, it is important to understand the role they played during the pandemic. Investigating the key factors and their relative strength in a unique market such as South Africa, which has emerging and developed market characteristics, will help drive further eCommerce growth in the market (Pentz et al., 2020a; Venkatesh et al., 2012). Academic research on this topic is limited in South Africa and the research performed in other countries such as India and Mauritius may not be as valuable in this market (Human et al., 2020; Tandon & Kiran, 2019).

1.3.1 Research Questions

Main question: Given the above context, using the Unified Theory of Acceptance and Use of Technology (UTAUT2) model, what are the factors that influenced the adoption of retail online shopping in South Africa, during the COVID-19 lockdown restrictions?

- **Sub-question 1:** Using the UTAUT2 model, how did consumers' behaviour change because of the COVID-19 lockdowns?
- **Sub-question 2:** What impact did perceived risk and trust have on the adoption of online shopping during the COVID-19 lockdowns?

1.4 Significance of the Study

1.4.1. Empirical contribution

The UTAUT2 has been studied quite comprehensively in developed countries but the research in emerging countries is still limited (Tandon et al., 2018). This research can contribute towards the existing body of knowledge on the adoption of online shopping. Expanding the UTAUT2 to include trust and perceived risk will provide a unique insight into how South African consumers adopted online shopping during the COVID-19 period.

1.4.2. Contextual contribution

This research will contribute to the contextual insights into South Africa from two perspectives – eCommerce growth and trust and perceived risk. Even though eCommerce growth has exploded in South Africa since the pandemic, it still lags behind other countries. The insights from this report can provide valuable insights into how the eCommerce market can continue to grow. South Africa may have different factors influencing its perceived risk and trust and it is important to understand those factors within the unique South African context (Cohen, 2021). These insights can help understand the challenges and opportunities within the eCommerce market.

1.4.3. Practical contribution

From a practical standpoint, understanding which factors are rated higher for consumers in adopting online shopping will allow businesses to implement signals that will help change consumers' perceptions. If SMME businesses understand what consumers perceive as the most important factors when shopping online, they can ensure their strategy factors in consumers' priorities and they can take the appropriate actions to drive adoption of their online usage.

1.5 Delimitations of the Study

The scope of the study is limited to:

i. Business-to-consumer retail online shopping as it looks at consumer factors
ii. South African websites only since the context of the research in South Africa during the COVID-19 lockdown period
iii. Urban areas due to the digital divide faced in South Africa

Beyond the scope of the study is:

i. Any business-to-business eCommerce
ii. Any cross-border online sales
iii. All other industries
iv. Rural areas

1.6 Definition of Terms

Table 2: Definition of Terms

Term	Definition	Reference
Digital Transformation	"The sum total of all organisational change efforts in response to technological disruption, that results in a marked change in the form and nature of the organization, especially so that the organisation's ability to thrive in the digital age is improved"	(Armstrong & Lee, 2021, p. 514)
eCommerce	"The ability for consumers to purchase products and services on-line using Internet technologies and associated infrastructure"	(Pavlou, 2003, p. 102)
NFC	Near field proximity. It is a form of contactless payment	(Morosan & DeFranco, 2016)
Perceived Risk	"The expectation of losses associated with purchase and, as such, acts as an inhibitor to purchase" behaviour	(Peter & Ryan, 1976)
R-Squared (R^2)	The square of a factor loading indicates how much of the variance of the indicator unobserved variable is explained by the unobserved latent variable	(Collier, 2020; Hair et al., 2019).
SPSS Statistics	Statistical software to conduct advanced statistical analysis	(IBM, 2023)
SPSS AMOS	Statistical software used to understand latent variables by conducting structural equation modelling (SEM) and path analysis	
Trust	"The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part"	(Mayer et al., 1995)

1.7 Assumptions

- The data was collected using survey methodology. It assumed that respondents completed the questionnaire truthfully and honestly. It also assumed that the respondents understood the questions clearly.
- It assumed that respondents were speaking about their general online shopping behaviour and any specific websites would need to be researched individually.

1.8 Chapter Outline.

The aim of this study is to provide researchers and small businesses with relevant insights to help them understand eCommerce better.

The next chapter will provide an overview of key literature to enable the reader to understand the eCommerce landscape better. It covers digital transformation, the structural factors that impact eCommerce, an overview of eCommerce, COVID-19's impact on eCommerce, the analytics model and the research framework.

Chapter 3 discusses the research methodology and covers the research approach, research design, data collection method and data analysis. It also outlines the limitations and challenges of the study as well as quality assurance measures.

Chapter 4 presents the results. It starts by providing insights into the demographic characteristics followed by lockdown-specific characteristics. It expands into the results of the measurement model and structural model. It concludes with the results regarding the hypotheses.

Chapter 5 provides discussions to the main problem and two sub-problems within the context of the UTAUT2 and based on the results of the structural model of the SEM.

Lastly, Chapter 6 closes out with the contextual, empirical and practical implication, limitations as well as suggestions for future research.

2 LITERATURE REVIEW

2.1 Introduction

To address the research problems outlined in Chapter 1, it is important to understand the context of the eCommerce landscape. The first part of this literature review covers the important areas that influence the eCommerce ecosystem. It starts with digital transformation in the retail sector and how it is evolving, followed by the factors that influence eCommerce, the global landscape, COVID-19 and eCommerce; next an overview of eCommerce and lastly the role of trust and perceived risk in eCommerce. The literature review proceeds then to understand the adoption models for technology and closes out with the research framework.

2.2 Digital Transformation in the Retail Sector

The retail sector faces high exposure to technology disruption based on the following measures: technology investment in the sector; when disruption is likely to occur; barriers to entry of disruptors and the impact of potential disruption (Yokoi et al., 2019). These factors are causing the sector to evolve at an accelerated pace. eCommerce is a significant portion of the digital transformation journey, and the retail sector is constantly evolving and leveraging new technologies. It is experiencing dual transformation as it shifts from multichannel to omnichannel customer experiences across multiple channels. An omnichannel experience allows brands to create a seamless customer experience where customers can pick up their transaction on a different channel compared to a multichannel experience which treats each channel independently (Birnbaum, 2019). During COVID-19, South African consumers opted for an omnichannel experience where they could order online and have it collected outside the store. They considered this a much safer shopping experience (Deloitte Digital, 2021). SMMEs need to understand and be on a digital transformation journey to remain competitive.

Dual transformation is the result of two factors –

1. transforming how the business operates by using technological advancements to improve their operations and business processes
2. and applying technology to create new value propositions, products, and services. The combination of both creates new business models that can be applied in the future (Anthony et al. as cited in Armstrong & Lee, 2021)

The creation and usage of websites as a sales channel is an example of the first factor where brands evolve their business processes. An online store serves as a 'ticket-to-the-game' and can serve as the foundation for other technologies. For this reason, it is important not only to have the channel but for consumers to switch to it as their preferred channel. By understanding digital transformation better, SMMEs can understand how to build an online site and drive traffic there.

There are two popular ways SMMEs choose to build their online business – building their own website with an eCommerce store or selling on an already established, reputable marketplace. Building their own websites may sound daunting, but brands, such as Shopify, facilitate all the steps to create online stores. They integrate into third-party functions, create secure online payment functionality and allow businesses to manage their experience end-to-end. This is beneficial for businesses that want to own the experience and have very specific ideas of how they want to operate their online presence. The downside is that it is a more expensive model and the businesses still need to drive traffic to their page. This means an SMME would need to define a marketing strategy in parallel. The other option that businesses could select is to use a platform marketplace, such as Amazon, Alibaba or Etsy, which allows multiple sellers to join the marketplace so that buyers have access to them in one place. The benefits of this model are the platform provides the sellers with tools to help them drive traffic, sellers only pay for what they list and they gain a pre-established customer base. The drawbacks of this type of model is it limits customisation and becomes more expensive as the businesses scale since fees are linked to sales volumes. Both these options help SMMEs set up their online presence, but they need to evaluate each option in terms of the business needs and resources (Norris, 2023; Parker et al., 2016).

The second part of digital transformation creates new business models and can be witnessed throughout the retail sector. The sector is already using fourth-industrial revolution technologies in the form of artificial intelligence, big data analytics and virtual reality to disintermediate competitors and create new services, products and value propositions. Market leaders are able to create market differentiation because they can invest in the technology and experiment with it. The platform business model, outlined earlier, is one of the biggest disruptors in the last decade. Well-known companies such as Google, Microsoft, Amazon, Airbnb and Uber are all examples of platform business models, which have changed the way that consumers interact with their computers, purchase online, book accommodation and hail a taxi (Parker et al., 2016).

These fourth industrial revolution technologies enable better customer experiences and internationally, brands have recognised the importance of creating unique customer experiences that more closely align their in-store experience with that of their online one. Beauty retailer, Sephora, piloted a smart card that allows shoppers to add products online as well as while browsing in-store to a virtual cart and complete the payment for both while in-store; Amazon has taken their business into brick-and-mortar with the creation of Amazon-Go, a self-checkout grocery store; and Rebecca Minkoff, a high-end fashion retailer, created a smart fitting room which can drive the omnichannel experience using data. Using RFID sensors can drive the customer through the marketing funnel, track what customers try on, what they purchase, provide personalisation offers for them and boost revenue (Rayome, 2018; Rose Displays, 2017; Tagiev, 2017; Thusi, 2021).

Large South African retailers are also focused on creating omnichannel experiences and have heavily invested in their digital capabilities. Checkers' investment in the digitisation race was most evident with the launch of their popular on-demand grocery service, Checkers Sixty-60, and most recently when they started piloting Checkers Rush, their self-checkout solution. Pieter Engelbrecht, the CEO of the Shoprite Group declared the brand's intention to be "Africa's most customer-centric retailer, and the launch of Shoprite^{x} represents [their] investment in fit-for-the-future precision retail, which is increasingly digital and data-led" (Bizcommunity, 2021a). Their competitor, Woolworths, to support exponential growth in their business, has spent over R 1 billion on digital capabilities. Their investment in digital skills and technology enables deep integration of technology solutions across their channels. This investment has enabled them to create their virtual try-on of makeup service using augmented reality, contactless shopping using NFC technology and personalised customer solutions using artificial intelligence. Additionally, they created their own on-demand grocery delivery service, Woolies Dash, which is gaining popularity (Bizcommunity, 2021b, 2021c). As a last example, the popular homeware store, @Home created the ‘Your Space’ app so that prior to purchase, buyers could use augmented reality to virtually see how the furniture will fit in their home (Sea Monster, 2018).

These disruptive technologies are enabling the personalisation of offers and recommendations which Morgan (2021a) has found to lead to a 91% increased likelihood of support for a brand and that it can lift revenue by up to 15%. The adoption of these solutions is mostly driven by Gen-Z and millennial consumers who are more open to using new technology and sharing their personal data to receive personalised offers (Morgan, 2021b). If SMMEs can drive usage of their websites, they can expand their services and offer even more customised solutions which in turn will drive future profitability.

Since technology is persistently changing, this causes various gaps in the ultimate usage of the technology, as illustrated in Figure 1. There is the adoption gap between the availability of the technology and individuals’ usage, the adaption gap where organisations use the technology and finally the assimilation gap which considers how the technology is assimilated into regulations, institutions, and legislations. These curves are exponential and if there is a point where the gaps are too large, some businesses can no longer compete and are forced to exit the market (Armstrong & Lee, 2021). COVID-19 helped bridge the adoption and adaption gaps faced by eCommerce as users were forced to overcome the learning costs of using new technology from necessity (Kim, 2020).

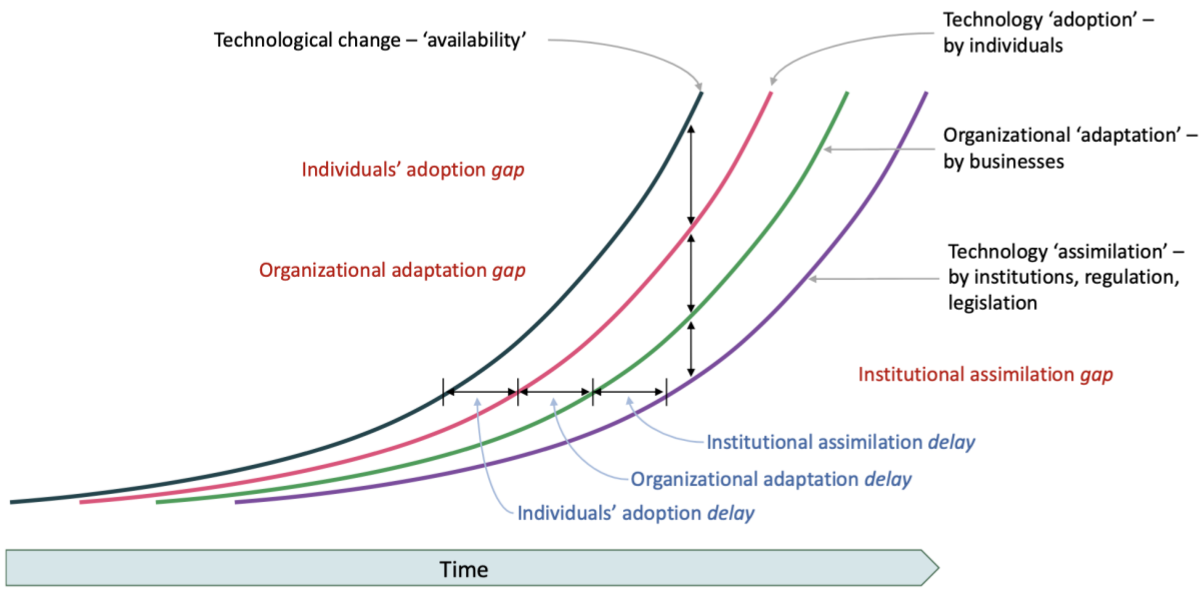

Figure 1: Technology Gaps reprinted from "Digital Business" (526), by Armstrong, B. & Lee, G., 2021, Silk Route Press, Copyright [2021] by Silk Route Press.

COVID-19 lockdowns accelerated these trends and the impact of the pandemic on the retail sector and eCommerce is expected to continue (Kim, 2020). In a South African context, research was done to explore the exposure to technological disruption of South African sectors against their contribution to the economy and total employment by that sector. The research shows that technological disruption is extremely high for the retail sector, but more importantly that it is the sector that contributes the largest to employment. Thus, it is critical for the sector to understand and actively be on the digital transformation journey to remain competitive, adapt their businesses and continue to contribute to the South African economy (Armstrong (2019) as cited in Armstrong & Lee, 2021).

SMME retail businesses need to understand what digital transformation means to them in practical terms. It is a complex process that factors in many elements including business processes, products and organisational culture and structures. In addition, it has an impact on internal and external stakeholders (Armstrong & Lee, 2021). This paper will give further insight into consumers' adoption of eCommerce as a component of digital transformation.

2.3 Overview of Structural Factors Impacting eCommerce

As discussed, digital transformation is critical in the retail sector, but the pace at which eCommerce can grow in a given country is constrained by its structural factors such as GDP per capita and network infrastructure (Cohen, 2021). Cohen (2021) conducted research to compare the eCommerce penetration across different developed and emerging countries. Their results show that structural conditions have a massive impact on the variation of eCommerce as a percentage of total retail, accounting for approximately about 80% of the variance. The adoption of eCommerce differs by country and a large influence of this is the structural constraints. These constraints limit the extent to which eCommerce can grow and it's important for businesses to understand the broader context in which they operate (Cohen, 2021).

Of the 15 factors that were researched, endogenous factors were identified to have the greatest statistical influence. GDP per capita was an expected influencer since wealth has an impact on connectivity and access to the internet, but surprisingly it was not the most significant factor. The network infrastructure had the largest significance, and it links to the online user penetration in a country. Access to the internet is a precursor to online shopping and if network connectivity isn't widely available, this creates limitations. Formal institutions also form a big role since they build trust and integrity in eCommerce. Closely linked is the credit card penetration, which is needed to complete an online shopping transaction and consumers are weary of inserting their credit card details into websites that they do not perceive as trustworthy (Makhitha et al., 2019). Cash-on-delivery is not easy to scale but other e-payment solutions can be explored to overcome the transaction processing barrier. Lastly, a skilled labour force is highly significant as the skills needed rely on experience and impacts the ability of a country as a whole to accelerate its eCommerce usage (Cohen, 2021).

2.3.1 Country Comparison of Structural Factors

Across the globe, eCommerce has progressively grown its contribution to total retail sales. Similar to South Africa, the structural factors of countries play a large role in a country's ability to scale its eCommerce adoption. Although it is considered a developing country, China has the largest eCommerce contribution, accounting for

46% of the global retail eCommerce total at $2.8 trillion and its 842 million eCommerce users comprise 39% of the total global online shoppers. The United States eCommerce market follows China as the second largest. Their contribution amounts to only a third of China's impressive market. This is followed by the UK (4.8%), Japan (3%) and South Korea (2.5%) making marginal contributions to global retail eCommerce (Keenan, 2022).

China and to a certain extent South Korea are outliers in the study by Cohen (2021) with their ratio of online shoppers to internet penetrations being much higher than both developed and developing markets. China outpaces these countries by creating a customer-centric omnichannel experience which bridges the gap between online and offline. Jack Ma, the founder of Alibaba described this phenomenon as the "New Retail". Alibaba focuses on a collaborative approach using personalisation and other customer-focused approaches to evolve the eCommerce ecosystem, which ultimately facilitates China's growth. This is discussed further in section 2.3.3 (Bird, 2018; World Wide Worx, 2018).

South Africa can be compared to its BRICS peers which include Brazil, Russia, India, China and South Africa. BRICS nations are all emerging markets that are expected to contribute significantly to the developing world economy (Lee & Barnes, 2016). China came in with the highest penetration of internet users to the total population at 64%, while Brazil and Russia had similar results at 38% and 35% respectively. India had a 22% penetration while South Africa came in the lowest at 14%. Besides China, relative to developed countries, eCommerce is still lagging in these markets (Cohen, 2021).

2.3.2 South African Context

South Africa is a unique market, having both emerging and developed characteristics which causes a digital divide in the South African consumer base (Pentz et al., 2020a). The growth in eCommerce is centred around the populated urban areas, which tracks with the structural factors explored earlier (Monzon, 2022). Consumers in regions such as Gauteng have higher disposable incomes and access to at least one smartphone (BusinessTech, 2016; Monzon, 2022). Delivery services within these areas can deliver within an hour for grocery services such as Checkers Sixty60, and an average of 2-5 working days, with the premium offer of same-day delivery, for large retailers (Checkers, 2023; Takealot, 2023). Convenience and instant gratification are priorities for these consumers, for which they are willing to pay a premium. In contrast, the rural areas have vastly different structural conditions. Network coverage in these areas is poor, the high cost of data means it's used for essentials only and delivery services take on average 3-7 working days, if at all, due to distance and lower population concentration levels. The variety of products and services in these areas is limited and it is expensive to access these areas for delivery purposes. These areas need an eCommerce model that tailors to the needs of these consumers, potentially in the form of fulfilment centres and Click-and-Collect functionality (Monzon, 2022). Furthermore, townships such as Tembisa, Khayelitsha and Soweto, while in urban areas, are excluded from delivery as retailers have yet to solve for the lack of formal addresses on Google Maps, informal roads, and the lack of education regarding addresses. These challenges make it difficult for eCommerce providers to offer convenient, affordable, and timely delivery. Each of these townships faces unique challenges and requires bespoke solutions which are complex and expensive. Despite these hurdles, delivery service providers have identified the need and opportunity in these underserviced areas and are actively pioneering solutions (Hamilton, 2022)

Additionally, part of the growth in online sales has been consumers' access to smartphones and the internet (iKhokha, 2023). South African internet penetration is estimated at 70% of the total population of approximately 60 million citizens (South African Government, 2021; Statista, 2022), yet the online shopping penetration in South Africa is still low relative to the number of internet users. While data costs still remain a challenge, consumers have access to more affordable smartphones and 78% of internet users access it using their mobile phones (Galal, 2022). Smartphones are expected to be a major driver of digital transformation as a whole as apps provide personalised offers, prioritise privacy, and enable communication through instant messaging and marketing on social media (Hundermark, 2020).

South Africa faces debilitating structural conditions, which are raising the operating costs for all businesses. The unstable supply of electricity, due to loadshedding, causes businesses to invest a substantial amount into alternative power sources to ensure that customers have an uninterrupted shopping experience. These costs are unplanned and even big corporates are feeling the impact on their bottom line with Pick-n-Pay spending approximately R 60 million a month on generators. The network infrastructure is also taking a strain, even though mobile network operators have invested extensively in their backup power and security for their towers. With the loadshedding severity increasing, it’s not possible to prevent network availability from being impacted. With SMMEs, they have smaller margins and loadshedding is impacting their revenue. A shift to online can help them diversify their revenue and reduce some of the costs. Since some businesses are being forced to close their brick-and-mortar stores, having an online store could be a cheaper alternative (Illidge, 2023).

The structural factors are being overcome in South Africa and SMME businesses need to be identifying the ways that they can participate and learn from global trends.

2.3.3 Chinese eCommerce Context

South African businesses can take insights from global eCommerce leaders, especially China whose online shopping penetration is the largest in the world (Cohen, 2021). Although China has the biggest eCommerce market globally, this is not concentrated on one specific player, but rather spread across its major eCommerce players. The size of these businesses is measured, in January 2023, by market cap. The largest market cap contributors are Alibaba ($303 billion), Meituan ($128 billion), Pinduoduo ($118 billion), and JD.com ($108 billion) (Saqib, 2023a, 2023b).

Alibaba, as the largest eCommerce provider in China, served as a catalyst for the substantial growth in the Chinese eCommerce economy. Its founder, Jack Ma, had a unique vision which was to create shared prosperity and support the most rural and impoverished parts of China using digital technology. His vision filtered wealth into communities that were previously excluded – women, Chinese workers, SMMEs and farmers. He created a platform business which facilitated payments to enable small businesses to provide their goods online and allow buyers to purchase online using digital payment mechanisms. By creating Alibaba, Jack Ma enabled tens of millions of businesses, that would’ve been too small to participate in the global economy individually, to connect with over a billion consumers (of which most were previously unbanked and operated outside of the mainstream economy). He took the model further and used it to educate entrepreneurs in other emerging markets with the Alibaba Global Initiative. This programme has trained entrepreneurs on how to create their own digital ecosystems, which has been largely successful (Wong, 2023).

In the 1980s, based on World Bank data, the percentage of the Chinese population living below $1.90 a day was 88% and had almost been eradicated in 2015 with a percentage of just 0.7%. This reduction has largely been fuelled by Alibaba and its peers driving the digitisation of the economy. As mentioned in the previous section, China is an outlier compared to its peers in terms of structural factors. Its mobile payment users comprise approximately 87% of the country's mobile phone users. This is almost that of the United States, which is the largest developed economy. Mobile payments make up approximately 50% of all payments compared to cash which contributes a mere 13%. This is no small feat as two decades ago, China was almost exclusively a cash economy. Alibaba's mission to serve the previously unbanked and help them participate not only helped its business to flourish but also supports China's broader economy (Cohen, 2021; Wong, 2023). China faces similar last-mile delivery challenges to South Africa. It also faces undeveloped infrastructure, high costs and lower service delivery to these areas. The Chinese government, platform providers and logistics enterprises are working together to overcome this barrier. The interim solution is to create multiple smaller warehouses so that there are collection points closer to consumers. However, a proposed solution is for multiple vendors to collaborate and share resources to lower the costs, leverage local transport such as buses and taxis to transport goods as well as passengers, and use the existing postal services (Zeng, 2019). China's eCommerce journey can provide inspiration for South African businesses large and small. With 56% of the South African population living below the poverty line, the Alibaba story demonstrates the benefits that eCommerce can play in the broader economy and some suggestions for solving the last-mile delivery challenges (World Bank, 2020).

2.3.1 United States eCommerce Context

Having an established economy, the United States does not have the same challenges to overcome as South Africa and China (Cohen, 2021). It boasts having the top two eCommerce players globally. Amazon is the biggest eCommerce platform in the world with a market cap of $960 billion. It is followed by Walmart, whose market cap is about 40% of Amazon's at $392 billion (Saqib, 2023a). In terms of understanding the eCommerce landscape in the United States, Amazon serves as an important case study.

Similar to Alibaba, Amazon has pioneered the eCommerce space. It has also adopted a platform business model, but it has expanded its role in the platform to be a seller as well as the platform provider. Amazon prioritises usability, and by using artificial intelligence, it personalises consumer offers and provides autocomplete and filtering for consumers when they search. In addition, it has enabled the scaling of the platform in various countries by having a system that contains more than 15 languages and it lowers the risk of cart abandonment by allowing 'One Click Order', which adds the item to the cart and takes the consumer straight to the checkout functionality. It has also enabled consumers to 'Share a Cart' which allows members of a household to add all their items into one basket for checkout. This is especially beneficial for Amazon Fresh, its grocery delivery service (Abdulrahman & Oreijah, 2020).

One of its biggest contributions that have shaped the global online shopping experience was the launch of Amazon Prime. For almost 20 years, Amazon has provided priority shipping to its members for a monthly fee and every year, it continues to increase its investment in logistics. It could be argued that the logistics investment by Amazon is what sets it apart from its competitors. Amazon owns the last-mile, giving it the ability to curate the customer experience from initiation to fulfilment. The ownership of this piece enables it to curate the customer experience and has enabled it to diversify its business (Abdulrahman & Oreijah, 2020). As the largest eCommerce store, Amazon has significantly contributed to job creation and the United States economy and will likely continue to grow and contribute.

It is clear that structural factors play a large part in the way an economy can grow and adopt eCommerce, but digitally transformed business models can fundamentally accelerate the natural growth of the industry. Key platforms can shift the contribution, but smaller firms can adopt the learnings from these players for adoption in their own businesses.

2.4 COVID-19 and eCommerce

eCommerce has been growing in its contribution to the retail sector, but the COVID-19 pandemic provided the perfect environment to accelerate the growth even further (Kim, 2020). When the World Health Organisation declared COVID-19 a pandemic in March 2020, one by one, countries around the world initiated an unprecedented protocol and systematically limited the movements of citizens and initiated country-wide lockdowns. They did this in an attempt to curb the spread of this highly infectious disease and help the hospitals cope with the potential influx of hospital admissions. These guidelines were created to enforce 'social distancing' in order to reduce the spread of COVID-19. These restrictions also caused individuals to fear leaving their homes due to the severity of COVID-19 and the associated fear of being infected (Heyns & Kilbourn, 2022).

In South Africa, a National State of Disaster was declared on the 15th of March 2020 and the most stringent lockdown level – Level 5, was initiated. Under this level, only essential industries and their workers were allowed to go into work premises, while all other individuals were forced to stay home and leave only for essential purchases. Furthermore, the products and services available for sale were restricted and citizens were not allowed to travel across provinces. Level 5 was scheduled to be three weeks long but continued for a total of five weeks. Once Level 5 passed, the government initiated lower levels of restrictions with Level 4 and Level 3 lockdown restrictions. During these levels, movement was still restricted and there was still a country-wide curfew. Beyond the movement restrictions, various businesses were forced to stay closed or could only operate with limited functionality. This had massive economic implications which lead to forced retrenchments, business closures and higher unemployment (Heyns & Kilbourn, 2022).

The contactless nature of eCommerce made it a desirable sales channel for consumers (Ali Taha et al., 2021). Studies show that while the behavioural shifts experienced during the pandemic track with other black swan events (such as financial crises, terrorist attacks and other health-related restrictions); the lockdown restrictions resulted in different consumer behavioural shifts, namely it forced consumers to be more digital, to use online shopping and caused businesses to evolve their sales channels to have an online sales presence (Heyns & Kilbourn, 2022; Thunström et al., 2020). A Mastercard (2020) study revealed that 68% of South Africans are shopping online more since the pandemic started; where 81% of respondents purchased data, 56% purchased clothing, 54% purchased groceries and 41% purchased an online educational course. As expected, 71% of them indicated that they plan to continue to shop online once the pandemic passes.

Major retailers enjoyed the benefit of the shift to online shopping with Checkers Sixty60 growing 150%; Mr Price growing by 48% online, and Pick ‘n Pay having compound growth over two years of 72.5%. It’s important to note, that the shift to online shopping is not from an increase in demand but more the shift from brick-and-mortar to online. (World Wide Worx, 2022). Consumers care about small businesses and 63% of respondents indicated that they made a concerted effort to support small businesses by shopping on their websites during COVID-19 lockdowns (Mastercard, 2020). SMMEs need to understand what drives consumers to shop online with them, especially now that COVID-19 restrictions have been relaxed, to strategically drive their digital transformation journey and take advantage of the trends.

The South African eCommerce market has become dominated by app-based shopping since consumers are shifting to more mobile shopping which is convenient. It has a few popular marketplace platforms, namely Takealot, Superbalist, Mr D, Bid or Buy and Facebook marketplace. Takealot reaped the benefits of the online shift with their six-month sales volumes growing by 72% and their revenue by 63% in September 2021. Mr D, a food delivery platform gained an 88% increase in orders and Superbalist, a fashion and home platform, saw a 77% increase in their sales volumes. Platform businesses have the benefit of multiple vendors selling on the platform so consumers can search for multiple needs there which increases traffic to the platform. For SMMEs, they gain the benefit of an existing consumer base and an easier transition to online (Norris, 2023). More recently, the Foschini Group launched the Bash app, a marketplace to host all the brands it owns. Bash has the benefit of all the retailers it can add to the platform at launch as well as it owns the last-mile delivery, which means it can curate the end-to-end customer experience (Business Tech, 2022; Neethling, 2023).

2.5 eCommerce Overview

eCommerce is expected to support the development of countries across different parts of the economy – economic, commercial and individual. It is expected to have a positive impact on both social and economic factors such as growth in employment, wage and labour productivity. It brings supply chains closer together and increases sales across the value chain. Furthermore, eCommerce benefits at a commercial level as it has evolved business models and enables new sources of revenue and value. From a consumer level, the benefit of eCommerce enables consumers to make purchases more conveniently, with more variety and better prices (Cohen, 2021). It can also be argued that eCommerce can reduce search costs and make it easier for consumers to complete purchases as they don't need to physically go to multiple stores to find what they need (Kim et al., 2008; Liu et al., 2019; Salvador et al., 2020).

While the benefits of eCommerce can ripple from a country level all the way down to an individual level, its growth still faces multiple hurdles. Consumers require a trusting relationship with a business to be willing to complete a purchase. With in-store shopping, trust is centred around the face-to-face personal relationship but in an online shopping interaction, it is harder to reduce the perceived risk due to the lack of face-to-face interaction. Consumers have an increased perceived risk when it comes to online shopping as there is an information asymmetry. The asymmetry arises because the seller has more information than the buyer. The risk that an asymmetric market creates is called a 'market for lemons' – a term defined by George Akerlof in 1970. A market for lemons is created where buyers have insufficient information to make a decision causing them to be unwilling to pay the full price for goods, due to the increased uncertainty. If this type of market prevails, high-quality sellers exit the market as they do not gain a fair price for their goods or services; resulting in only poor-quality sellers remaining in the market and the average price declining. Ultimately, the market collapses (Chatterjee & Kumar, 2017; Devos et al., 2012).

In a virtual space, such as online shopping, it is harder to establish the seller's trustworthiness or the quality of goods. This is not unexpected as sellers could exploit consumers with misrepresentation, making it harder for buyers to identify true quality products and services. The information asymmetry is exacerbated by the time-based and geographic gap between payment and receipt of goods; buyers not being able to verify the quality of goods prior to purchase; the identity of the seller being unclear; the lack of direct contact; and privacy and security risks. Further, online sellers could use their anonymity to their advantage and fail to deliver on the product or service sold, provide misleading information, escalate prices, or violate consumers' privacy.

Consumers focus on the transactional processes in an effort to determine the trustworthiness and offset the perceived risk that the seller will not fulfil their obligations. Thus, trust and perceived risk become critical factors to drive the adoption of online shopping and SMMEs should understand the role that they play in eCommerce and which elements to focus on as trust-building mechanisms. Understanding the decision-making process that consumers follow, consumer motivation and signalling from eCommerce businesses help to identify what impacts trust and perceived risk for consumers (Kim et al., 2008; Liu et al., 2019; Mavlanova et al., 2012; Mou et al., 2015; Pan, 2010).

2.5.1 Signalling

Signals are extrinsic signals that indicate credibility to consumers about sellers unobservable qualities. Signals reduce the information asymmetry and help consumers to build trust in sellers' quality (Pee et al., 2018). Sellers need to understand which signals consumers look for to reduce the information asymmetry and prevent an unsustainable market for lemons (Liu et al., 2019). Signals lower the probability of making an adverse choice for consumers, increasing the probability of them completing online sales. Additionally, they can convey integrity to the seller in a virtual context. Trust can be transferred between a source and a target. Where a business has a physical business, the online store inherits the trust from that presence;

however, with SMME businesses, if they only have an online business, they need to rely on signals such as third-party signals (TPS). It is worth noting that Kim et al. (2008) found that TPS did not increase trust, but rather reduced perceived risk. This is potentially due to low consumer education where consumers are not aware of the value of TPS. There are three considerations for signals – how much they cost, verifiability and whether they are internal or external (Pee et al., 2018). Consumers value easy-to-verify signals (such as contact information and live chat) and high-cost signals (such as website quality and order fulfilment tracking) the most as these signals would remove low-value sellers from the market. However, external signals such as payment gateways and secure connections are also important signals (Mavlanova et al., 2012). SMMEs need to mitigate the information asymmetry that their websites face by using internal and external signals to help build trust. They need to pick signals that are clear, credible, easy to understand, costly and recognisable to drive trust in their business (Dimoka et al., 2012).

Mavlanova et al. (2012) proposed splitting online shopping signals into three phases – pre-purchase, during purchase and post-purchase. During pre-purchase, consumers look at website quality and usability as a strong signal which is a high-cost and easy-to-verify signal. Low-quality sellers would not make the sizeable investment needed for this, rather opting to restart a new domain instead. Higher-quality websites link to increased customer satisfaction and reduce cart abandonment in sales (Pee et al., 2018; Sivaji et al., 2011; Tandon & Kiran, 2019).

2.5.1.1 Pre-purchase Signals

New shoppers on a website, look for signals on the website to determine if it is safe or not. For many consumers, their first interaction with a brand is on their website so it serves as a strong signal. Usability is an intrinsic factor of that signal. It includes ease-of-use on the website, website design (content, picture and layout quality) and ease-of-navigation (Pee et al., 2018). As outlined earlier, Amazon prioritises usability which translates directly into sales (Abdulrahman & Oreijah, 2020). Further, security and privacy are critical factors as well as customisation, consistency and website design (Tandon et al., 2018). For consumers who were trying to overcome the learning costs and try online shopping for the first time, these would be important signals. Beyond the website itself, building an emotional connection is also an important signal of trust and can increase customer lifetime value dramatically. This can be done through the creation of a social media presence, which creates a trust transference to the experience by creating a human presence. Additionally, the presence of people in photos makes them more personal and builds better trust (Kim, 2020; Sivaji et al., 2011; Stewart, 2003).

Consumers tend to rely on the information cascade when uncertain during an online shopping experience. They trust the collective experience of others over their own personal one and believe others to have more information than them. Users rely on eWord-of-Mouth (eWOM) in the form of recommendations, ratings and reviews (3Rs) to help them make a decision (Kim, 2020). It’s difficult to look at the impact of one of the 3Rs in isolation as they are all interrelated (Liu et al., 2019). Users' repurchase intention is determined by prior experience and perceived risk, the 3Rs can serve as a proxy for a user where the collective experience of others can help inform their decision (Pee et al., 2018). An important caveat is the 3Rs need to be reliable and verifiable to offset the risk of fake reviews (López & Sicilia, 2014). The form of recommendations has evolved, with consumers trusting online influencers who have similar values, demographics and preferences. This reflects in Falls (2021)’s article where 63% of consumers trust influencers’ opinions more than a brand’s direct messaging and 58% of them bought a product in the last six months based on an influencer’s recommendation. Section 2.5.3 elaborates further on the impact of social commerce.

2.5.1.2 During Purchase Signals

Security of the transaction is considered the most important risk factor when shopping online due to low trust in eCommerce. Another risk that consumers face is paying for goods without having experienced them in person, compounded with the risk of the purchase never being fulfilled. This can be mitigated through encryption for security and integration with well-known payment providers (Mavlanova et al., 2012; Sivaji et al., 2011). Thus, payment mechanisms are critical in building trust in the online experience. Users look for options to make cash-on-delivery payments as well as alternative payment mechanisms on the site such as payment gateways, which are costly for the seller but can be easily verified (Mavlanova et al., 2012; Tandon & Kiran, 2019). Reputable platforms such as Shopify and Etsy can help serve as third-party signals for SMMEs, as consumers will trust that the payment mechanism is trustworthy. Additionally, they create a better usability and customer experience with their standardised templates, which could also serve as a signal to potential customers (Norris, 2023). These signals are supported by the Mastercard (2020) study which found that 64% of shoppers consider secure checkout to be fundamental and World Wide Worx (2022) supported the need for increased security when shopping online.

2.5.1.3 Post-purchase Signals

Once the purchase has been completed, consumers wait to see if the performance expectation is met. If it is met, it increases trust inherently as it influences the likelihood of repurchase intention and customer satisfaction (Kim et al., 2009). Repurchase intention is impacted by users' perceptions and cannot be considered objective. Using the Expectation-Confirmation Theory, users look to confirm their expectations, with a positive outcome creating customer satisfaction. This step is critical for sellers as it encourages buyers to make a repeat purchase which is vital for the future profitability of a business (Pee et al., 2018). Email confirmation, coupons and order tracking are signals which build post-purchase trust (Mavlanova et al., 2012). This is supported by 62% of consumers having stated that they look for promotions and loyalty when shopping online (Mastercard, 2020). Additionally, businesses can ensure to invest in customer service, which is a high-cost signal, and offer returns and refunds if customers aren't happy. Due to the time and distance gap, these features can set a business apart from its competitors and reduce the information asymmetry (Chatterjee, 2015; Deloitte Digital, 2021; Mou et al., 2017).

While these factors cannot be assumed to be all-encompassing, they do indicate some of the key signals influencing trust and risk perceptions.

2.5.2 Utilitarian and Hedonic Motivations

Consumers have two primary motivations to shop online – utilitarian and hedonic. Utilitarian value covers the practical factors which consumers value such as convenience, variety of products, stability, quality of product information, payment processing and cost savings. In contrast, hedonistic covers the entertainment, fun and interaction components such as keeping up with trends, adventure, shopping for others, finding bargains, sharing with others and the social component (Chiu et al., 2014).

Understanding these motivations can help businesses understand what causes shopping cart abandonment. Benson and Ndoro (2022) determined three key factors causing cart abandonment, namely perceived costs, perceived security risks and items added purely for research purposes. To overcome these barriers, the authors suggest that businesses can provide comparisons of prices for goods which can then be added to the card from the comparison view; run educational campaigns discussing the security features of their shopping platforms; and lastly send reminders to nudge consumers back onto the platform to complete their purchase. Implementing these features would help businesses drive the utilitarian aspects of their websites.

In a Mastercard (2020) study, 78% of respondents found the price to be the most important factor when purchasing online while 75% of shoppers spent hours online to find the best bargain – the first showing that utilitarian factors are important and the second showing hedonistic is important.

The experience of shopping online creates hedonistic motivations as consumers get an adrenaline rush and a dopamine release from the instant gratification of making a purchase. The adrenaline rush of finding something desirable can push a consumer to complete the purchase. Interestingly, dopamine is not released when the reward is received but rather in anticipation of the reward. Moreover, unpredictability increases anticipation and in turn the dopamine release. With online shopping, consumers place their order and the anticipation of the wait increases their dopamine. Moreover, the unpredictability of deliveries coming earlier than expected or finding an unexpected bargain, increases dopamine even further. On average, 70% of consumers polled in the UK, the U.S., Brazil and China stated that receiving their online deliveries was more exciting than in-store purchases (Macit et al., 2018; Szeto, 2020; Weinshenk Ph.D., 2015).

Some consumers turned to online shopping as an escape mechanism during COVID-19, where consumers were faced with anxiety, uncertainty and helplessness from the lack of control over what was happening. They used online shopping to cheer themselves up and loved having ‘gifts’ on their way to them (Djinis, 2022). Moreover, consumers impulse shop due to loneliness, anxiety, fear or even boredom. 72% of respondents in a U.S. study stated that they impulsively shopped during the pandemic to help them feel better (Moore, 2021).

While hedonic motivators help drive online shopping, consumers can get addicted to the dopamine release which lifts their mood and numbs any negative emotions temporarily. Consumers then repeat the cycle to get that dopamine rush again. Because of the prolonged period of the pandemic, the risk of online shopping becoming an addiction increased. Three factors have been identified as drivers of the addiction – the marketing of retailers to prompt consumers onto their website or to complete a sale; social media perceptions determining what people should be buying and the virtual nature of bank accounts making the impact of money spent harder to see. With physical cash, consumers could see how much was in their wallet whereas a bank account shows just a reduction of numbers (Djinis, 2022; Moore, 2021). The pandemic exacerbated these emotions in consumers and potentially served as a key driver for online shopping adoption.

Both utilitarian and hedonistic motivations are significant for consumers, with utilitarian being slightly more significant. Both of these components need to be catered for by retailers when shopping online as consumers look for both (Chiu et al., 2014).

2.5.3 Social Commerce

South Africans primarily access the internet using their phones, mostly for social media but also for online shopping (Hundermark, 2020). This makes social commerce a key topic in a South African context.

Social commerce also has high hedonistic motivations and serves as a pre-purchase signal, especially due to the proliferation of social media and the way in which consumers interact with it in their daily activities. Social media promotes social interactions which builds trust, making it an important factor for online shopping (Miah et al., 2022). Moreover, consumers are turning to social media, instead of Google, when searching for a product or when they look for recommendations (Huang, 2022; Mastercard, 2020).

Businesses have started curating their social media to create a competitive advantage. Using social media, they can form customer relationships, market their brands and share information with their customers. While social media has helped improve business financials and overall performance, SMMEs haven't fully adopted these social media platforms to achieve strategic goals as they don't have access to the same resources or technical skills to achieve similar results. Adoption of social media also reduces costs and SMMEs, with their more flexible operations, could adopt these platforms faster than larger corporates (Ur Rahman et al., 2020). Social media is transforming at an accelerated pace and in order for social commerce to continue to deliver value, businesses need to understand the various platforms, their popularity and the purpose for which people are using them. Businesses need to remain current and evolve and adapt their strategy as these shifts occur (Brooks, 2021).

A study in the United States found that the majority of respondents turn to social media on their shopping journey. They use social media to search for products and turn to influencers to learn about products. Further, about 16% of users will follow a brand after having a good interaction, which could help businesses determine if their signals achieved their purpose (Brooks, 2021). Since South African consumers could not browse physical stores during COVID-19 lockdowns, they shifted to social media as a way to find new sellers, with 63% using Facebook and 41% using Instagram (Mastercard, 2020). Consumers are shifting towards searching for their products not only on Google but also on social media channels. Gen Z consumers have been turning to TikTok, trusting the personalised short videos of people's opinions over the lengthy and anonymous feel of a website. Further, consumers use Amazon to search for products and Instagram to stay on trend. Some consumers perceive Google results to be biased due to advertisers paying to appear higher in search results. With TikTok, consumers believe they can search for more honest reviews and the comments on videos help provide more insight (Huang, 2022).

During COVID-19, consumers had limited contact and were isolated in their homes. Social media enabled them to connect with family, friends, and colleagues. It also served as a distraction, a source of fun and a way to spend free time. In an Italian study, registrations for social media went up with TikTok (475%) being the highest followed by Pinterest (30.5%) and Twitter (24.2%). Consumers also increased their use of messaging apps such as WhatsApp and Facebook. Businesses used social media to launch promotions and encouraged consumers to share these with their friends. Social media also drove impulse behaviour as mentioned earlier. Moreover, at the start of the pandemic, social media played a vital role in consumers' panic buying. Consumers swarmed groceries stores and emptied their shelves of essentials out of fear of not having enough food and toiletries (Ali Taha et al., 2021).

With this constant evolution and acceleration of platforms and sales channels, it is hard for SMME businesses to keep up with the various channels. However, if SMMEs understand the underlying behaviours that drive usage on these channels, it would enable them to drive the behaviours that create better adoption of their online channels.

2.6 Trust and Perceived Risk in Online Shopping

The impact of trust and perceived risk on online shopping comes through strongly in the research. This section breaks down the types of each and how they can be measured.

2.6.1 Perceived Risk

As discussed in section 2.5.1, since consumers cannot assess the quality of goods or determine online vendors' trustworthiness when shopping online, this information asymmetry causes consumers to perceive the risk of shopping online to be higher than an in-store experience (Mavlanova et al., 2012). Mistrust in online shopping results in an increase in shopping cart abandonment which has a potential loss of R 34 billion per annum in South Africa (Pentz et al., 2020b). As a result, users look for signals to help them reduce their perceived risk when shopping online. Perceived risk has been defined as ''the potential for loss in the pursuit of a desired outcome of using an e-service'' (Featherman & Pavlou, 2003, p. 454). Featherman and Pavlou (2003) identified several risk factors which include: performance risk, financial risk, time risk, psychological risk, social risk, privacy risk and overall risk. Understanding which of these risks have a significant influence on online shopping adoption will guide SMME businesses as to which trust-building signals to use (Pee et al., 2018).

Table 3: Perceived Risk Facets as defined by (Featherman & Pavlou, 2003)

Perceived Risk Facet	Definition
Performance risk	"The possibility of the product malfunctioning and not performing as it was designed and advertised and therefore failing to deliver the desired benefits." (Featherman & Pavlou, 2003, p. 455)
Financial risk	"The potential monetary outlay associated with the initial purchase price as well as the subsequent maintenance cost of the product. The current financial services research context expands this facet to include the recurring potential for financial loss due to fraud" (Featherman & Pavlou, 2003, p. 455)
Time risk	"Consumers may lose time when making a bad purchasing decision by wasting time researching and making the purchase, learning how to use a product or service only to have to replace it if it does not perform to expectations." (Featherman & Pavlou, 2003, p. 455)
Psychological risk	"The risk that the service will lower the consumer's self-image." (Featherman & Pavlou, 2003, p. 455)
Social risk	"The risk that using a product or service may lead to embarrassment before one's social group." (Featherman & Pavlou, 2003, p. 455)
Privacy risk	"Potential loss of control over personal information, such as when information about you is used without your knowledge or permission." (Featherman & Pavlou, 2003, p. 455)
Overall risk	"A general measure of perceived risk when all criteria are evaluated together." (Featherman & Pavlou, 2003, p. 455)

2.6.2 Trust

In an online shopping context, the trust required stems from the transaction process being fulfilled compared to in-store which is based on the face-to-face interaction. Trust is expected to lower perceived risk and have a positive impact on a consumer's intention to purchase (Kim et al., 2008). For merchants who have an existing brick-and-mortar store, they have the benefit of a trust transference from their physical to their virtual presence as consumers would perceive that a reliable merchant would not create an unreliable website. For purely virtual merchants, they need to create a presence where their website creates a trust transference to the merchant (Thatcher et al., 2013). Thatcher et al. (2013) further explained that trust can be general (trust in the infrastructure and the institutional mechanisms) and specific trust (trust in merchant and trust in the website). Their research finds that trust in the merchant has the most significant influence on consumers' intention to purchase.

Table 4: Trust Types as defined by (Thatcher et al., 2013)

Trust Level	Sub-Category	Definition
General	Infrastructure	Belief that the environment is safe and encrypted to facilitate transactions
	Institutional	Belief that transactions will be conducted effectively
Specific	Merchant	Belief that the merchant will uphold their commitments to fulfil the transaction
	Website	Belief that the website has the functionality to successfully complete the transaction

Research indicates that trust has a direct and indirect impact on purchase intention (Kim et al., 2008) and plays an integral role in the online shopping landscape. Trust and perceived risk are critical factors in driving the adoption of SMME online shopping and have been included in the adapted UTAUT2 Model for this study.

2.7 Analytical Framework

2.7.1 Theories and Models of Technology Adoption

Technology adoption has been the focus of many research papers over the last few years to test adoption in various ways. The main models are summarised below:

- The Theory of Reasoned Action (TRA) was developed to consider the behavioural intention, attitude (positive or negative) and subjective norms (perceived social pressure) as factors to determine whether users would use technology if they could perceive benefits from using it (Fishbein et al., 1975).
- The TRA model (Fishbein et al., 1975) was extended to the Theory of Planned Behaviour (TPB), by Ajzen (1991), who included the Perceived Behavioural Control (PBC) to the original TRA factors to determine behavioural intention. The PBC uses a prior experience to help determine a user's perception of the ease or difficulty of acting on a current behaviour (Ajzen, 1991). This factor

could help understand the learning costs associated with technology adoption (Kim, 2020).

- The Technology Acceptance Model (TAM) was also an extension of the TRA model (Fishbein et al., 1975). It was used to better understand usage by introducing two new constructs: perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). The TAM has been found to be useful in predicting consumers' purchase behaviour and attitude towards online shopping (Basak et al., 2016).
- Venkatesh et al. (2003) combined eight previous models of technology adoption to create the Unified Theory of Technology and Usage Theory (UTAUT). The models included the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), the combined TPB and TAM, the model of PC Utilisation, the Innovation Diffusion Theory, and the Social Cognitive Theory.
- Venkatesh et al. (2012) identified the need to extend their research and created the Unified Theory of Technology and Usage Theory 2 (UTAUT2) which extended the model to include behavioural factors. In addition, the moderating factors were updated. This is discussed further in the next section.

2.7.2 Unified Theory of Acceptance Use of Technology 2 (UTAUT2)

The UTAUT model has been applied in various markets and contexts, but the authors found that often the model wasn't being used in its entirety. Further, the original UTAUT was focused on employee acceptance of technology (Venkatesh et al., 2003). To factor in consumer use and to create a more versatile model, Venkatesh et al. (2012) added hedonic motivators, costs and habits. This ensured the model factored in how much a user enjoys the experience and their willingness to repeat the behaviour. Further, by including costs, it shifted the behaviour towards consumers who have a voluntary need to use a technology (Tandon & Kiran, 2019; Venkatesh et al., 2012). The UTAUT2 has been extended to online gaming, mobile health, public acceptance of automated cars, artificial intelligence and various other contexts (Duarte & Pinho, 2019; Gansser & Reich, 2021; Nordhoff et al., 2020; Ramírez-Correa et al., 2019). Since it incorporates previous theories, it can be applied to a variety of contexts and can be used in multiple future scenarios. One could argue that it is one of the most comprehensive technology adoption models.

Behavioural intention, which is a dependent variable, is the measure of a person's intention to perform an act voluntarily. Further, it measures how much effort a person is willing to put in order to perform a behaviour. Behavioural intention has been found to be a high predictor of usage (Islam et al., 2013; Venkatesh et al., 2012).

The UTAUT2 model measures seven determinants of behaviour to form an understanding of what impacts consumers' intention to purchase (Behavioural Intention) as ultimately the behavioural intention translates to usage (Use Behaviour). It measures consumers' perception that the technology will behave as expected (Performance Expectancy); the perceived ease-of-use of the system (Effort Expectancy); the influence of others on their use of the technology (Social Influence); the perception that the resources are adequate for them to complete the purchase (Facilitating Conditions); how enjoyable the experience is (Hedonic Motivation); the perceived value of the purchase (Price Value); and their likelihood to continue using the system (Habit) (Venkatesh et al., 2003; Venkatesh et al., 2012).

The UTAUT2 has been extensively researched in various developed and developing markets; however, each market has unique behaviours, which result in the model needing to consider specific factors to create a specific lens per country. For example, India has a more significant impact on referrals than the United States and cash-on-delivery is an important factor due to the transacting behaviour of Indian consumers (Tandon et al., 2018).

In emerging markets, the adoption of online technologies has been a topic of research attention as it supports the development of these markets (Human et al., 2020). In the accelerated digital transformation landscape, Gupta et al. (2022) have suggested that the UTAUT2 needs to be modified to reflect the current landscape. Even though Venkatesh et al. (2012) derived the UTAUT2 model with the intention for it to be tested in different markets and cultures, since its development in 2012, it has not been studied as extensively as the original model (Gupta et al., 2022). Studying online shopping in a South African context will add to the contextual research. Perceived risk and trust are critical variables to consider in an online shopping context and have been included in this study, similar to previous studies, which have also extended the UTAUT2 to include them (Human et al., 2020).

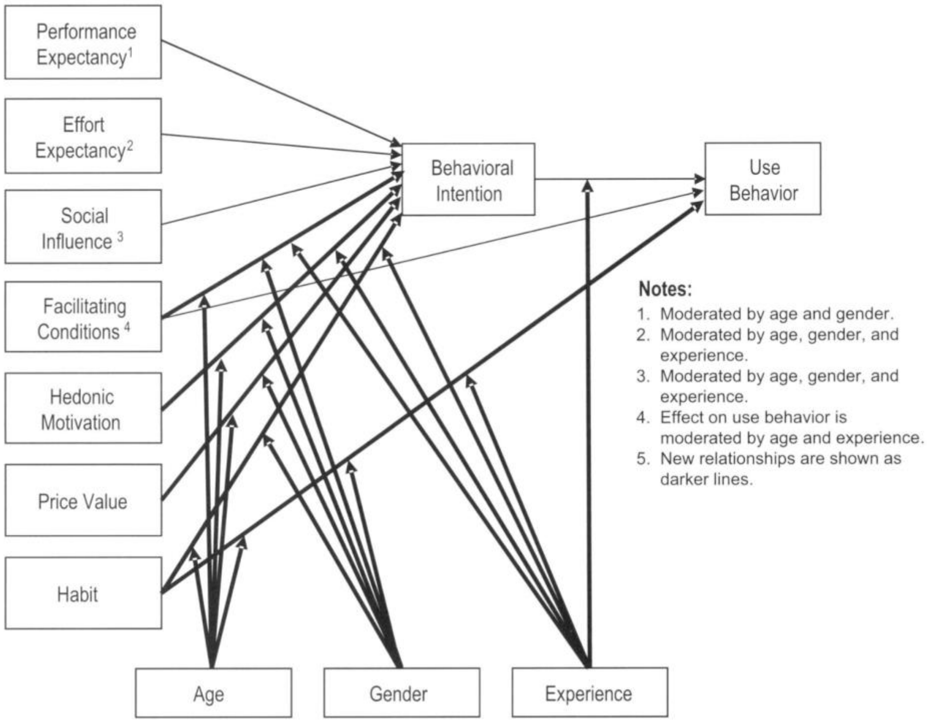

Figure 2: UTAUT2 Model as defined by Venkatesh et al. (2012)

2.8 Research Framework and Hypotheses

A conceptual model has been proposed to understand the factors that influence the adoption of online shopping. The model extends the UTAUT2 model to include trust and risk. The model considers nine factors that drive behavioural intention. Behavioural intention is the dependent variable in the model but ultimately has an impact on whether a consumer completes a purchase online (Venkatesh et al., 2003). The questions for the research model have been updated to include the impact of lockdowns due to COVID-19.

2.8.1 Behavioural Intention

Behavioural Intention is the dependent variable of the UTAUT2. In their study, Venkatesh et al. (2012) found that the UTAUT2 explained about 70% of the variance in intention to use technology. When a consumer’s behavioural intention is subconscious, this is a result of it becoming a habit in their mind. The faster that consumers respond, the higher the strength of the habit (Aarts et al., 1998). Behavioural intention links to the future use of a channel and is a key factor in understanding the adoption of eCommerce. The hypotheses linked to behavioural intention are discussed next.

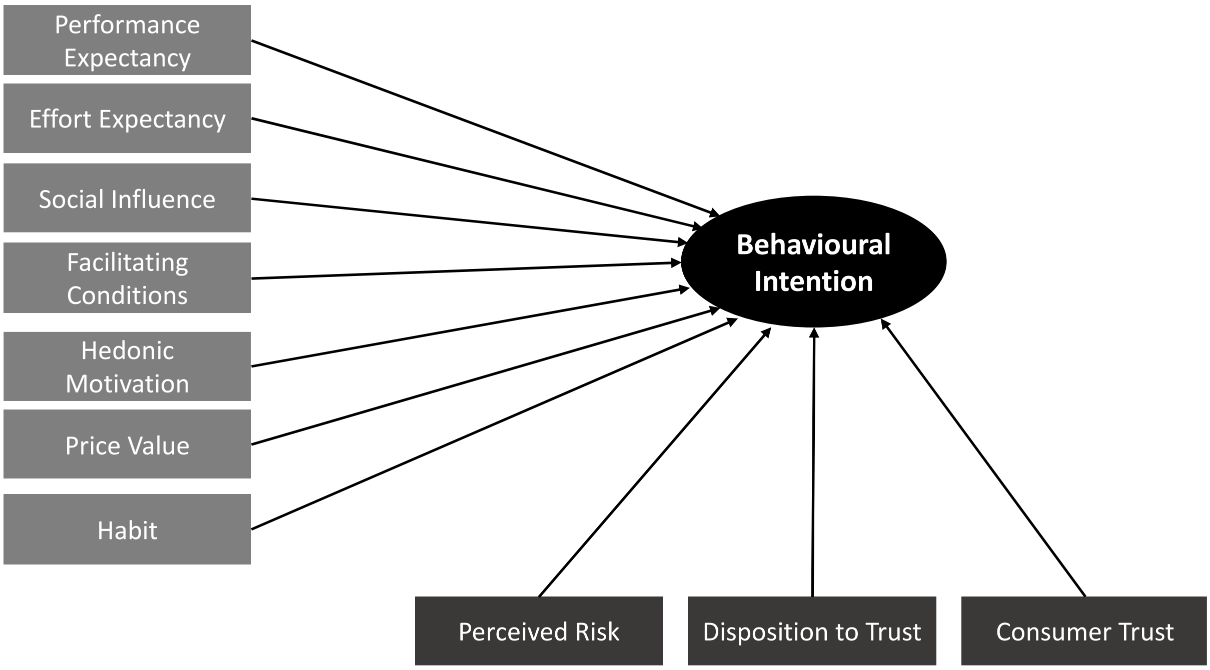

Figure 3: Proposed Extended UTAUT2 Model

2.8.2 Performance Expectancy

Performance expectancy measures the degree to which the consumer believes will help them attain gains (Venkatesh et al., 2003). In the online shopping context, this will measure the extent to which the consumer believes that the online shopping experience helps them to complete their purchase. This links closely to the pre-purchase signal of website usability (Pee et al., 2018) and can be considered a utilitarian motivation (Chiu et al., 2014), as outlined in section 2.3. Since online shopping was a learning cost that users overcame during COVID-19 (Kim, 2020), performance expectancy will be a valuable contribution to the study.

H1. Performance Expectancy has a positive correlation to Behavioural Intention

2.8.3 Effort Expectancy

Effort expectancy measures how easy it is to use a system (Venkatesh et al., 2003). This will measure how easy consumers believe online shopping was during the COVID-19 restrictions. Similar to performance expectancy, effort expectancy looks at the pre-purchase signal of website usability, since it influences ease-of-use and navigation (Pee et al., 2018) and it is also a utilitarian motivation (Chiu et al., 2014).

H2. Effort Expectancy has a positive correlation to Behavioural Intention

2.8.4 Social Influence

Social influence measures the influence others have on the consumer to use a system (Venkatesh et al., 2003). This will measure how much importance a consumer places on other people's opinions during the COVID-19 lockdown period. Social commerce has rising popularity and is considered a hedonistic motivation (Ur Rahman et al., 2020). Further, Millennials and Gen Z have been found to trust the opinions of influencers as a form of eWOM (Huang, 2022). Consumers not only use social media channels (Facebook, Instagram, YouTube and TikTok) for reviews but also to browse and complete purchases while forced to social distance (Mastercard, 2020).

H3. Social Influence has a positive correlation to Behavioural Intention

2.8.5 Facilitating Conditions

Venkatesh et al. (2003) define facilitating conditions as the extent to which a consumer believes the infrastructure will support the use of an online channel. This will measure whether the resources that consumers had were sufficient to complete purchases online and if their usage changed due to COVID-19 lockdown restrictions. It evaluates how much help consumers need to complete a purchase independently. This links closely to Thatcher et al. (2013)'s indication that general trust in institutions is important in eCommerce.

H4. Facilitating Conditions has a positive correlation to Behavioural Intention

2.8.6 Hedonic Motivation

Hedonic motivation measures the fun derived from using the technology (Venkatesh et al., 2012). In an online shopping context, this measures to what extent a consumer enjoys shopping online. As discussed in Section 2.3.2, hedonic motivation is the fun factor and leads to a dopamine rush; but more importantly, it is considered a significant factor for online shopping (Chiu et al., 2014).

H5. Hedonic Motivation has a positive correlation to Behavioural Intention

2.8.7 Price Value

When the UTAUT model was extended to UTAUT2, price value was added because the consumers must pay for transactions, unlike the original model which catered for organisational structures, where employees are not responsible for monitoring costs (Venkatesh et al., 2012). For online shopping, it is an important factor to measure as consumers want to feel like they are getting value-for-money and a bargain – making it both a utilitarian and hedonistic motivation (Chiu et al., 2014). Further, online shopping reduces search costs (Salvador et al., 2020) and 78% of consumers indicated that price value is an important factor for them (Mastercard, 2020).

H6. Price Value has a positive correlation to Behavioural Intention

2.8.8 Habit

Habit was also part of the 2012 extension to the UTAUT2 model. It measures how likely a user is to continue using a system (Venkatesh et al., 2012). In online shopping, this is an increasingly important factor as a business would want continued use of their platforms by their customers and repurchase intentions (Pee et al., 2018). Since the pandemic led to an increased usage of online shopping during lockdowns, this research will examine if consumers intend to continue that behaviour (Heyns & Kilbourn, 2022).

H7. Habit has a positive correlation to Behavioural Intention

2.8.9 Perceived Risk

For this study, perceived risk has been added to the original UTAUT2 model. In online shopping, perceived risk has a significant impact on consumer behaviour and willingness to interact with a website. Product, financial and overall perceived risk will be tested, as aligned to the Kim et al. (2008) study. The impact of higher perceived risk is posited to have a negative impact on consumer purchase intentions (Kim et al., 2008).

H8. Perceived Risk has a negative correlation to Behavioural Intention

2.8.10 Trust

For this study, trust has been added to the UTAUT2 model as it has an impact on consumer adoption. It will be measured with two factors: consumers' general trusting nature and their specific trust in the merchant and website, as aligned to the Kim et al. (2008) study.

H9. Consumer Disposition to Trust has a positive correlation to Behavioural Intention

H10. Consumer Trust in Website has a positive correlation to Behavioural Intention

2.9 Conclusion of Literature Review

This chapter covered literature related to business-to-consumer eCommerce development across the globe. It investigated how the retail sector is digitally transforming, the structural factors that enable eCommerce and how Alibaba and

Amazon have contributed towards their respective economies by overcoming some of the barriers. Next, the impact of COVID-19 was highlighted, followed by an overview of eCommerce. This covered various factors which contribute to eCommerce, namely why consumers are hesitant to shop online, signalling, utilitarian and hedonistic motivations and social commerce. The chapter continued into the types of trust and perceived risk that are measured, followed by the analysis framework. The chapter closes with the research framework and hypotheses for this study which are summarised in Table 5.

The eCommerce growth trend is expected to continue and if SMME businesses wish to participate in the online economy, they will need to strategically drive their online presence. Since there are multiple factors that impact behavioural intention and little research has been conducted in South Africa, there is a need to better understand online shopping behaviours.

Businesses need to understand what drives consumers to shop online with them, especially now that COVID-19 restrictions have been relaxed, in order to strategically drive their digital transformation journey and take advantage of the trend. This is harder for SMMEs to analyse as they do not have the same resources as many larger businesses. This study could form a foundation for them in understanding the factors influencing online shopping to enable their digital presence.

Table 5: Hypothesis Summary

Hypothesis	Description
H1	Performance expectancy has a positive correlation to Behavioural Intention to shop online
H2	Effort Expectancy has a positive correlation to Behavioural Intention to shop online
H3	Social Influence has a positive correlation to Behavioural Intention to shop online
H4	Facilitating Conditions has a positive correlation to Behavioural Intention to shop online
H5	Hedonic Motivation has a positive correlation to Behavioural Intention to shop online
H6	Price Value has a positive correlation to Behavioural Intention to shop online
H7	Habit has a positive correlation to Behavioural Intention to shop online
H8	Perceived Risk has a negative correlation to Behavioural Intention to shop online
H9	Consumer Disposition to Trust has a positive correlation to Behavioural Intention to shop online
H10	Consumer Trust in Website has a positive correlation to Behavioural Intention to shop online

3 RESEARCH METHODOLOGY

The literature review evaluated the main factors that influence the adoption of online shopping. This chapter describes the research methodology. It covers the research design, the research approach using the Saunders et al. (2019)'s research onion, details of the data collection and statistical analysis as well as other considerations to address the main problem.

3.1 Research Approach

Figure 4 demonstrates the Saunders Research Onion (Saunders et al., 2019) was used to develop the research methodology. Starting with the research philosophy, a positivism approach was taken. Positivism is based on positing a hypothesis and following the scientific method. It is used to create a hypothesis and test the outcome through the collection of data (Creswell & Creswell, 2017; Saunders et al., 2019). A deductive approach to theory development is used when a theory is developed and tested by means of data collection. Since the UTAUT2 was already developed and tested by Venkatesh et al. (2012), this study also uses a deductive approach to test a similar conceptual model and hypothesis. Similar to other UTAUT2 studies, this study used a mono-method quantitative study as the methodological choice and for the strategy, it used surveys to elicit the data. Using survey methodology allowed for standardised data to be collected, and it tested the hypotheses in a way that the data can be validated (Rattray & Jones, 2007). A cross-sectional approach was taken to test the behaviour of respondents at a point in time, namely the COVID-19 lockdown restrictions period. The research tested the relevant importance of factors that influence the adoption of online shopping as well as the impact of perceived risk and trust. The output of this research will assist SMMEs to know which factors to prioritise when curating the online shopping experience for their customers to build trust, reduce perceived risk and drive long-term adoption of online shopping.

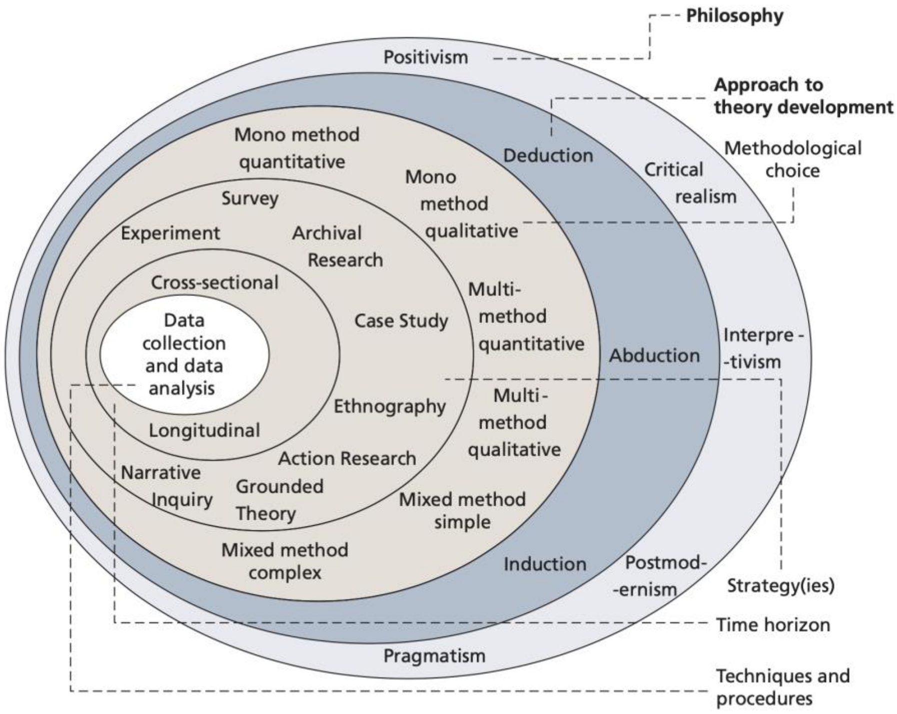

Figure 4: Saunder's Research Onion as defined by Saunders et al. (2019)

3.2 Research Design

A quantitative survey method was used to gather the required data points, similar to other UTAUT2 studies. The research methodology was based on the UTAUT2 model as initially applied by Venkatesh et al. (2012) and Tandon and Kiran (2019). The aim of this quantitative study was to test the hypotheses and to provide responses to the research questions. The survey questionnaire was completed by respondents online using Qualtrics. The link to the research was shared through email and social media channels (including WhatsApp, Instagram, LinkedIn and Facebook). A 47-question survey was sent out and analysed.

3.3 Data Collection Methods

A non-probability methodology, using convenience sample methodology with snowball sample method was used to get the highest level of responses. Non-probability sampling does not allow for sampling errors to be measured and may experience sampling bias. The survey was created on Qualtrics and the link to complete the questionnaire was shared on WhatsApp, Facebook, Instagram and LinkedIn. Further, respondents were requested to share it with their extended network, in order to reach a sufficient sample size (Bhattacherjee, 2012; Schindler, 2019).

3.3.1 Population

The population of the study included all consumers over 18 who have completed a purchase on an online website in South Africa. The eCommerce penetration is approximately 37% with an estimated 22 million consumers having shopped online in 2020. Respondents required internet access as the survey was completed online using Qualtrics. English-speaking respondents were needed as the survey is only available in English, but respondents were not required to have English as their first language.

3.3.2 Sample and Sampling Method

When conducting research, it is critical that the sample size is big enough to represent the population and that the sample used must be representative of the population (Lee, 2015; Sarmah & Hazarika, 2012). To get a sufficient sample size, there need to be five times as many observations as there are variables (Habing, 2003). Since there were 47 questions, 235 respondents were needed at a minimum to have an adequate sample size. The number of surveys sent out exceeded the number of respondents to ensure that the adequate sample size could be reached.

3.4 The Research Instruments

An online survey questionnaire was used where respondents were asked to complete a set of questions using a 5-point Likert scale, as applied by Tandon and Kiran (2019). A Likert scale measures attitude with the respondent having the option to respond favourably or unfavourably on a scale (Gliem & Gliem, 2003). The questions were structured and uniform. APPENDIX A: Survey Questionnaire outlines the questions which were split between the different variables of the UTAUT2 model being applied: demographic, lockdown specific, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic, motivation, price value, habit, consumer disposition to trust, consumer trust and perceived risk.

3.5 Procedure for Data Collection

- **Define survey questions:** To collect the data, survey questions were drafted, as outlined in APPENDIX A: Survey Questionnaire, based on the UTAUT2 model applied by Venkatesh et al. (2012) and Tandon and Kiran (2019). The trust and perceived risk questions were based on Kim et al. (2008).
- **Pre-test questions:** The survey questions were pre-tested to ensure the respondents understood the questions clearly. It also tested if there are any questions that respondents refuse to answer because they were badly written. This increased the probability of retrieving responses (Krosnick, 1999). The survey was sent out to three respondents to complete and each of them provided feedback for potential amendments.
- **Amend questionnaire:** Based on the feedback in the pre-test step, the survey was amended.
- **Distribute questionnaire:** The questionnaire was distributed online and respondents were asked to complete the survey. The survey was reshared daily on social media channels for a two-week period to elicit a sufficient sample size.
- **Consolidate responses:** The responses were consolidated and any incomplete responses were excluded (as discussed in 4.2).
- **Data clean:** The results were reviewed and cleaned up to enable analysis.

3.6 Analysis

The results were analysed using both SPSS and SPSS AMOS software packages. The data analysis applied a multivariate statistical analysis, using structural equation modelling (SEM). SEM enables direct and indirect effects and causal relationships to be tested (Tandon & Kiran, 2019). In order to test a structural equation model (SEM), the analysis was split into two parts – the measurement model and the structural model (Collier, 2020; Hair et al., 2019).

The measurement model tested the relationship between the latent variables (factors) and their respective indicator (questions) variables. The model was tested for fit, reliability and validity. Once the model was amended and considered acceptable, the structural model analysis was conducted (Collier, 2020; Hair et al., 2019).

The structural model, in the form of a path diagram, tested the statistical significance and strength of each hypothesis by testing the relationship between the dependent variable (Behavioural Intention) and the latent variables (Collier, 2020; Hair et al., 2019).

Table 6: Variable Names

Code	Variable Name	Variable Type
PE	Performance Expectancy	Latent
EE	Effort Expectancy	Latent
SI	Social Influence	Latent
FC	Facilitating Conditions	Latent
HM	Hedonic Motivation	Latent
PV	Price Value	Latent
H	Habit	Latent
DT	Disposition to Trust	Latent
CT	Consumer Trust in Website	Latent
PR	Perceived Risk	Latent
BI	Behavioural Intention	Dependent

3.6.1 Measurement Model

For this study, the measurement model was conducted using a confirmatory factor analysis (CFA). When using a CFA, a conceptual model is created prior to the collection of data. Once the data is collected, the model can then be assessed to see how well the model fits. The conceptual model for this study is rooted in the original UTAUT2, as determined by Venkatesh et al. (2012), with the addition of perceived risk and trust as variables. Thus, a CFA is a good way to confirm the pre-existing model. A confirmatory factor model was tested by creating a covariance between each of the latent variables and fixing a regression weight to 1 for one indicator per latent variable (Collier, 2020; Hair et al., 2019). This model was run in SPSS AMOS and checked against the model fit indices and factor loadings. A few iterations were run to establish the best fit. Thereafter, reliability and validity tests were run to ensure that the model is reliable and valid. Several iterations were run to ensure a good model fit. The details are provided in APPENDIX B: Establishing a Model Fit. The visual representation of the model used for analysis is depicted in Figure 5**.**

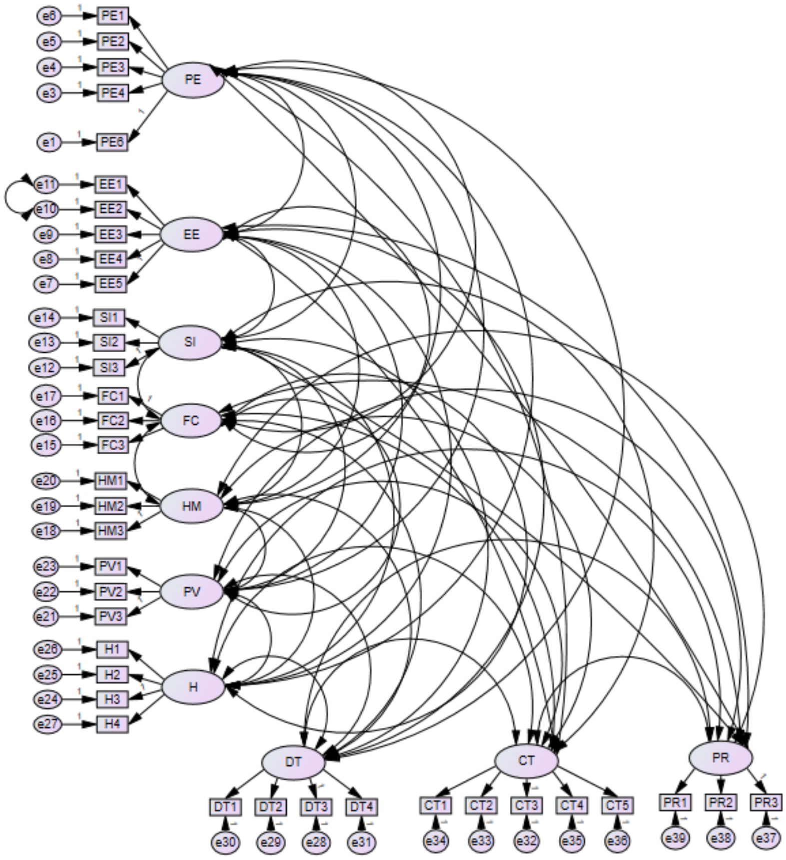

Figure 5: Model 5 - Final CFA Diagram

3.6.1.1 Model Fit

Various model fit statistics have been established to enable researchers to have certainty that the data used is measuring the model to expectation. The recommendation is to use a mix of the model fit statistics as each has its own strength and to ensure the model fits within the recommended ranges (Collier, 2020; Hair et al., 2019). The model fit statistics used for this model are as follows:

- Relative Chi-Square test (χ^2/df): Historically, the chi-square (χ^2) goodness-of-fit test has been widely used to establish model fit by comparing the hypothesised model and null model covariance matrices; however, in larger samples sizes, it has been found to be unreliable. Since the sample size for this study was over 300, the relative chi-square test was used as it takes the chi-square value and divides it by the degrees of freedom (χ^2/df) to reduce the reliance on sample size. The recommended value is less than 3 (< 3) for a good model fit (Kline, 2011).

- Goodness-of-fit Index (GFI): This measure assesses the overall fit of the model to the data by estimating how much better the model fits when compared to no model. The recommended value for a good model fit is a score greater than 0.9 (>0.9) (Hair et al., 2019; Jöreskog, 2004).
- Comparative Fit Index (CFI): This measure compares the covariance matrices of the model to the null hypothesis to test the relative fit of the model to other models. The recommended value for a good model fit is a score greater than 0.9 (>0.9) which indicates that 90% of the model can replicate 90% of the covariance in the model (Bentler, 1990; Collier, 2020).
- Tucker-Lewis Index (TLI): This measure assesses complexity by using the chi-square values for the model and the null model. The recommended value for a good model fit is a score greater than 0.9 (>0.9) (Bentler, 1990; Hair et al., 2019).
- Standardized Root Mean Square Residual (SRMR): Using the residuals created from the error terms, this measure compares the differences in residuals of the predicted and observed covariances. A value less than 0.08 (<0.08) is considered a good model fit (Collier, 2020; Hair et al., 2019; Hu & Bentler, 1998).
- Root Mean Square Error of Approximation (RMSEA): This measure can accommodate complexity and sample size and is used as an alternative to the Chi-square goodness-of-fit. A value less than 0.05 (<0.05) is considered a good model fit (Hair et al., 2019; Hu & Bentler, 1998).

Once the model fit was established, the composite reliability, convergent validity and discriminant validity tests were conducted.

3.7 Quality Assurance

3.7.1 Reliability

To test for the reliability of the questionnaire, a pre-test was sent out and tested. Once the survey was conducted, the composite reliability test was completed in the measurement model of the SEM to confirm the reliability of the model (Collier, 2020).

3.7.1.1 Composite Reliability

Composite reliability is measured to see if a set of variables gives consistent output in terms of what it's trying to measure (Straub et al., 2004). In other words, if the model provides the same results when tested with different respondents, that consistency means the model is reliable.

The most popular method to measure reliability is Cronbach's alpha; however, when there are many variables for a model, Cronbach's alpha can be overestimated. In a structural equation model (SEM), the model tests what influence the factor loadings of indicators have on the model and if it is significant, but Cronbach's alpha also assumes all indicators have the same influence making it an unsuitable measure for an SEM analysis. As an alternative, the 'composite reliability' was used to measure SEM (Hair et al., 2019).

The composite reliability test does not assume equal-weighted factor loadings for indicators, instead, it takes those factor loadings as calculated in the confirmatory factor analysis (CFA) to get a weighted loading and this creates a better representation for SEM which has been found to better represent the reliability within a measurement model (Collier, 2020). For the purposes of this study, the composite reliability test was conducted.

3.7.1 Validity

3.7.1.1 External Validity

External validity refers to whether the research was extended to other groups. It refers to the generalisation of the research and if it could be applied to other groups (Ritchie et al., 2013). The external validity of the model was ensured by collecting a set of standardised questions based on the works of Venkatesh et al. (2012), Tandon and

Kiran (2019) and Kim et al. (2008). The research used a convenience and snowball sampling method, to ensure that the research was transferable to other demographic groups that share similar characteristics, which in turn creates generalisability.

3.7.1.2 Internal Validity

Internal validity refers to whether or not the study examined what it set out to examine (Ritchie et al., 2013). The UTAUT2 has been extensively studied and the questions have been empirically tested in multiple studies. To uphold the validity, wherever possible, questions used have been selected from prior research. Once the survey was conducted, convergent and discriminant validity tests were completed in the measurement model of the SEM to confirm the validity of the model (Collier, 2020).

3.7.1.3 Convergent Validity

Convergent validity measures whether the indicators will converge to measure the proposed model. A high correlation indicates that the indicators are measuring the model as intended. To calculate this, the average variance extracted (AVE) is calculated. The AVE is calculated by summing the R^2 of each indicator divided by the number of indicators. The R^2 is the square of a factor loading and indicates how much of the variance of the unobserved variable is explained by the latent variable. An AVE greater than 0.5 has been established as a benchmark because it indicates that more than half of the indicator factor loadings variance is accounted for in the model and thus, it can be concluded that there is convergent validity in the model (Collier, 2020; Hair et al., 2019).

3.7.1.4 Discriminant Validity

Discriminant validity measures the degree to which concepts are different and if the construct is different from others. Historically, shared variance was used to assess the discriminant validity as outlined by (Fornell & Larcker, 1981). However, research has shown it is not able to fully capture the discriminant validity between constructs. As an alternative, the heterotrait-monotrait ratio of correlations (HTMT) technique has been favoured since it examines the correlation of variables between constructs to those within them. Using an implied correlation matrix from SPSS AMOS, the HTMT correlation is created by taking the heterotrait correlation (the relationship between two latent variables) over the square root of the two monotrait correlations multiplied (the average of the indicators within a factor). The recommended benchmark is for this value to be less than 0.9. Using the variables, PE and EE as an example, Equation 1 illustrates the formula (Collier, 2020; Hair et al., 2019).

Equation 1: HTMT Ratio

$$\textbf{HTMT Ratio} = \frac{\text{(AVERAGE) PE-EE}}{\text{SQUARE ROOT (AVERAGE (PE)*AVERAGE (EE))}}$$

3.8 Structural Model

Once the measurement model was confirmed, the structural model was created in SPSS AMOS to test the factor loadings. A seconder-order factor model (Figure 6: Structural Model**)** was created to measure the effect of Behavioural Intention (BI) on the first-order constructs established in the measurement model (PE, EE, SI, FC, HM, PV, H, DT, CT, PR) (Byrne, 2016; Kline, 2011). A reflective second-order confirmatory factor model was created, with a variance set to 1 for BI to ensure the second-order factor loadings can be estimated accurately. Since the latent variables are now dependent variables, the covariance between them was removed. The model was run in SPSS AMOS, the SEM statistical software package, to test the hypotheses (Byrne, 2016). Based on the output, the model fit statistics were checked, followed by the p-values and t-values for significance and the standard regression weights, which were evaluated as factor loadings against the hypotheses (Byrne, 2016; Kline, 2011).

3.9 Ethical Considerations

The study will adhere to the ethical standards of Wits Business School. To meet these standards, the following steps will be taken:

- Prior to being distributed, the research proposal and survey questions were approved by the WITS Ethics Committee.
- The survey has an initial step that requested and recorded the consent from respondents to complete the survey,

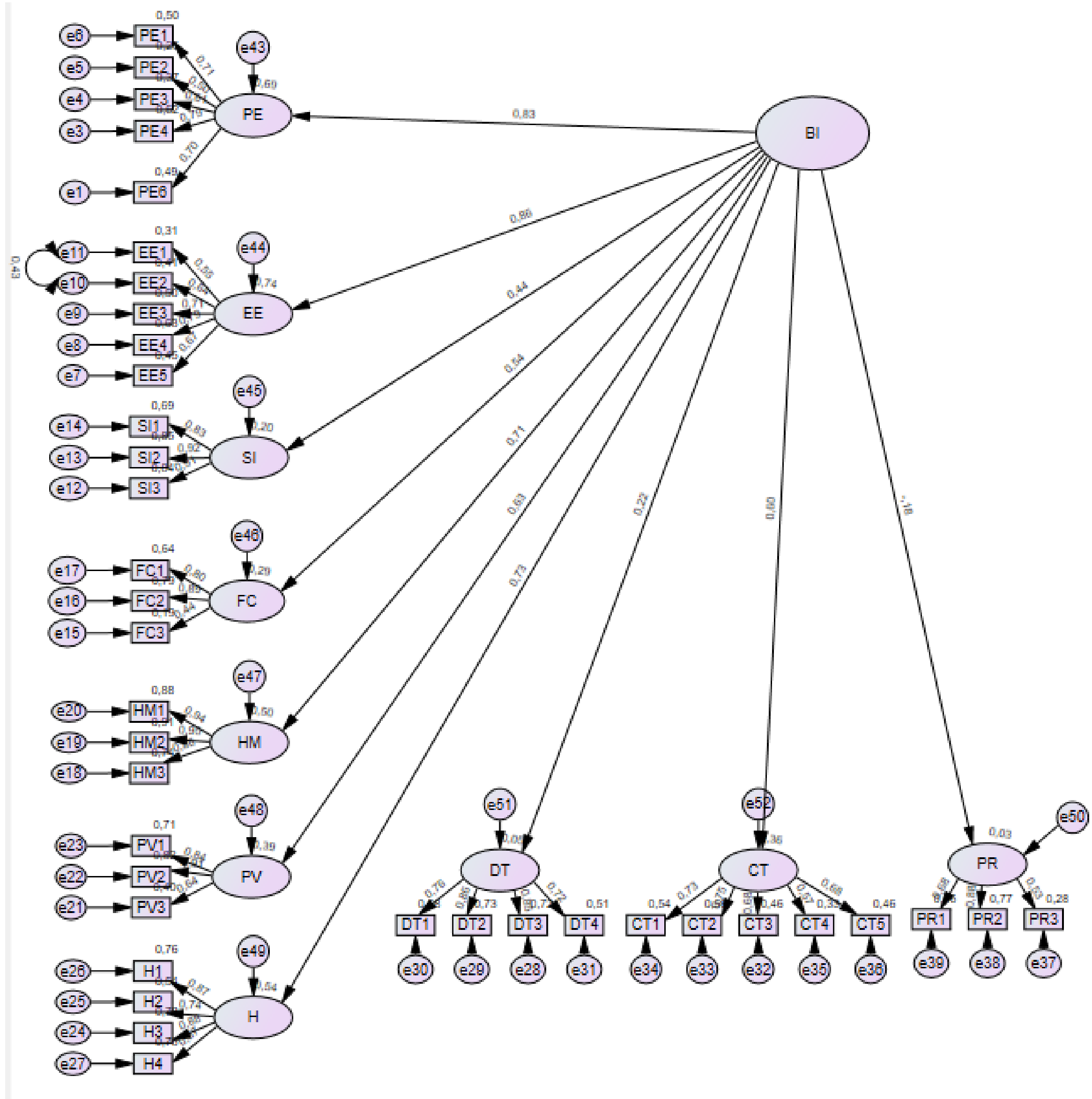

Figure 6: Structural Model

- Respondents were not identifiable and no personal information was captured.
- The survey did not request any confidential information and all demographic identifiers were requested in ranges as opposed to specifics.
- The results of the study will be made available to respondents if requested.
- The research paper will go through the sign-off process from Wits Business School, to meet the minimum ethics standards.

4 Presentation of Results

4.1 Introduction

This study was designed to identify the key factors influencing consumers' adoption of online shopping during the COVID-19 lockdown in South Africa. It also determined whether or not trust and perceived risk had an impact on consumer adoption. The results of the analyses are discussed below. It covers the demographic characteristics of respondents followed by their lockdown-specific characteristics. Thereafter, the measurement and structural models were analysed and linked back to the hypotheses and research questions.

4.2 Data Screening, Missing Values and Outliers

The survey was open between 6 – 21 November 2022 reaching a total of 473 respondents. In total 386 respondents successfully completed the survey which lead to an 82% response rate. A search was done in SPSS for missing values and four (4) responses were removed. Thereafter, outliers were checked for a standard deviation less than 0.25 and one (1) respondent was identified as having a standard deviation of 0 in their response and was removed. This left the total sample size at 381 (Byrne, 2016; Collier, 2020).

4.3 Demographic Characteristics of Respondents

4.3.1 Gender

Men and women display different behaviours when shopping, making gender differences important to note. Notably, women have shown a preference for in-store shopping which brings social and interpersonal connection. When shopping online,

Table 7: Demographic Characteristics Of Respondents

Characteristic	%
Gender	
Male	34.67%
Female	65.33%
Prefer not to say	0.00%
Age	
18 – 24 (Gen Z)	8.03%
25 – 34 (Millennial)	34.25%
35 – 44 (Millennial)	23.47%
45 – 54 (Gen X)	13.74%
55 – 64 (Baby Boomer)	11.84%
65 and over (Baby Boomer)	8.67%
Annual Income	
Less than R 200 000	33.55%
R 200 001 - R 350 000	11.90%
R 350 001 - R 500 000	8.01%
R 500 001 - R 750 000	9.52%
R 750 001 - R 1 000 000	13.20%
R 1 000 001 - R 1 500 000	12.77%
More than R 1 500 000	11.04%
Province	
Gauteng	77.26%
KwaZulu-Natal	7.51%
Western Cape	6.62%
Limpopo	3.75%
North West	2.43%
Mpumalanga	1.32%
Northern Cape	0.88%
Eastern Cape	0.22%
Free State	0.00%

men have been found to prefer well-known websites and spend more online compared to women (Melović et al., 2021). However, women have a more hedonistic approach to shopping while men display utilitarian characteristics (Faqih, 2022; Melović et al., 2021). Additionally, women use smartphones and social media more as well as look for bargains (Santosa et al., 2021). From the survey, 35% of the respondents were male and 65% were female with no respondents preferring not to say. Since COVID-19 forced people to stay home, it is not unexpected that more women than men shifted online. Moreover, this gender distribution tracks with other studies on online shopping in different markets with women being the larger respondent group (Cao et al., 2018;

Melović et al., 2021; Sumarliah et al., 2022). This study didn't cover the different types of online shopping and perhaps in more specific contexts, the responses would differ. This creates a potential future research opportunity.

4.3.2 Generational Behaviours

As outlined in Table 8, from a demographic perspective, age-groups are clustered as generations which have unique characteristics based on the economic climate, technological advancements, world events and social shifts. These factors influence the behaviours of the generation and provide meaningful insight into their behaviour and as a comparison to other generations. The age groups for this study were not expressly aligned to the generations as it took respondents from the age of 18 and split them into 10-year ranges; however, the ranges formed are similar to the generation definitions and thus will be used for insight.

Figure 7 shows the ages from the study as defined by the generational ages. Generation Z (Gen Z) is the youngest group with age in this study aligning to the 18 – 25 years age-group, followed by Millennials who make up two age ranges in this study 25 – 34 and 35 – 44. Generation X (Gen X) is covered by the 45 – 54 age-group and the remaining two groups of respondents align with the Boomers in the 55 plus age-group. Many studies have observed the behaviours of generations to draw insight and have found that online shopping patterns seem to differ by the generational designations (Dimock, 2019; Eneizan et al., 2022; Melović et al., 2021; Pentz et al., 2020a).

Table 8: Generation Names in 2023 as defined by Beresford Research (2023)

Generation	Ages
Gen Z	11 – 26 years old
Millennials	27 – 42 years old
Gen X	42 – 58 years old
Boomers	59 – 68 years old

The focus of most literature has been on Millennial and Gen Z behaviour, having found that Millennials and Gen Z are more inclined to be constantly connected online/digitally and to shop online (Melović et al., 2021). Gen Z have even higher expectations of online shopping since they've never ever experienced life without it and, as a result, find online shopping more natural than in-store (IOL Business, 2022). Eneizan et al. (2022) state that the over-60 age group has been excluded from behavioural studies, in favour of younger generations. The perception was that this age group was the most vulnerable during COVID-19 due to health risks and that they were also less likely to have internet during this time, but the authors argue that, in Jordan, they are also the largest population size of all the groups and have the highest level of income and wealth (Eneizan et al., 2022). They elaborate that retailers have untapped potential to better serve this generation in terms of tailored marketing and helping to drive their online adoption. (Santosa et al., 2021).

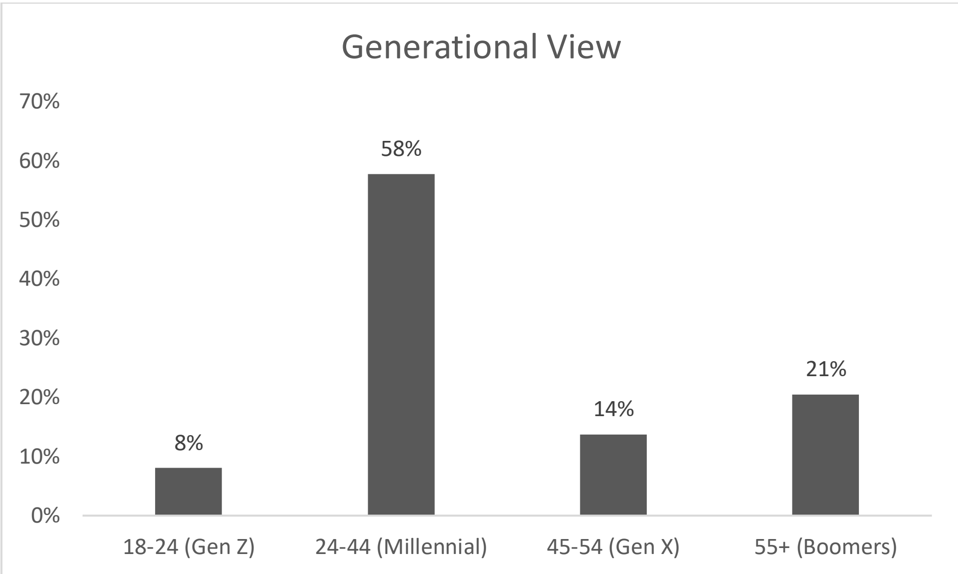

Figure 7: Generational View

The most popular age group of respondents is 25 – 34, followed by 35 – 44. As depicted in Figure 7, this is closely consistent with the millennial age group, which is not unexpected as the majority of the millennial population are comfortable using technology, have more hedonistic behaviours than previous generations and have larger disposable income causing them to impulse shop. Many retailers have specific messaging to target Millennials as they are perceived to be a profitable demographic group (Pentz et al., 2020a). The 18 – 24 age group participation is still quite small and this is possibly due to them not being in the workplace yet and currently having lower disposable income (Fromm, 2022). However, they are poised to have future buying power and retailers have been encouraged to understand their shopping behaviour which differs from prior generations (IOL Business, 2022). Interestingly, 20.5% of participants were over 55 which is more than double the Gen Z participation. This is not unexpected since Boomers have been in the workforce the longest, thus having the highest disposable income and wealth of all segments. This result supports the argument that they are a lucrative generation for which businesses should be catering (Eneizan et al., 2022).

4.3.1 Annual Income

In terms of the responses received the R 0 – 200 000 annual income made up the majority at 34%. While this tracks with the average income range per province being within this range (BusinessTech, 2016), it is somewhat unexpected. Upon deeper investigation, it is clear that lower-income households have been shifting online as they save on transport costs and time and enjoy the convenience of the experience. They still prefer in-store shopping for perishables and for products which they need to see first (Stiehler-Mulder & Mathabathe, 2022). When combined, the income ranges over R 750 000 constitute 37% of respondents, which tracks with the expectation that online shopping is dominated by higher-income households who can overcome the structural limitations better and have higher disposable income (Cohen, 2021).

4.3.1 Province Distribution

77% of respondents were from Gauteng which is not unexpected since Gauteng has the highest GDP per capita, the largest population density and the highest disposable income as of 2016. Johannesburg alone contributed 15% to GDP, while Cape Town contributed 10% (BusinessTech, 2016).

4.4 Lockdown-Specific Characteristics

Figure 8 demonstrates that prior to the COVID-19 lockdown, more than 50% of respondents were purchasing online only 2 – 3 times a year or every 2 – 3 months. This indicates that it was not a regular habit. However, since the lockdown, there has been a shift with over 50% of respondents now purchasing online weekly or 2 – 3 times a month. Interestingly, 3.8% of shoppers shop daily now and prior to the lockdown, no respondents indicated that they purchased online daily. This behaviour is not unexpected since consumers turned to online shopping at major retailers such as Clicks, Checkers, and Pick ‘n Pay for their essentials when they were forced to stay home and social distance (Business Insider SA, 2020; Heyns & Kilbourn, 2022). This also tracks with the Mastercard (2020) study where 68% of respondents stated that they were shopping more since the start of the pandemic. Further, the results are similar to Deloitte Digital (2021) which had a higher daily usage result at 7%, but similar weekly (27%) and monthly (36%) results. The research indicates that the top three reasons to shop online were convenience, COVID-19 and time-saving.

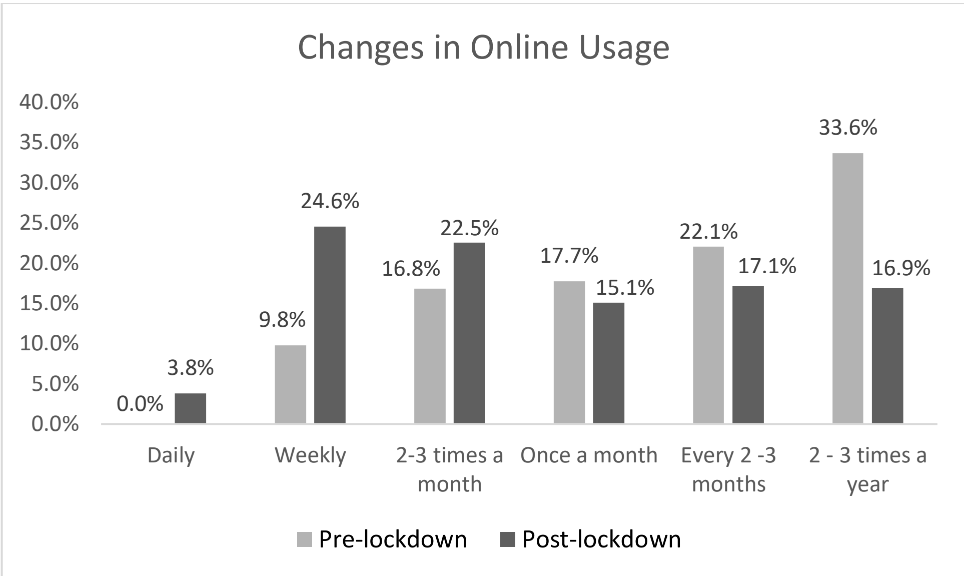

Figure 8: Changes in Online Usage

Respondents were asked questions about their online shopping behaviour. Figure 9 demonstrates that 71% of respondents agreed somewhat or strongly agreed that they will continue to shop online now that the COVID-19 lockdown restrictions have been eased and Figure 10 shows 71% of respondents also agree somewhat or strongly COVID-19 lockdown restrictions have changed their online behaviour. This tracks with the Mastercard (2020) study where 71% of respondents stated that they will continue to shop online. In addition, the Deloitte Digital (2021) survey found, in 2021, that two-thirds of respondents are planning to shop more. The structural equation model will provide insight into which factors contributed the most to these behaviours.

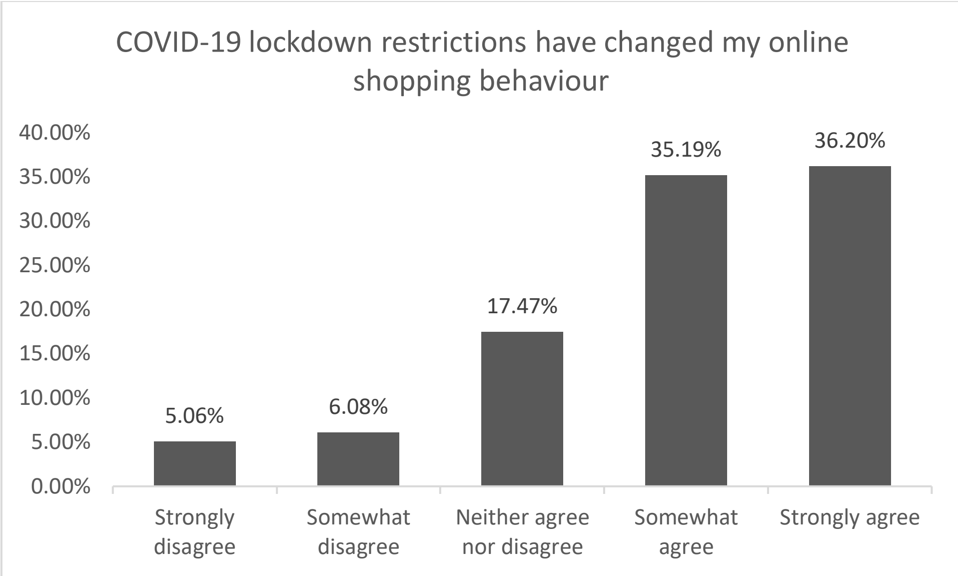

Figure 9: COVID-19 lockdown restrictions have changed my online shopping behaviour

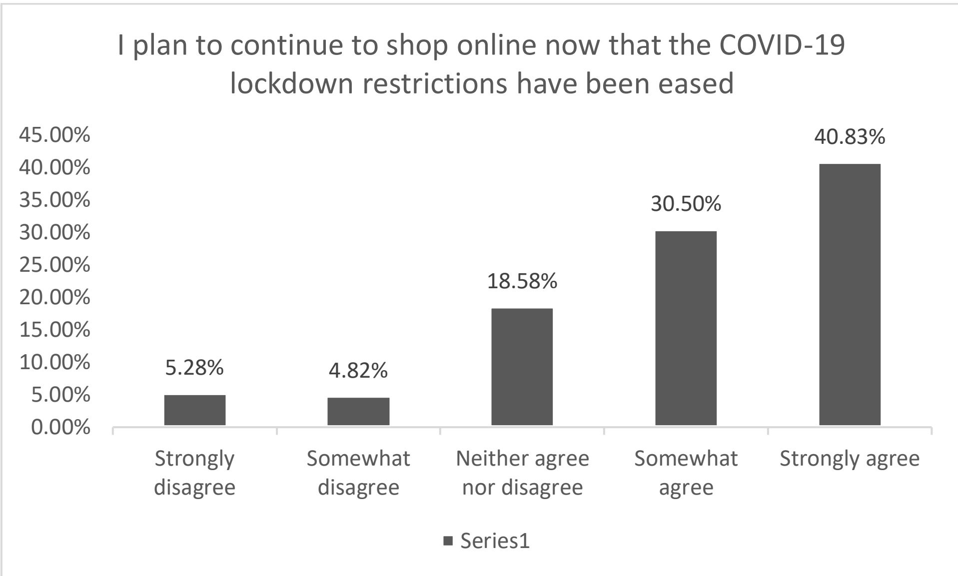

Figure 10: I plan to continue to shop online now that the COVID-19 lockdown restrictions have been eased

4.5 Structural Equation Modelling (SEM)

As described in Chapter 3, the analysis of the structural equation model (SEM) was split into two parts – the measurement model and the structural model.

The measurement model was first tested for model fit. Once the model was amended and considered to have a good fit, the composite reliability, convergent validity and discriminant validity tests were run. After all of these steps were completed and within acceptable ranges, the structural model analysis was conducted.

The structural model tested the statistical significance and strength of each hypothesis by testing the relationship between the dependent variable (Behavioural Intention) and the latent variables (Collier, 2020; Hair et al., 2019). For ease of reference, the variables are restated in Table 9 below.

Table 9: Variable Names

Code	Variable Name	Variable Type
PE	Performance Expectancy	Latent
EE	Effort Expectancy	Latent
SI	Social Influence	Latent
FC	Facilitating Conditions	Latent
HM	Hedonic Motivation	Latent
PV	Price Value	Latent
H	Habit	Latent
DT	Disposition to Trust	Latent
CT	Consumer Trust in Website	Latent
PR	Perceived Risk	Latent
BI	Behavioural Intention	Dependent

4.5.1 Measurement Model

For this study, a confirmatory factor analysis (CFA) was established and checked against the factor loadings and model fit statistics. Once a goodness-of-fit was established and all recommended values were within range, the reliability and validity of the measurement model were calculated. If a standard regression weight (SRW) or factor loading is less than 0.5, it is recommended that it should be removed from the model as it accounts for less than 50% of the variance in the indicator (Collier, 2020). Several iterations were run to ensure a good model fit. The final model removed PE5 and added a covariance between error terms 10 and 11. More details about the iterations are provided in APPENDIX B: Establishing a Model Fit. All further analysis was based on this model.

4.5.1.1 Model Fit

Table 10 shows the mode fit indices, which include χ2/df, GFI, CFI, TLI, SRMR and RMSEA, were all within an acceptable range and the model is considered to have a good model fit. The definitions of these indices are available in Chapter 3 in the Model Fit section. The next step is to measure composite reliability.

As summarised in Table 10, the Chi-squared over degrees of freedom (χ^2/df) is less than 3 which is considered a good fit. Similarly, the CFI and TLI are greater than 0.9 and the SRMR is less than 0.08 and the RMSEA is on the recommended threshold of less than 0.05, suggesting a good model fit. The GFI was at the threshold of 0.9, making it an adequate fit. Once the model was determined to have a good fit, the composite reliability was tested.

Table 10: Model Fit Statistics for the Measurement Model

Fit Indices	Recommended Value	Source(s)	Model 5
χ^2/df	<3	(Kline, 2011)	1.851
GFI	>0.90	Hair et al. (2019)	0.857
CFI	>0.90	Bentler (1990)	0.935
TLI	>0.90	Bentler (1990)	0.927
SRMR	<0.08	Hu and Bentler (1998)	0.054
RMSEA	<0.05	Hu and Bentler (1998)	0.047

4.5.1.2 Composite Reliability

Nunnally and Bernstein (1994) determined 0.7 as a benchmark for an acceptable reliability measure. As per Table 11, all the variables were greater than 0.7, indicating that the variables in the study are considered reliable and will yield consistent results (Collier, 2020; Hair et al., 2019).

4.5.1.1 Convergent Validity

As per Table 10, the average variance extracted (AVE) is greater than 0.5 for all measures except PE, EE and CT. PE, EE and CT are less than 0.5, which means these variables explain less than 50% of the variance, which is caused by measurement error. Fornell and Larcker (1981) indicated that AVE could be considered a more conservative measure of the validity of the model and it should be considered with composite reliability (CR) to see if the CR is greater than 0.7. If this holds true and the AVE is close to 0.5 (PE = 0.48, EE = 0.46, CT = 0.47), then convergent validity can still be considered adequate (Fornell & Larcker, 1981; Lam, 2012). The analysis then proceeded to calculate the discriminant validity

Table 11: Composite Reliability and AVE Results

Variable	Composite Reliability	No. of Items	Square Root	AVE
PE	0.82	5	0.69	0.48
EE	0.81	5	0.68	0.46
SI	0.92	3	0.89	0.79
FC	0.77	3	0.74	0.54
HM	0.94	3	0.92	0.84
PV	0.84	3	0.80	0.64
H	0.91	4	0.84	0.71
DT	0.88	4	0.80	0.64
CT	0.81	5	0.68	0.47
PR	0.75	3	0.71	0.51

4.5.1.2 Discriminant Validity

The calculations for the HTMT can be found in APPENDIX C: HTMT Calculations. Table 12 displays the calculated HTMT values. All HTMT values for this model are less than 0.9 and discriminant validity was established (Collier, 2020; Hair et al., 2019).

Table 12: HTMT Correlations

Variable	PE	EE	SI	FC	HM	PV	H	DT	CT	PR
PE										
EE	0.744									
SI	0.339	0.356								
FC	0.464	0.604	0.123							
HM	0.586	0.578	0.276	0.331						
PV	0.479	0.506	0.350	0.329	0.459					
H	0.614	0.546	0.429	0.313	0.627	0.493				
DT	0.133	0.177	0.022	0.169	0.083	0.099	0.123			
CT	0.474	0.539	0.249	0.329	0.345	0.443	0.384	0.531		
PR	-0.136	-0.133	-0.040	-0.090	-0.180	-0.071	-0.133	-0.153	-0.185	

4.6 Structural model

4.6.1 Model Fit

The model fit statistics were assessed to ensure that the structural model is measuring what it intended. Since these were already tested in the measurement model and the purpose of this was to assess the hypotheses, no changes were considered to improve the fit.

Table 13: Model Fit of the Structural Model

Fit Indices	Recommended Value	Source(s)	Path Analysis
χ^2/df	<3	(Kline, 2011)	2.082
GFI	>0.90	Hair et al. (2019)	0.837
CFI	>0.90	Bentler (1990)	0.913
TLI	>0.90	Bentler (1990)	0.907
SRMR	<0.08	Hu and Bentler (1998)	0.072
RMSEA	<0.05	Hu and Bentler (1998)	0.053

As summarised in Table 13 The model fit statistics were assessed to ensure that the structural model is measuring what it intended. Since these were already tested in the measurement model and the purpose of this was to assess the hypotheses, no changes were considered to improve the fit.

The Chi-squared over degrees of freedom (χ^2/df) is less than 3 which is considered a good fit. Similarly, the CFI and TLI are greater than 0.9, the SRMR is less than 0.08 and the RMSEA is on the recommended threshold of less than 0.05, suggesting a good model fit. However, the GFI is slightly less than 0.9, similar to Model 1 of the measurement model, which is below the recommended threshold and suggests a less than adequate fit. However, the usage of GFI has declined with the introduction of other indices and in complex models such as an SEM analysis, a fit of 0.8 can be considered an acceptable fit (Doll et al., 1994; Hair et al., 2019). Thus, the GFI is also considered within range. The structural model is considered to have a good fit and the hypotheses can be tested as the next step.

4.6.2 Hypothesis Test Results

Table 14 summarises the hypothesis test results. The SPSS AMOS output indicates that all the independent variables have a significant relationship with Behavioural Intention (BI). P-values indicate the significance of the factor loading whereas higher standard regression weight (SRW) indicate greater strength of correlation (Research with Fawad, 2021). The p-values are all statistically significant at a level of 0.1% since they are all less than 0.001. It is important to note that only perceived risk has a negative correlation as hypothesised due to its negative impact on the intention to purchase online.

These results suggest that all the independent variables are predictors of Behavioural Intention in online shopping in the context of the COVID-19 lockdown restrictions. They are all statistically significant in the intention of consumers to purchase online.

Once the statistical significance was established, the next step was to assess the strength and direction of the correlation. As discussed previously, the higher the standard regression weight or factor loading (SRW), the stronger the correlation. the results show a strong positive correlation to effort expectancy, performance expectance, hedonic motivation and habit with factor loadings greater than 0.7. Facilitating conditions and price value, and consumer trust in website had a modest positive correlation with factor loadings greater than 0.5. However, social influence with a factor loading of 0.442 has a low-to-modest correlation, perceived risk has a negative and weak correlation with a -0.183 factor loading and disposition to trust has a weak correlation of 0.222.

These results support that all the hypotheses are significant where performance expectancy, effort expectancy, hedonic motivation and habit played the strongest role in driving consumer behaviour during the COVID-19 lockdowns.

Table 14: Hypotheses Test

Hypothesis	P-Value	T-Value	Standard Regression Weight (SRW)	Hypothesis
Performance Expectancy has a positive correlation to Behavioural Intention	<0.001	12.467	0.830	Supported and significant
Effort Expectancy has a positive correlation to Behavioural Intention	<0.001	9.999	0.862	Supported and significant
Social Influence has a positive correlation to Behavioural Intention	<0.001	7.832	0.442	Supported and significant
Facilitating Conditions has a positive correlation to Behavioural Intention	<0.001	8.634	0.537	Supported and significant
Hedonic Motivation has a positive correlation to Behavioural Intention	<0.001	14.022	0.708	Supported and significant
Price Value has a positive correlation to Behavioural Intention	<0.001	10.833	0.625	Supported and significant
Habit has a positive correlation to Behavioural Intention	<0.001	13.771	0.734	Supported and significant
Perceived Risk has a negative correlation to Behavioural Intention	0.003	-2.929	-0.183	Supported and significant
Disposition to Trust has a positive correlation to Behavioural Intention	<0.001	3.770	0.222	Supported and significant
Consumer Trust in Website has a positive correlation to Behavioural Intention	<0.001	9.588	0.603	Supported and significant

Variable	R^2
EE	0.743
PE	0.689
H	0.539
HM	0.501
PV	0.391
CT	0.364
FC	0.289
SI	0.195
DT	0.049
PR	0.033

Model Fit Statistics
$\chi 2$/df = 2.082, GFI = 0.837, CFI = 0.913, TLI = 0.907, SRMR = 0.072, RMSEA = 0.053

5 DISCUSSION OF THE RESULTS OR FINDINGS

5.1 Introduction

This study contributed to a deeper understanding of online shopping in a South African context during the COVID-19 lockdown restrictions. It provides empirical evidence into which factors had the largest contribution to consumers' behavioural intention when shopping online during this time. It further incorporated perceived risk and trust into the study and provided insight into how consumer behaviour has changed due to the pandemic.

South Africa has multiple structural factors that impede eCommerce growth but there are pockets of opportunities for both large and SMME businesses. This study will enable SMME businesses to understand the evolving retail landscape and the role eCommerce plays. Further, it will help them understand the various facets of eCommerce and which ones to prioritise in order to effectively sell online. The retail landscape is experiencing digital transformation and evolving at a rapid pace. SMMEs need to be aware of this transformation and identify the best ways to apply their resources and use these advancements in their businesses to provide better customer experiences.

5.2 Discussions Regarding Main Research Question Findings

The main objective of this study was to understand the factors that influenced the adoption of retail online shopping in South Africa, during the COVID-19 lockdown restrictions. The results of the structural equation model indicate that all the hypotheses were significant and supported. As mentioned earlier, the R^2 is the square of a factor loading and indicates how much of the variance of behavioural intention (BI) is explained by a specific variable. This can be interpreted as the strength of the relationship. By understanding this, SMMEs can use these insights to prioritise where to use their limited resources. Most of the R^2 are relatively high except for perceived risk and disposition to trust. The details and implications are discussed below.

5.2.1 Effort Expectancy

Unsurprisingly, effort expectancy (EE) had the highest R^2 (0.743), indicating that ease-of-use has the largest impact on behavioural intention. As a pre-purchase signal and utilitarian motivation, this is an important function for businesses to prioritise. This links to 88% of respondents indicating a smooth checkout process influenced their choice of online store. Since much of the market is dominated by app-based platforms and major retailers, these businesses have the resources to create an easy online shopping experience. For SMMEs, they can choose to provide their services on the existing platforms such as Mr D, Takealot or Superbalist. Alternatively, if they prefer to create their own website, they can use reputable third parties such as Shopify to ensure great usability.

5.2.1 Performance Expectancy

Closely linked to effort expectancy (EE) is performance expectancy (PE), which measures if the technology is working as expected. With an R^2 of 0.689, it has a significant impact on the relationship with behavioural intention. It is also a pre-purchase signal and has utilitarian motivation. As mentioned, the shift to online shopping has been dominated by large retailers or eCommerce platforms such as Takealot, which makes these results expected. These businesses have the means to invest in website features that drive usability and will work as expected. Further, Takealot owns Mr D so they have control over the last-mile and can ensure the customer experience is as expected. There may be times when businesses do not deliver as expected – such as the system could experience a failure, the payment could fail to process or perhaps there is a logistics issue. An additional challenge is loadshedding causing instability in networks and electricity as well as ripple effects.

Businesses need to be prepared for these unavoidable scenarios, but they can mitigate the impact by having customer service teams that can help resolve any of these service interruptions. Having good customer service that communicates changes in delivery, provides updates on returns, and has clear communication with customers influences customers' choosing to shop at a particular online store. 86% of respondents affirm that customer experience is a priority for them. Customer service as a priority will continue to grow in importance as eCommerce grows since it provides personal engagement with consumers and builds trust in the store. Lastly, it serves as a high-cost signal. Prioritising the usability of their online experience supported by customer experience can help SMMEs flourish in a virtual environment.

5.2.2 Habit

The next highest R^2 is habit (H) at 0.539, which links closely to the results of this study, where respondents confirm they are planning to continue to shop online now that the COVID-19 restrictions have been eased (71%) and that the lockdown restrictions have changed their online shopping behaviour (71%). Consumers' behaviours have clearly shifted, with 66% of respondents shopping online at least once a month since COVID-19, compared to 44% prior to the pandemic. As mentioned earlier, the more consumers buy online, their behavioural intention becomes subconscious which means that consumers choose a specific website by default. Once SMMEs get customers into the habit of shopping on their online store, the effort they need to get the customer to shop is lowered. Habit is discussed further in section 5.3.

5.2.3 Hedonic Motivation

Habit links into Hedonic Motivation (HM) (R^2 = 0.501) which was the last variable that explained over 50% of the variance. As discussed earlier, while consumers were stuck at home they turned to online shopping as a source of entertainment. They enjoyed the dopamine rush of shopping online and found awaiting deliveries to be exciting. Some consumers became addicted to online shopping which is why habit and hedonic motivations are so closely linked. Also unsurprisingly, women are more inclined to hedonic motivations when shopping, and this is supported by two-thirds of the respondents for this survey being women. SMMEs need to build hedonic motivations into their website as the enjoyment factor plays a significant role in online shopping. They can do this in the form of loyalty, promotions and creating a social component to their online shopping experience.

5.2.4 Social Influence

Since social commerce is also a hedonistic motivation, one would expect the social influence (SI) to be just as high as hedonic motivations, however, it is only 20% of the variation. Upon deeper investigation into the survey, it is clear that the questions were not poised around social commerce or the influence of social media. For future studies updating these questions could be highly beneficial. In addition, consumers switched to online out of necessity while social distancing, so influence from others may not play as much of a role in this context. Social commerce is expected to increase in its influence on online shopping behaviour, especially with marketers targeting Gen Z more as their disposable income increases. Further, the way that brands market is expected to shift towards social media platforms and relying on influencers. SMMEs need to build an online community to create the social elements for marketing as well as trust-building signals in order to effectively sell online.

5.2.5 Price Value

Price value accounts for almost 40% of the variation which tracks with the consumers stating that price is the most important factor when shopping online. Another important cost factor that influences consumers' decision to purchase is the delivery costs. For low-income households, this can make online shopping unattractive. As observed in this study, the less than R 200 000 annual income bracket was the highest group of respondents at 24%. Based on them being cost conscience, these results were surprising and warrant further research. As mentioned, a possible cause is consumers not wanting to share their true income and selecting the lowest income. With the tough economic conditions, consumers are becoming even more price conscious. SMMEs need to ensure that their value proposition demonstrates value-for-money. One way of supporting this strategy is to have loyalty where consumers get rewarded as they shop more online. This builds a habit, loyalty to the brand and value for money.

5.2.1 Facilitating Conditions

Facilitating conditions (FC), where consumers believe they have adequate resources to complete their purchase, accounts for 29% of the variation. As mentioned in the hypothesis, this links closely to the research that indicated the importance of general trust in institutions in eCommerce. The results indicate that consumers found it easy to shift to online shopping and that they could help if need be. This help could be in the form of customer service channels as outlined in 5.2.1. Considering the high impact of performance expectancy and effort expectancy, it correlates that the facilitating conditions should be important too. One could argue that the better the utilitarian factors such as usability and ease-of-use, the more likely it would be that the online store would perform to expectations. SMMEs need to ensure that their website performs as expected and by investing in a reliable website provider, they can ensure that this occurs.

5.2.2 Trust and Perceived Risk

Consumers' trust in the website (CT) also has a significant impact with 36% of the variation. This is likely because consumers have been shifting from in-store to online with their well-known stores and it results in a trust transference and overcomes the information asymmetry. Moreover, this shift to online has been dominated by larger platforms and retailers. As mentioned earlier, creating an online presence is expensive, consumers don't trust the payments to be secure and SMMEs don't have the knowledge on how to start or run a business. SMMEs can rely on a trust transference from reputable third-parties by using them as payment providers as well as using brands such as Shopify to create their online presence.

Consumers disposition to trust (DT) and perceived risk (PR) accounted for the least variation with R^2 of 4.9% and 3.3% respectively. Consumers' general trust in humanity does not seem to be as important as their trust in the website. Perceived risk and trust are discussed further in 5.4,

The results of this analysis can provide insights to SMMEs into the key drivers of online shopping and which ones to prioritise. It is clear that the main priority is to start with the utilitarian motivations such as usability, ease-of-use, value-for-money and customer service which closely link to performance expectancy, effort expectancy, facilitating conditions and price value. The next priority is to focus on the hedonic motivations which drive the social component of the shopping experience, the enjoyment factor and building a habit. This links closely to hedonic motivation as a variable, social influence and habit. Lastly, trust and perceived risk need to be considered; however, this is elaborated on in 5.4.

5.3 Discussions Regarding Sub-Question 1 Findings

In addition to the main research question, this study aimed to understand how consumer behaviour changed because of the COVID-19 lockdowns. The current literature indicates that consumers' adoption of online shopping was accelerated due to the pandemic based on the above factors. Consumers were forced to be more digital and shop online, a habit that data suggests will continue. Prior to the pandemic, the majority of consumers were shopping less than once a month (44%), with most only shopping 2 – 3 times a year. As little as 10% of consumers were shopping weekly, 17% were shopping 2 – 3 times a month and 18% were shopping once a month. This has shifted considerably since the pandemic, where the majority of consumers are shopping multiple times a month (51%). Interestingly, 4% of consumers are now shopping daily and a quarter of respondents (25%) shop weekly. This has been the largest shift in behaviour and is likely due to the launch of grocery delivery services just prior to or during the pandemic. Consumers enjoyed the convenience of these services when social distancing. Two-thirds of consumers in this study (66%) now shop at least once a month which implies that the shift to online shopping is here to stay and is a habit for many.

The convenience and 24/7 availability of online shopping are expected to continue to drive these trends. The results indicate that online shopping has become a habit for many consumers. SMMEs can benefit from consumer behaviour changes. By using the insights from this research, they can prioritise the signals that consumers look for to reduce perceived risk and build trust. In addition, they can add the utilitarian and hedonic motivations that consumers rely on to build their customer experience in such a way that consumers keep returning and build a habit of shopping on their website.

5.4 Discussion Regarding Sub-Question 2 Findings

Further to the above, the study evaluated the impact of perceived risk and trust on the adoption of online shopping during the COVID-19 lockdowns. The structural equation model results support the hypotheses that perceived risk, consumer disposition to trust and consumer trust in the website have an impact on behavioural intentions. All p-values, T-values and factor loadings were significant.

Consumer trust in websites was the most significant, with a factor loading of 0.603 and an R^2 of 36%. Consumers trust in the brand will influence their choice in shopping online on a particular website. As mentioned earlier, providing good customer service is important to consumers building trust in the website and choosing to shop there. Additionally, businesses can build trust by providing returns and refunds and providing a clear signal online in the form of details about returns and refunds.

Disposition to trust has a factor loading of 0.222 with a 5% R-squared. For the purposes of online shopping, consumers do not seem to need to trust everyone, but they do need to trust the website. Perceived risk has a negative correlation, since the higher it is, the less likely a consumer is to purchase. It has a factor loading of -0.183 and accounts for just 3% of the variance. It is potentially low as the questions in the survey were aimed at general perceived risk; however, for future studies, it would be beneficial to include questions around specific risk types for online shopping such as performance, financial, time, privacy and overall risk to enable richer insights.

As mentioned earlier, there is low inherent trust in online shopping due to the information asymmetry. Trust and perceived risk will influence customers' intention to purchase and SMMEs can use the factors tested to identify which factors will provide the strongest signals to build trust in their brands. SMMEs need to lower the perceived risk by implementing these signals to indicate that they will fulfil their obligations.

Trust is a critical component of both sales and technology adoption. SMMEs need to establish their online presence and build consumer trust in using it. Once they achieve this step, they can continue to evolve their digital transformation journey and compete in the omnichannel customer experience.

6 RECOMMENDATIONS AND CONCLUSION

6.1 Introduction

This study examined the factors that influenced the adoption of retail online shopping in South Africa, during the COVID-19 lockdown restrictions. The study used the UTAUT2 model to understand how consumers' behaviour changed. Further, the UTAUT2 was extended it to understand the role that trust and risk play in the adoption of online shopping.

6.2 Empirical contribution

This research adds to the body of knowledge by extending the UTAUT2 to include perceived risk and trust. The results of the UTAUT2 indicate how consumers' behaviour changed due to the lockdown period and the impact of the behaviour. The empirical results confirm the value of using UTAUT2 to assess online shopping adoption. All the hypotheses were significant and supported in the use of online shopping, including the additional variables of perceived risk (PR), consumers disposition to trust (DT) and consumer trust in the website (CT). This study further contributes to the theory by ranking the importance of the factors where effort expectancy, performance expectancy, hedonic motivation and habit all account for R-squared values greater than 50%. This indicates that these factors have the highest influence on behavioural intention. The results of social influence, perceived risk and disposition to trust suggest that these questions could be amended for future studies to provide more insight into online shopping.

6.3 Contextual contribution

The results from this report provide contextual insights into eCommerce growth in South Africa. The results show how consumers behaviour changed as a result of the pandemic but moreover which were the major factors in a South African specific context. These results factor in South Africa's urban adoption but it has not covered the digital divide in the underserved parts of the market. Consumers trust in the merchant website plays a critical role in the adoption of online shopping but the roles of perceived risk and consumers disposition to trust should be explored further.

6.4 Practical contribution

SMMEs can use the results of this study to help them understand consumers' priorities when shopping online. SMMEs have unique hurdles to overcome such as limited resources, lower trust transference and higher perceived risk. By applying the insights of this research into their business to create the appropriate trust-building signals, apply hedonic and utilitarian motivations and implement social commerce strategies, they will be able to establish their online shopping footprint. These results help them understand how consumers' behaviour changed and which factors to prioritise to enable more effective usage of their resources.

6.5 Possible Limitation and Suggestions for Further Research

Some limitations of this study could be caused by using a non-probability sampling method as well as it being a cross-sectional study. A longitudinal study where respondents are polled after various intervals and the application of a stratified random sampling method could allow for deeper insight. This would ensure that the study is more generalised and more representative of the unique characteristics of South African consumers. Since the study was limited to South African residents only and the results in South Africa may differ from other countries, this model could be run in other markets to compare behaviours, especially by other BRICS countries.

The factors analysed were limited to the UTAUT2, with perceived risk and trust added as additional factors; however, if there are significant factors beyond the conceptual model, they were not considered. Additionally, the risk perceptions in the study did not provide a robust view of perceived risk when shopping online. Adding questions for each risk type would provide deeper insights into consumers' behaviour. The annual income results were surprising, in that the less than R 200 000 group was the largest respondent group. Consumers may consider this information to be too personal and future research could give respondents the option not to share their annual income, which could prevent any potential bias in the data. In addition, the social influence questions did not capture the full impact of social commerce. For future research, amending these questions to include social media and influencers would provide valuable insight.

To enrich the insights, it would be valuable to add in the channels that consumers use to shop online (app-based, mobile websites, online websites etc.) and how their usage differs between big retailers and platform businesses such as Takealot and SMMEs. In addition, adding in the categories of online shopping would help with the understanding of what consumers purchase online (such as clothing, groceries, technology etc). The survey was only applied to urban areas and did not address online shopping adoption in rural areas. To understand the digital divide better, future research could include rural vs urban as an indicator and investigate some of the structural factors, especially the impact of loadshedding. This study evaluated the general impact on online shopping, but to provide deeper insights using age and gender as moderators would support SMMEs understanding of more personalised marketing approaches for these demographics.

APPENDIX A: Survey Questionnaire

Table 15: Survey Questions with Coding

Category	Code	Question	Reference
Demographic	D1	1. How old are you?	
	D2	2. What is your gender?	
	D3	3. What is your annual income bracket?	
	D4	4. Which province do you live in?	
Lockdown Specific	L1	5. How often do you shop online since the COVID-19 lockdown restrictions have been lifted?	
	L2	6. How often did you shop online prior to the COVID-19 lockdown restrictions?	
	L3	7. COVID-19 lockdown restrictions have changed my online shopping behaviour	
	L4	8. I plan to continue to shop online now that the COVID-19 lockdown restrictions have been eased	
Performance Expectancy (PE)	PE1	9. Online shopping provides a wide assortment of products useful in my daily life	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	PE2	10. Online shopping helps me to find product information within the shortest time frame	
	PE3	11. While shopping online I can find some products that are not easily available in physical stores	
	PE4	12. Online shopping enabled me to accomplish shopping more quickly than traditional stores during COVID-19 lockdown restrictions	
	PE5	13. Returning products online is an easy experience	
	PE6	14. Shopping online takes less time than traditional shopping from search of products to transaction completion	
Effort Expectancy (EE)	EE1	15. It was easy for me to learn how to shop online	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	EE2	16. It was easy for me to use online shopping during the COVID-19 lockdown restrictions	
	EE3	17. The language used by online retailers is easy to understand	
	EE4	18. Online shopping websites are easy to use	
	EE5	19. Information provided by online retailers help me to purchase products	
Social Influence (SI)	SI1	20. People who are important to me thought that I should adopt online shopping due to COVID-19 lockdown restrictions	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	SI2	21. People who influence my behaviour thought that I should adopt online shopping due to COVID-19 lockdown restrictions	
	SI3	22. People whose opinions I value preferred that I use online shopping during COVID-19 lockdown restrictions	

Category	Code	Question	Reference
Facilitating Conditions (FC)	FC1	23. I have the necessary resources to shop online	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	FC2	24. I have the necessary knowledge to shop online	
	FC3	25. I can get help from others when I have difficulties shopping online	
Hedonic Motivation (HM)	HM1	26. Shopping online is an exciting experience for me	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	HM2	27. Shopping online is fun for me	
	HM3	28. Shopping online is very entertaining	
Price Value (PV)	PV1	29. Online products are reasonably priced	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	PV2	30. Online shopping provides me with good value for money	
	PV3	31. Online discounts and promotions offered are often attractive which provide me with value for money	
Habit (H)	H1	32. The use of online shopping has become a habit for me since the COVID-19 lockdown restrictions	(Tandon & Kiran, 2019; Venkatesh et al., 2012)
	H2	33. I am addicted to shopping online since the COVID-19 lockdown restrictions	
	H3	34. Online shopping has become natural to me since the COVID-19 lockdown restrictions	
	H4	35. I plan to shop online more now, than prior to the COVID-19 lockdown restrictions	
Consumer Disposition to Trust (DT)	DT1	36. I generally trust other people.	(Kim et al., 2008)
	DT2	37. I generally have faith in humanity.	
	DT3	38. I feel that people are generally reliable.	
	DT4	39. I generally trust other people unless they give me reasons not to.	
Consumer Trust in Website (CT)	CT1	40. I generally believe online shopping websites are trustworthy	(Kim et al., 2008)
	CT2	41. I generally believe my data is safe when shopping on online websites	
	CT3	42. Online shopping retailers give the impression that they keep promises and commitments.	
	CT4	43. The after-sales service of online shopping retailers helps build trust	
	CT5	44. I believe that online shopping retailers have my best interests in mind.	
Perceived Risk (PR)	PR1	45. Purchasing online would involve more product risk (i.e. incorrect product, defective product) when compared with more traditional ways of shopping.	(Kim et al., 2008)
	PR2	46. Purchasing online would involve more financial risk (i.e. fraud, hard to return) when compared with more traditional ways of shopping.	
	PR3	47. How would you rate your overall perception of risk from online shopping compared to in-store shopping?	

APPENDIX B: Establishing a Model Fit

Multiple iterations were run in SPSS AMOS to establish the best model fit. Model 1 was run in SPSS AMOS and the output (Table 18: Standardised Regression Weights) indicated that two factor loadings or standard regression weights (SRW) were below 0.5 (PE5 and FC3) and the modification indices indicated that error term e10 and e11 the error terms for Effort Expectancy (EE) which had a high covariance (41 560). Various scenarios were run to establish the best model fit and they are outlined in Table 16 and the goodness-of-fit statistics are shown in Table 17.

Table 16: CFA Models

Model	Description
Model 1 (Figure 11: Model 1 - Original CFA Diagram	• All questions from the questionnaire
Model 2	• Remove PE5
Model 3	• Remove PE5 and • Remove FC3
Model 4	• Remove PE5, • Remove FC3, • Covariance between e10 and e11
Model 5 (Error! Reference source not found.**)**	• Remove PE5, • Covariance between e10 and e11 • Add Back FC3

- The output of Model 1 had five of the model fit indices within the recommended range(χ^2/df = 1.944, CFI = 0.925, TLI = 0.915, SRMR = 0.056, RMSEA = 0.05), however, the GFI (GFI = 0.844) was not within range.
- Model 2 was run by removing PE5 (SRW = 0.465), which had a low factor loading. The results showed similar model fit statistics (χ^2/df = 1.927, GFI = 0.849, CFI = 0.929, TLI = 0.92, SRMR = 0.055, RMSEA = 0.049). GFI was still slightly low
- Model 3 was run by removing FC3 (SRW = 0.431), in addition to PE5. This resulted in an improvement in the GFI being 0.852. (χ^2/df = 1.93, CFI = 0.932, TLI = 0.923, SRMR = 0.053, RMSEA = 0.049).

Table 17: Model Fit Statistics for the Measurement Model

Fit Indices	Recommended Value	Source(s)	Model 1	Model 2	Model 3	Model 4	Model 5
χ^2/df	<3	(Kline, 2011)	1.944	1.927	1.93	1.849	1.851
GFI	>0.90	Hair et al. (2019)	0.844	0.849	0.852	0.861	0.857
CFI	>0.90	Bentler (1990)	0.925	0.929	0.932	0.938	0.935
TLI	>0.90	Bentler (1990)	0.915	0.920	0.923	0.930	0.927
SRMR	<0.08	Hu and Bentler (1998)	0.056	0.055	0.053	0.052	0.054
RMSEA	<0.05	Hu and Bentler (1998)	0.050	0.049	0.049	0.047	0.047

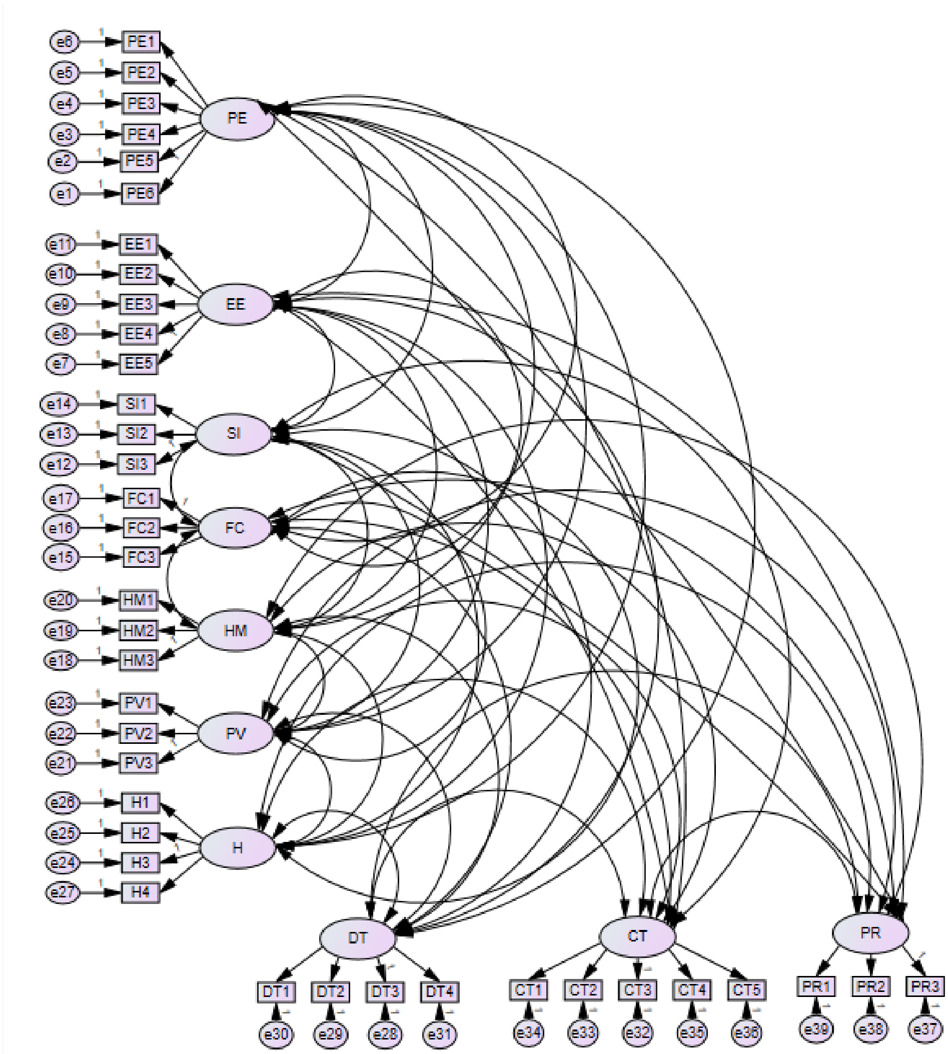

Figure 11: Model 1 - Original CFA Diagram

- Model 4 added a covariance between e10 and e11, and showed an even better improvement on the GFI (χ^2/df = 1.849, GFI = 0.861, CFI = 0.938, TLI = 0.93, SRMR = 0.052, RMSEA = 0.047).
- Since Model 4 showed an improvement on prior models, Model 5 was run by adding back FC3, since best practice suggests a minimum of three variables

per latent variable to ensure the model can be effectively established (Hair et al., 2019). Model 5 was marginally different from Model 4 (χ^2/df = 1.851, GFI = 0.857, CFI = 0.935, TLI = 0.927, SRMR = 0.054, RMSEA = 0.047). As mentioned in 4.6.1, the usage of GFI has declined with the introduction of other indices and in complex models such as an SEM analysis, a fit of 0.8 can be considered an acceptable fit (Doll et al., 1994; Hair et al., 2019). Thus, the GFI was also considered within range. Based on the results, all further analysis was done on Model 5 as it established a good model fit.

Table 18: Standardised Regression Weights

Standardised Regression Weights	Model 1	Model 5
PE6 <--- PE	0.702	0.690
PE5 <--- PE	0.465	*REMOVED*
PE4 <--- PE	0.777	0.777
PE3 <--- PE	0.606	0.616
PE2 <--- PE	0.640	0.648
PE1 <--- PE	0.707	0.710
EE5 <--- EE	0.625	0.658
EE4 <--- EE	0.747	0.776
EE3 <--- EE	0.683	0.703
EE2 <--- EE	0.726	0.665
EE1 <--- EE	0.663	0.592
SI3 <--- SI	0.913	0.913
SI2 <--- SI	0.925	0.925
SI1 <--- SI	0.831	0.831
HM3 <--- HM	0.862	0.862
HM2 <--- HM	0.952	0.952
HM1 <--- HM	0.939	0.939
PV3 <--- PV	0.639	0.639
PV2 <--- PV	0.902	0.901
PV1 <--- PV	0.844	0.844
H3 <--- H	0.878	0.878
H2 <--- H	0.742	0.742
H1 <--- H	0.873	0.873
H4 <--- H	0.873	0.873
DT3 <--- DT	0.840	0.840
DT2 <--- DT	0.855	0.855
DT1 <--- DT	0.770	0.770
DT4 <--- DT	0.723	0.723
CT3 <--- CT	0.647	0.646
CT2 <--- CT	0.757	0.758
CT1 <--- CT	0.772	0.772
CT4 <--- CT	0.546	0.545
CT5 <--- CT	0.667	0.669
PR3 <--- PR	0.536	0.534
PR2 <--- PR	0.877	0.882
PR1 <--- PR	0.681	0.678
FC2 <--- FC	0.906	0.898
FC1 <--- FC	0.788	0.795
FC3 <--- FC	0.431	0.433

APPENDIX C: HTMT Calculations

	FC1	FC2	FC3	PR1	PR2	PR3	CT5	CT4	CT1	CT2	CT3	DT4	DT1	DT2	DT3	H4	H1	H2	H3	PV1	PV2	PV3	HM1	HM2	HM3	SI1	SI2	SI3	EE1	EE2	EE3	EE4	EE5	PE1	PE2	PE3	PE4	PE6
FC1																																						
FC2	0.714																																					
FC3	0.344	0.389																																				
PR1	-0.047	-0.053	-0.026																																			
PR2	-0.061	-0.069	-0.033	0.597																																		
PR3	-0.037	-0.042	-0.02	0.362	0.471																																	
CT5	0.171	0.193	0.093	-0.083	-0.107	-0.065																																
CT4	0.139	0.157	0.076	-0.067	-0.088	-0.053	0.364																															
CT1	0.197	0.223	0.107	-0.095	-0.124	-0.075	0.516	0.42																														
CT2	0.194	0.219	0.106	-0.094	-0.122	-0.074	0.507	0.413	0.585																													
CT3	0.165	0.187	0.09	-0.08	-0.104	-0.063	0.432	0.352	0.499	0.49																												
DT4	0.095	0.107	0.052	-0.074	-0.096	-0.058	0.256	0.208	0.295	0.29	0.247																											
DT1	0.101	0.114	0.055	-0.079	-0.102	-0.062	0.273	0.222	0.315	0.309	0.264	0.557																										
DT2	0.112	0.127	0.061	-0.087	-0.114	-0.069	0.303	0.247	0.349	0.343	0.293	0.618	0.659																									
DT3	0.11	0.125	0.06	-0.086	-0.112	-0.068	0.297	0.242	0.343	0.337	0.287	0.607	0.647	0.718																								
H4	0.212	0.24	0.116	-0.078	-0.101	-0.061	0.223	0.182	0.258	0.253	0.216	0.077	0.082	0.091	0.09																							
H1	0.212	0.24	0.116	-0.078	-0.102	-0.062	0.224	0.182	0.258	0.253	0.216	0.077	0.082	0.091	0.09	0.762																						
H2	0.181	0.204	0.098	-0.066	-0.086	-0.052	0.19	0.155	0.219	0.215	0.184	0.066	0.07	0.078	0.076	0.648	0.648																					
H3	0.214	0.241	0.116	-0.078	-0.102	-0.062	0.225	0.183	0.259	0.255	0.217	0.078	0.083	0.092	0.09	0.766	0.767	0.651																				
PV1	0.215	0.243	0.117	-0.04	-0.052	-0.032	0.248	0.203	0.287	0.282	0.24	0.06	0.064	0.071	0.07	0.361	0.362	0.307	0.363																			
PV2	0.23	0.26	0.125	-0.043	-0.056	-0.034	0.265	0.216	0.306	0.301	0.257	0.064	0.068	0.076	0.075	0.386	0.386	0.328	0.388	0.761																		
PV3	0.163	0.184	0.089	-0.03	-0.04	-0.024	0.188	0.153	0.217	0.213	0.182	0.045	0.048	0.054	0.053	0.274	0.274	0.233	0.275	0.539	0.576																	
HM1	0.242	0.273	0.132	-0.113	-0.147	-0.089	0.216	0.176	0.25	0.245	0.209	0.056	0.059	0.066	0.065	0.513	0.513	0.436	0.516	0.361	0.386	0.274																
HM2	0.245	0.277	0.134	-0.115	-0.15	-0.091	0.219	0.179	0.253	0.249	0.212	0.057	0.06	0.067	0.066	0.52	0.52	0.442	0.523	0.366	0.391	0.277	0.893															
HM3	0.222	0.251	0.121	-0.104	-0.135	-0.082	0.199	0.162	0.229	0.225	0.192	0.051	0.055	0.061	0.06	0.471	0.471	0.401	0.474	0.332	0.354	0.251	0.809	0.82														
SI1	0.079	0.09	0.043	-0.022	-0.029	-0.018	0.138	0.112	0.159	0.156	0.133	0.013	0.014	0.015	0.015	0.311	0.311	0.265	0.313	0.244	0.261	0.185	0.215	0.218	0.197													
SI2	0.088	0.1	0.048	-0.025	-0.033	-0.02	0.153	0.125	0.177	0.174	0.148	0.015	0.016	0.017	0.017	0.346	0.346	0.294	0.348	0.272	0.29	0.206	0.239	0.242	0.22	0.769												
SI3	0.087	0.099	0.048	-0.025	-0.032	-0.019	0.152	0.123	0.175	0.172	0.147	0.014	0.015	0.017	0.017	0.342	0.342	0.291	0.344	0.268	0.287	0.203	0.236	0.239	0.217	0.759	0.844											
EE1	0.285	0.322	0.155	-0.054	-0.07	-0.043	0.218	0.178	0.252	0.247	0.211	0.077	0.082	0.092	0.09	0.289	0.289	0.246	0.291	0.257	0.275	0.195	0.329	0.333	0.302	0.179	0.2	0.197										
EE2	0.321	0.362	0.175	-0.061	-0.079	-0.048	0.245	0.2	0.283	0.278	0.237	0.087	0.093	0.103	0.101	0.325	0.325	0.276	0.327	0.289	0.309	0.219	0.37	0.375	0.34	0.202	0.224	0.222	0.632									
EE3	0.339	0.383	0.185	-0.064	-0.084	-0.051	0.259	0.211	0.299	0.294	0.251	0.092	0.098	0.109	0.107	0.343	0.344	0.292	0.345	0.306	0.327	0.232	0.391	0.396	0.359	0.213	0.237	0.234	0.416	0.468								
EE4	0.374	0.423	0.204	-0.071	-0.092	-0.056	0.286	0.233	0.331	0.325	0.277	0.101	0.108	0.12	0.118	0.379	0.379	0.322	0.381	0.338	0.361	0.256	0.431	0.438	0.396	0.235	0.262	0.259	0.459	0.516	0.546							
EE5	0.317	0.358	0.173	-0.06	-0.078	-0.047	0.243	0.198	0.28	0.275	0.235	0.086	0.092	0.102	0.1	0.321	0.321	0.273	0.323	0.286	0.306	0.217	0.366	0.371	0.336	0.199	0.222	0.219	0.389	0.438	0.463	0.511						
PE1	0.256	0.29	0.14	-0.065	-0.084	-0.051	0.224	0.183	0.259	0.254	0.217	0.068	0.073	0.08	0.079	0.38	0.381	0.323	0.383	0.286	0.305	0.216	0.391	0.396	0.359	0.2	0.222	0.22	0.32	0.36	0.381	0.42	0.356					
PE2	0.234	0.264	0.127	-0.059	-0.077	-0.046	0.205	0.167	0.236	0.232	0.198	0.062	0.066	0.073	0.072	0.347	0.347	0.295	0.349	0.261	0.278	0.197	0.356	0.361	0.327	0.182	0.203	0.2	0.292	0.328	0.347	0.383	0.325	0.46				
PE3	0.222	0.251	0.121	-0.056	-0.073	-0.044	0.195	0.159	0.225	0.221	0.188	0.059	0.063	0.07	0.069	0.33	0.33	0.281	0.332	0.248	0.265	0.188	0.339	0.344	0.311	0.173	0.193	0.19	0.278	0.312	0.33	0.364	0.309	0.438	0.399			
PE4	0.281	0.317	0.153	-0.071	-0.092	-0.056	0.245	0.2	0.283	0.278	0.237	0.074	0.079	0.088	0.086	0.416	0.416	0.354	0.418	0.312	0.334	0.237	0.427	0.433	0.392	0.219	0.243	0.24	0.35	0.394	0.416	0.46	0.389	0.552	0.504	0.479		
PE6	0.249	0.281	0.136	-0.063	-0.082	-0.049	0.218	0.177	0.251	0.247	0.211	0.066	0.07	0.078	0.077	0.369	0.369	0.314	0.371	0.277	0.296	0.21	0.379	0.384	0.348	0.194	0.216	0.213	0.311	0.349	0.369	0.408	0.346	0.49	0.447	0.425	0.536	

Figure 12: Implied Correlations (to Calculate HTMT)

Table 19: HTMT Ratio

Correlation	Heterotrait Correlation	Variable 1	Variable 2	Variable 1 Monotrait Correlations	Variable 2 Monotrait Correlations	HTMT Ratio
PE-EE	0.356	PE	EE	0.473	0.484	0.744
PE-SI	0.207	PE	SI	0.473	0.791	0.339
PE-FC	0.221	PE	FC	0.473	0.482	0.464
PE-HM	0.370	PE	HM	0.473	0.841	0.586
PE-PV	0.261	PE	PV	0.473	0.625	0.479
PE-H	0.355	PE	H	0.473	0.707	0.614
PE-DT	0.073	PE	DT	0.473	0.634	0.133
PE-CT	0.220	PE	CT	0.473	0.458	0.474
PE-PR	-0.065	PE	PR	0.473	0.477	-0.136
EE-SI	0.220	EE	SI	0.484	0.791	0.356
EE-FC	0.292	EE	FC	0.484	0.482	0.604
EE-HM	0.369	EE	HM	0.484	0.841	0.578
EE-PV	0.278	EE	PV	0.484	0.625	0.506
EE-H	0.320	EE	H	0.484	0.707	0.546
EE-DT	0.098	EE	DT	0.484	0.634	0.177
EE-CT	0.254	EE	CT	0.484	0.458	0.539
EE-PR	-0.064	EE	PR	0.484	0.477	-0.133
SI-FC	0.076	SI	FC	0.791	0.482	0.123
SI-HM	0.225	SI	HM	0.791	0.841	0.276
SI-PV	0.246	SI	PV	0.791	0.625	0.350
SI-H	0.321	SI	H	0.791	0.707	0.429
SI-DT	0.015	SI	DT	0.791	0.634	0.022
SI-CT	0.150	SI	CT	0.791	0.458	0.249
SI-PR	-0.025	SI	PR	0.791	0.477	-0.040
FC-HM	0.211	FC	HM	0.482	0.841	0.331
FC-PV	0.181	FC	PV	0.482	0.625	0.329
FC-H	0.183	FC	H	0.482	0.707	0.313
FC-DT	0.093	FC	DT	0.482	0.634	0.169
FC-CT	0.154	FC	CT	0.482	0.458	0.329
FC-PR	-0.043	FC	PR	0.482	0.477	-0.090
HM-PV	0.332	HM	PV	0.841	0.625	0.459
HM-H	0.483	HM	H	0.841	0.707	0.627
HM-DT	0.060	HM	DT	0.841	0.634	0.083
HM-CT	0.214	HM	CT	0.841	0.458	0.345
HM-PR	-0.114	HM	PR	0.841	0.477	-0.180
PV-H	0.328	PV	H	0.625	0.707	0.493
PV-DT	0.062	PV	DT	0.625	0.634	0.099
PV-CT	0.237	PV	CT	0.625	0.458	0.443
PV-PR	-0.039	PV	PR	0.625	0.477	-0.071
H-DT	0.082	H	DT	0.707	0.634	0.123
H-CT	0.218	H	CT	0.707	0.458	0.384
H-PR	-0.077	H	PR	0.707	0.477	-0.133
DT-CT	0.286	DT	CT	0.634	0.458	0.531
DT-PR	-0.084	DT	PR	0.634	0.477	-0.153
CT-PR	-0.086	CT	PR	0.458	0.477	-0.185

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