FACTORS THAT INFLUENCE CONSUMERS' NON-ADOPTION OF FMCG ONLINE SHOPPING POST COVID-19 IN SOUTH AFRICA

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CLEOPATRA MOIPONE MATLI

21649403

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APPROVED FOR FINAL SUBMISSION

Supervisor: ____________________ Date: 30.03.2026

DECLARATION

I, the undersigned, Cleopatra Moipone Matli, do hereby declare that unless otherwise indicated, this thesis is solely the result of my own work. The work has not been previously submitted to any other institution of higher learning for the purpose of obtaining an academic qualification. Furthermore, all sources that have been cited or quoted have been duly acknowledged through a comprehensive list of references. I hereby give consent for this work to be made available for inter-library loan, photocopying and made available to outside interested organisations and students.

Cleopatra Moipone Matli

Date
2026.03.30

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DEDICATION

This PhD is dedicated to the memory of my beloved uncle, Sabata Buti Joseph Matli. Though you are no longer with us in body, your spirit, wisdom, and love have been a constant presence throughout this journey. You believed in me long before I believed in myself, and your stubborn faith in me, unwavering love and encouragement laid the foundation for this achievement.

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Continue watching over us Sebata, Namane e tshehla. Tau!

ABSTRACT

The study investigates the factors influencing the *non-adoption* of online shopping for Fast-Moving Consumer Goods (FMCG) among South African consumers. Despite high internet penetration, advanced payment systems, and growing e-commerce infrastructure, the adoption of online FMCG shopping remains low. Existing literature predominantly focuses on adoption, leaving a critical gap in understanding resistance behaviours. This study addresses this gap by developing and empirically testing an integrated theoretical model that inverts the Unified Theory of Acceptance and Use of Technology (UTAUT), the Social Exchange Theory (SET), Trust Transfer Theory (TTT), Social Presence Theory (SPT) and incorporates Technophobia. Adopting a post-positivist paradigm and a quantitative, cross-sectional design, data were collected from 414 respondents who had never purchased FMCG online. Using Structural Equation Modelling (SEM), the study tested the hypothesised relationships among twelve constructs. The results revealed that while traditional technology-related factors such as negative performance expectancy, effort expectancy, social influence, and facilitating conditions were not significant predictors of non-adoption, relational and trust-based constructs were pivotal. Specifically, perceived lack of reciprocity and distrust in online shopping channels significantly influenced reluctance to shop online, with distrust in online payment systems and lack of social presence emerging as strong antecedents of distrust. The findings highlight that non-adoption stems less from usability or access issues and more from a deficit in trust and social exchange integrity. The study contributes theoretically by inverting the adoption paradigm and practically by offering insights for research practitioners and retailers to design interventions that foster trust and inclusive digital participation in South Africa's evolving e-commerce landscape.

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LIST OF ABBREVIATIONS AND GLOSSARY OF TERMS

AI	Artificial Intelligence
AISPF	AI-Supported Pricing Functions
AR	Augmented Reality
AVE	Average Variance Extracted
BI	Behavioural Influence
CAGR	Compound Annual Growth Rate
CB-SEM	Covariance Based Structural Equation Modelling
CESE	Cost-Effective Service Excellence
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
COMP	Competition
COVID-19	Corona Virus Disease - 2019
CR	Composite Reliability
DiIl	Digital Illiteracy
DOI	Diffusion of Innovation
DOPS	Distrust in Online Payment Systems
DOSC	Distrust in Online Social Channels
DPS	Data and Payment Security
DWLS	Diagonally Weighted Least Squares
EDI	Electronic Data Interchange
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
e-SERVQUAL	Electronic Service Quality
eWOM	Electronic Word-Of-Mouth
FC	Facilitating Conditions
FMCG	Fast Moving Consumer Goods
GFI	Goodness of Fit Index
IBM AMOS	International Business Machines Analysis of Moment Structures

IBM SPSS	International Business Machines Statistical Package for the Social Sciences
ICT	Information and Communication Technologies
IDT	Innovation Diffusion Theory
IP	Internet Protocol
LCA	Latent Class Analysis
LRCP	Lack of Reciprocity
LSCM	Logistics and Supply Chain Management
LSP	Lack of Social Presence
MAR	Missing at Random
MCAR	Missing Completely at Random
ML	Maximum Likelihood
MLR	Robust Maximum Likelihood
MNAR	Missing Not at Random
MSV	Maximum Shared Variance
NEE	Negative Effort Expectancy
NFC	Negative Facilitating Conditions
NFI	Normed Fit Index
NISO	No Intention to Shop Online
NPE	Negative Performance Expectancy
NSI	Negative Social Influence
NWOM	Negative Word-Of-Mouth
O2O	Online-To-Offline
ORD	Organisational Readiness
PBC	Perceived Behavioural Conditions
PCA	Component Factor Analysis
PDA	Personal Digital Assistants
PDA	Personal Digital Assistants
PE	Performance Expectancy
PIS	Participant Information Sheet
PIS	Participant Information Sheet

PMT	Protection Motivation Theory
POPIA	Protection of Personal Information Act
PPC	Pay-Per-Click
PPE	Poor Promotional Effort
RMSEA	Root Mean Square Error of Approximation
RO	Research Objectives
RQ	Research Questions
SABRIC	South African Banking Risk Information Centre
SCT	Social Cognitive Theory
SEM	Structural Equation Modelling
SET	Social Exchange Theory
SI	Social Influence
SNA	Social Network Advertisements
SP	Social Presence
SPT	Social Presence Theory
SRMR	Standardized Root Mean Square Residual
SSL	Secure Sockets Layer
TAM	Technology Acceptance Model
TLI	Tucker-Lewis Index
TOE	Technology-Organisation-Environment
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TTT	Trust Transfer Theory
TV	Television
UFR	User-Friendliness
UGC	User-Generated Content
UID	User Interface Design
USA	United States of America
USAT	User Satisfaction
UTAUT	Unified Theory of Acceptance and Use of Technology

VIF	Variance Inflation Factor
VR	Virtual Reality
WWW	World Wide Web

CHAPTER ONE

OVERVIEW OF THE STUDY

1.1 INTRODUCTION

The adoption of online shopping in South Africa has followed a trajectory of significant growth since its emergence in the 1990s. This expansion accelerated markedly in the post-2000 era, largely propelled by the widespread penetration of internet and mobile technologies (Kemp 2024), and reached a critical inflection point during the COVID-19 pandemic. The human movement restrictions during this period positioned e-commerce not merely as a convenience, but as an essential channel for accessing goods, thereby compelling a wave of adoption. Consequently, a substantial body of scholarly work has emerged investigating the drivers of e-commerce adoption, including within the South African context.

However, this focus on adoption created a significant theoretical and practical blind spot: a systematic understanding of non-adoption. The persistent reluctance of a substantial consumer segment to engage in online shopping, particularly for Fast-Moving Consumer Goods (FMCG), remains an under-explained phenomenon. This gap renders the present study both pertinent and critical, as it seeks to contribute to the literature on e-commerce resistance by shifting the analytical lens from the factors that attract consumers to those that actively prevent them.

This chapter serves as the foundational introduction to the entire thesis. It is structured to logically guide the reader from the broad context to the specific contribution of this research. The chapter begins by delineating the Context of the Study, which identifies the research gaps and provides the foundational motivation for the inquiry. This is followed by a clear problem statement that formalises these gaps. Subsequent sections outline the research objectives and research questions formulated to operationalise the research problem. The chapter then clarifies the delimitations of the study to define its conceptual and methodological boundaries. A brief literature review synthesises key existing knowledge and situates the study within the academic conversation. An overview of the research methodology is then provided, followed by a summary of key findings. The chapter concludes by presenting the thesis structure and providing a final chapter summary.

1.2 CONTEXT OF THE STUDY

Online shopping, defined as the demand-side aspect of e-commerce involving the purchasing of products via digital platforms backed by advanced information and communication technologies (Chaffey and Ellis 2019), has undeniably precipitated a paradigm shift in global retail. This transformation is driven by factors such as technophilia, the pursuit of convenience, and the influx of digital-native generations (Martínez-Córcoles, Teichmann and Murdvee 2017; Ronit 2011). The COVID-19 pandemic further accelerated this shift, acting as a catalyst that forced a global surge in e-commerce adoption as lockdowns restricted physical store access (Guo, Liu, Shi and Chen 2020; Pantano, Pizzi, Scarpi and Dennis 2020).

In South Africa, this was evidenced by a 66% spike in online sales in 2020 (ITA 2024), with revenue projected to reach ZAR 400 billion by 2025 (BusinessTech 2022) and ZAR 1.3 trillion, equivalent to US$75 billion by 2033 (Renub Research 2025). The country's digital commerce infrastructure comprised high internet penetration (78.9%), near-universal smartphone adoption (Kemp 2024), sophisticated payment systems, and enhanced logistics networks (Renub Research 2025). South Africa's e-commerce landscape features established domestic platforms including Takealot, Checkers Sixty60, and Woolworths Online (Kemp 2024; Goga, Paelo and Nyamwena 2019), while recent market entries by international e-commerce platforms such as Amazon, Temu, and Shein have intensified cross-border commerce activity and competitive dynamics within the sector.

Despite this conducive environment and the global trend towards digital consumption, the adoption of online shopping for FMCG in South Africa remains nascent and disproportionately low (Pillay and Mayayise 2021; Pentz, du Preez and Swiegers 2020). Fast Moving Consumer Goods which include frequently purchased, low-cost items such as food, beverages, and personal care products represent a cornerstone of the retail sector. Therefore, the reluctance of a substantial consumer segment to migrate this essential form of shopping behaviour to an online format presents a significant paradox. This is compounded by reports that even amidst growth, a staggering 71% of South African online shoppers abandon their carts at the digital checkout point (Rogerwilco 2019), hinting at deep-seated barriers that extend beyond mere access.

The scholarly discourse on online shopping has been overwhelmingly skewed towards understanding the drivers of adoption, utilising established theoretical frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation

(DOI), Technology-Organisation-Environment (TOE) and the Technology Acceptance Model (TAM) to explain positive behavioural intention (Venkatesh, Morris, Davis and Davis 2003; Davis 1989; Rogers 1995; Tornatzky and Fleischer 1990). While valuable, this adoption-centric focus has created a critical gap in understanding the rationale of the "non-adopter" – the individual who consciously resists or avoids online shopping channels.

The existing literature reveals a clear schism; numerous studies investigate what motivates online shopping in South Africa (for example, Goga, Paelo and Nyamwena 2019; Gaoaketse, Ligaraba and Chuchu 2023; Makhitha, Van Scheers and Mogashoa 2019; Moeti, Mokwena and Malebana 2021), yet virtually none exclusively targeted the factors influencing the non-adoption of FMCG online shopping. As Nery-da-Silva, de Araujo and de Souza Meirelles (2024) aptly decried, "non-shoppers are seldom addressed alone." Previous research that touches on barriers, such as Pentz, du Preez and Swiegers (2020) who studied perceived risks, typically sampled individuals with prior online shopping experience, thereby investigating repeat purchase behaviour rather than fundamental non-adoption. This is a crucial distinction, as non-adoption behaviour is not merely the inverse of adoption; using adoption findings in reverse may not adequately explain the complex reasons for refusal (Mainardes, de Souza and Correia 2020; Richetin, Conner and Perugini 2011). The few international studies that have focused on non-adoption, such as those in Brazil and the Philippines, have identified key barriers including distrust, perceived risk, operational difficulties, and a lack of perceived utility (Nery-da-Silva de Araujo and de Souza Meirelles 2024). However, the unique socio-economic and technological context of the South African market necessitates a localised investigation.

It is against this backdrop that the present study is conceived. The research is driven by the need to invert the dominant narrative and rigorously investigate the factors that predict the reluctance to shop for FMCG online in post-pandemic South Africa. The rationale for this study is to bridge the identified knowledge gap by developing and testing an integrated theoretical model that deliberately inverts and extends established theories. Drawing from the UTAUT, the study employs negative performance expectancy, negative effort expectancy, negative social influence, and negative facilitating conditions to frame non-adoption. This core is integrated with constructs from the Social Exchange Theory (SET) (perceived lack of reciprocity), the Trust Transfer Theory (TTT) (distrust in online payment systems and shopping channels), and the Social Presence Theory (SPT) (lack of social presence) to provide a holistic explanation.

Furthermore, the model incorporates the moderating effects of poor promotional effort and digital illiteracy to understand how marketing and skill deficiencies exacerbate these barriers. Therefore, this study does not seek to re-examine why people adopt online shopping, but rather to provide a seminal, theory-grounded explanation for why a significant portion of the South African market resists it, thereby offering valuable insights for academia and practical strategies for retailers and policymakers aiming to foster inclusive digital transformation.

1.3 PROBLEM STATEMENT

The digital transformation of retail, particularly in the FMCG sector, is a critical driver of economic efficiency and consumer convenience in the 21st century. In South Africa, despite a conducive environment of high internet penetration, advanced payment systems, and a competitive e-commerce landscape, the adoption of online FMCG shopping remains disproportionately low and nascent (Pillay and Mayayise 2021; Pentz, du Preez and Swiegers 2020; Statista 2025). This non-adoption by a substantial consumer segment represents a significant paradox.

It signifies a failure of the digital market to achieve inclusivity, potentially exacerbating digital divides and foregoing substantial economic opportunities for both businesses and consumers. The magnitude of this challenge is evidenced by South Africa's modest online shopping adoption rate of approximately 19% in 2025, projected to reach only 33% by 2029 (Statista 2025), significantly below global benchmarks. Ecommerce accounts for only about 16.2% of retail activity (Ramos, Martinez, Martinez, Abreu. and Rubio 2025). Additionally, the 71% cart abandonment rate (Rogerwilco 2019) suggested that barriers transcend infrastructural access limitations, reflecting deeper psychological and perceptual impediments rooted in consumer cognition and trust formation processes. Consequently, identifying and addressing the fundamental drivers of e-commerce resistance constitutes not merely an academic inquiry but a critical policy imperative for advancing digital economic inclusion and equitable participation in South Africa's evolving digital economy.

Central to this investigation is a critical gap in existing e-commerce scholarship: an overwhelming predominance of adoption-centric research has created systematic theoretical and empirical gaps in understanding non-adoption phenomena. Both global and South African literature exhibits myopic focus on explaining technology acceptance, leaving the determinants that actively deter consumers from e-commerce participation systematically underexplored.

Existing scholarship fails to provide comprehensive, theoretically grounded models that exclusively investigate non-adoption determinants within specific contextual parameters.

This knowledge gap is compounded by fundamental methodological limitations in barrier-focused research. Studies examining e-commerce barriers frequently sample existing online shoppers (e.g. Daroch, Nagrath and Gupta 2020; Soundrapandian and Priya 2024), thereby investigating repeat purchase intentions rather than foundational adoption decisions. Other investigations lack explicit sampling criteria transparency regarding non-adopter inclusion (Pentz, du Preez and Swiegers 2020), while additional studies conflate experienced and inexperienced consumers within single analytical samples (e.g. Braun and Osman 2024; Clemes, Gan and Zhang 2014). Nery-da-Silva, de Araujo and de Souza Meirelles (2024) argued convincingly that failing to exclusively sample non-adopters render their motivations, perceptions, and psychological barriers both theoretically and practically invisible, perpetuating incomplete understanding of e-commerce rejection mechanisms.

This study is driven by the need to fill this void. It systematically addresses the problem by developing and empirically testing an integrated theoretical model that deliberately inverts the adoption-centric paradigm. The proposed research moves beyond simply identifying barriers to constructing a predictive model that explains how key factors, including inverted UTAUT constructs, technophobia, perceived lack of reciprocity, and multifaceted distrust, interact to influence non-adoption. Furthermore, it investigates how these relationships are exacerbated or mitigated by contextual factors like digital illiteracy and poor promotional efforts. By providing a seminal, evidence-based explanation for FMCG e-commerce resistance in post-pandemic South Africa, this research will equip academics, retailers, and policymakers with the insights needed to develop targeted strategies to convert non-adopters and bridge the digital commerce divide.

1.4 RESEARCH OBJECTIVES

The primary aim of this research is to develop and empirically test an integrated theoretical model that explains the factors influencing the non-adoption of online shopping for FMCG among South African consumers. In this study, non-adoption is conceptualised as encompassing both active resistance (deliberate rejection of online shopping) and passive non-use (the absence of adoption due to lack of perceived need, opportunity, or access). To achieve this aim, the following specific secondary objectives are formulated:

- **RO1:** To examine the extent to which negative performance expectancy, negative effort expectancy, negative social influence, and negative facilitating conditions predict consumers' reluctance to shop for FMCG online.
- **RO2:** To determine the direct influence of technophobia, perceived lack of reciprocity, and distrust in online shopping channels on consumers' reluctance to shop for FMCG online.
- **RO3:** To investigate the relationships between (i) perceived lack of reciprocity, (ii) distrust in online payment systems, and (iii) lack of social presence, and how these factors contribute to the development of distrust in online shopping channels.
- **RO4:** To assess how poor promotional effort moderates the relationship between (i) negative performance expectancy and (ii) technophobia on consumers' reluctance to shop online.
- **RO5:** To evaluate the moderating effect of poor promotional effort on the relationship between distrust in online payment systems and distrust in online shopping channels.
- **RO6:** To explore the extent to which digital illiteracy moderates the relationship between (i) negative performance expectancy, (ii) negative effort expectancy, and (iii) technophobia on consumers' reluctance to shop online.
- **RO7:** To propose a framework to assist retailers in enhancing the adoption of FMCG online shopping.

1.5 RESEARCH QUESTIONS

To operationalise the research objectives, this study is guided by the following research questions (RQs):

1.5.1 Primary Research Question:

What integrated set of factors, drawn from inverted technology adoption and social theories, best predicts and explains the reluctance to adopt online shopping for FMCG in the South African context?

1.5.2 Secondary Research Questions:

- **RQ1:** To what extent do negative performance expectancy, negative effort expectancy, negative social influence, and negative facilitating conditions significantly predict reluctance to shop for FMCG online?

- **RQ2:** What is the direct influence of technophobia, perceived lack of reciprocity, and distrust in online shopping channels on the reluctance to shop for FMCG online?
- **RQ3:** What are the relationships between (i) a perceived lack of reciprocity, (ii) distrust in online payment systems, (iii) a lack of social presence, and the development of distrust in online shopping channels?
- **RQ4:** How does poor promotional effort moderate the effect of (i) negative performance expectancy, and (ii) technophobia on the reluctance to shop online?
- **RQ5:** How does poor promotional effort moderate the effect of distrust in online payment systems on distrust in online shopping channels?
- **RQ6:** To what extent does digital illiteracy moderate the effect of (i) negative performance expectancy, (ii) negative effort expectancy, and (iii) technophobia on reluctance to shop online?

1.6 SCOPE (DELIMITATIONS) OF THE STUDY

This study's scope was deliberately bounded to ensure a focused investigation into the non-adoption of online shopping for FMCG in South Africa. The research was conceptually delimited to an integrated theoretical framework combining the inverted UTAUT with the SET, TTT, and SPT. This framework was selected for its comprehensive ability to capture the multifaceted technological, social, and trust-based barriers to adoption (Venkatesh *et al.* 2003; Stewart 2003; Blau 1964), thereby excluding other potential models or external variables like personality traits.

Furthermore, the study was sectorally confined to the FMCG retail segment, encompassing frequently purchased items like food and personal care products, as this area represents a critical yet underpenetrated segment of the online market, distinct from high-involvement categories like electronics or fashion (Goga, Paelo and Nyamwena 2019; Statista 2025).

Geographically and temporally, the inquiry was contextualised within South Africa's unique socio-economic and digital landscape in the post-pandemic era, providing a contemporary snapshot of non-adoption barriers without claiming direct generalisability to other national or temporal contexts (Kemp 2024; Statista 2025).

The chosen scope inherently introduces limitations, primarily concerning methodological generalisability and the constraints of the research design. The use of a non-probability sampling method, while necessary to access the specific population of non-adopters, limits the statistical generalisability of the findings to the entire South African population (Saunders, Lewis and Thornhill 2019). To mitigate this, the study employed a substantial sample size (n $\geq$ 385) determined by Cochran's formula and utilised Structural Equation Modelling (SEM), technique robust for theory testing and identifying relationships within such samples (Hair, Page and Brunsveld 2020; Kline 2016). Additionally, the cross-sectional, self-report design carries the risk of common method bias and precludes definitive causal inferences. To attenuate these concerns, procedural remedies were incorporated into the questionnaire design, and statistical tests for common method variance were employed (Podsakoff, MacKenzie, Lee and Podsakoff 2003). While this establishes critical predictive relationships, it is acknowledged that future longitudinal or experimental studies are required to confirm causality, a common and accepted progression in behavioural research (Sekaran and Bougie 2016).

1.7 LITERATURE OVERVIEW

E-commerce discourse has been overwhelmingly dominated by an adoption-centric paradigm, utilising established theories like UTAUT (Venkatesh *et al*. 2003), TAM (Davis 1989), and the Theory of Planned Behaviour (TPB) (Ajzen 1991) to explain positive behavioural intention. In the South African context, this has resulted in a significant body of work investigating what drives online shopping (e.g. Heyns and Kilbourn 2022; Ligaraba *et al*. 2023; Makhitha Van Scheers and Mogashoa 2019; Moeti, Mokwena and Malebana 2021), while systematically neglecting the rationale of the non-adopter. This study posits that non-adoption is not merely the inverse of adoption (Mainardes, de Souza and Correia 2020) and seeks to fill this critical gap by inverting the analytical lens.

This investigation's theoretical foundation deliberately inverts the UTAUT framework to illuminate non-adoption mechanisms. While UTAUT establishes performance expectancy, effort expectancy, social influence, and facilitating conditions as positive predictors of behavioural intention (Venkatesh *et al*. 2003), this study posits that their negative manifestations constitute primary determinants of e-commerce resistance. Empirical evidence supports this theoretical repositioning: perceived utility deficits (Oematan, Rahayu and Trisnawati 2024), navigational complexity, especially for the elderly users (Bringula 2016), negative social influence from important referents (Ajzen 1991; Baethge, Klier, Klier and Lindner 2017), and unfavourable facilitating conditions such as poor connectivity or a lack of support (Lawrence and Tar 2010) undermine adoption intentions. This theoretical inversion establishes the technological and utilitarian foundations of the proposed non-adoption model, demonstrating that rejection mechanisms operate through distinct psychological pathways rather than simply representing adoption factors' absence. Beyond utilitarian barriers, the literature reveals profound psychological and relational impediments. Technophobia, defined as an exaggerated fear or anxiety towards technology (Osiceanu 2015), is identified as a key obstacle to technology adoption (Subero-Navarro Pelegrín-Borondo, Reinares-Lara and Olarte-Pascual 2022) and is hypothesised to directly influence online shopping reluctance. Furthermore, the SET illuminates the role of reciprocity. Consumers engage in a cost-benefit analysis, often trading personal data for personalised value (Degutis, Urbonavičius, Hollebeek and Anselmsson 2023; Urbonavicius, Degutis, Zimaitis, Kaduskeviciute and Skare 2021). A perceived lack of reciprocity, where consumers feel their data disclosure is not adequately rewarded or their privacy is threatened, can erode the foundation of this exchange, leading to non-participation (Luo 2002).

Consumer trust, defined as the belief in the reliability and integrity of online retailers, can be undermined when consumers perceive a lack of reciprocity in their interactions with digital platforms (Maluleke, Motseki, Mokwena and Dlamini 2021). This perceived imbalance, where consumers feel that retailers do not deliver fair value or act in their best interest, weakens relational trust. According to TTT, such diminished trust in specific online vendors can transfer to a broader distrust of online shopping channels (Stewart, 2003).

The impersonal nature of digital interfaces introduces another critical barrier: a lack of social presence. Rooted in the SPT, this concept refers to the perceived presence of others in mediated communication (Short, Williams and Christie 1976). In online shopping, the absence of non-verbal cues and human interaction can undermine psychological intimacy and trust (Lu, Fan and Zhou 2016; Leong and Meng 2022). This study argued that this perceived lack of social presence fosters apprehension about an online business's reliability, thereby feeding into the broader construct of distrust in online shopping channels (Lee, Ahn, Song, and Ahn 2018).

Finally, the model acknowledges that these core relationships are not static but are exacerbated or mitigated by contextual factors. The study integrates the moderating roles of digital illiteracy and poor promotional effort. Digital illiteracy, a lack of the skills and confidence to use technology effectively (Fernando and Jain 2022), is expected to amplify the negative effects of performance and effort expectancy, as well as technophobia. Concurrently, poor promotional effort by e-commerce businesses fails to assuage fears, educate consumers, and articulate the value proposition, thereby strengthening the barriers posed by negative performance expectations, technophobia, and distrust (Belch and Belch 2016).

In summary, this brief review establishes that a comprehensive explanation of non-adoption requires moving beyond a simple inversion of adoption models. It necessitates an integrated

Theoretical framework that combines the inverted UTAUT's utilitarian barriers with the psychological barrier of technophobia, the relational fractures explained by SET and TTT, and the human-centric void captured by SPT, all while accounting for the critical moderating influence of user capability and marketer communication. It is this integrated model that the present study employs to address the identified gap in the literature. Figure 1.1 depicts the conceptual framework and hypothesised relationships which underpin the study.

Grounded in the extended UTAUT, SET, TTT, and SPT, this study sought to understand the factors that hinder consumers' intention to adopt online grocery shopping platforms in South Africa. While previous research has largely focused on drivers of technology adoption, this study adopts an inverse perspective by examining factors that may contribute to non-adoption or resistance toward online shopping. In this context, the hypotheses were formulated to test the influence of negative perceptions of technology-related constructs.

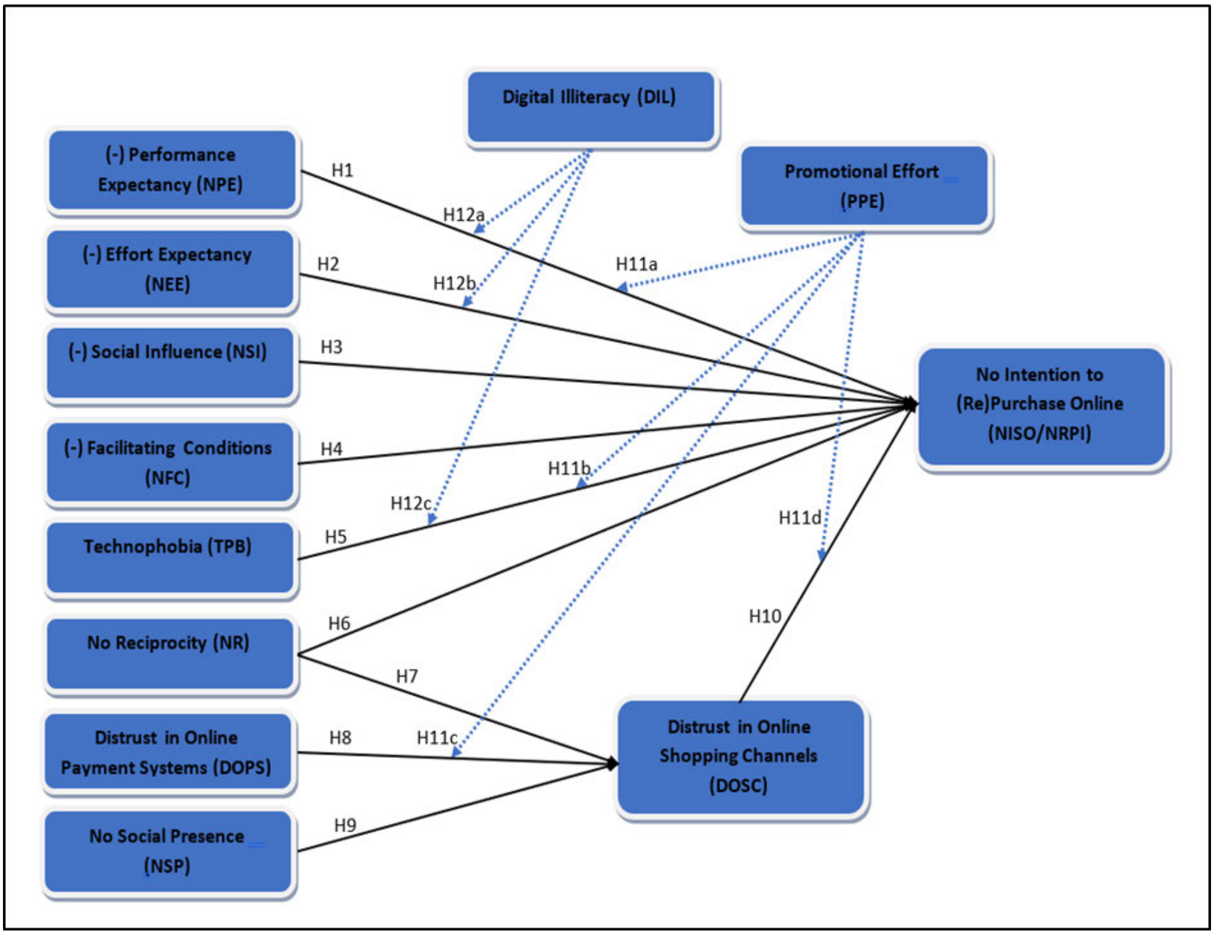


Figure 1.1: Integrated Conceptual Framework

Source: Researcher 2025

H1: Negative performance expectancy significantly predict a lack of intention to shop online.

H2: Negative effort expectancy significantly predict a lack of intention to shop online.

H3: Negative social influence significantly predicts a lack of intention to shop online.

H4: Negative facilitating conditions significantly predict a lack of intention to shop online.

H5: Technophobia significantly predicts a lack of intention to shop online.

H6: Perceived lack of reciprocity significantly predict a lack of intention to shop online.

H7: Perceived lack of reciprocity significantly influence distrust in online shopping.

H8: Distrust of online payment systems significantly influence distrust in online shopping channels.

H9: Lack of social presence significantly influence distrust in online shopping channels.

H10: Distrust of online shopping channels significantly predict a lack of intention to shop online.

H11a: Poor promotional effort positively moderates the effect of negative performance expectancy on the lack of intention to shop online.

H11b: Poor promotional effort positively moderates the effect of technophobia on the lack of intention to shop online.

H11c: Poor promotional effort positively moderates the effect of distrust in online payment systems on distrust of online shopping channels.

H11d: Poor promotional effort positively moderates the effect of distrust in online shopping systems on the lack of intention to shop online.

H12a: Lack of digital literacy positively moderate the effect of negative performance expectancy on the lack of intention to shop online.

H12b: Lack of digital literacy positively moderate the effect of negative effort expectancy on the lack of intention to shop online.

H12c: Lack of digital literacy positively moderate the effect of technophobia on the lack of intention to shop online.

1.8 METHODOLOGY OVERVIEW

This study is situated within the post-positivist research paradigm, which acknowledges an objective reality while recognising the fallibility of human observation and measurement (Guba and Lincoln 1994; Iofrida, De Luca, Strano and Gulisano 2018). This paradigm was deemed appropriate as it allows for the systematic and objective investigation of the factors influencing online shopping reluctance, a social phenomenon that exists independently of the researcher (Bryman 2016; Saunders, Lewis and Thornhill 2019). Ontologically, the study adopts a critical realist stance, viewing the constructs under investigation as objective entities that can be quantified. Epistemologically, it employs an objectivist approach, using scientific methods to generate reliable and generalisable knowledge (Neuman 2014). Methodologically, a mono-method quantitative approach was selected to statistically test the hypothesised relationships within the proposed conceptual framework (Sekaran and Bougie 2016).

The research design is a cross-sectional, descripto-explanatory survey (Bellamy 2012; Saunders, Lewis and Thornhill 2019). This strategy enables both a description of the characteristics of the target population and an explanation of the causal relationships between the variables influencing the reluctance to shop for FMCG online. The study was conducted in a natural, non-contrived setting with minimal researcher interference, as no variables were manipulated (Sekaran and Bougie 2016).

The target population consisted of individuals aged 18 years and above, residing in South Africa, who have never purchased FMCG online. A combination of convenience and snowball sampling techniques was employed to recruit participants (Collis and Hussey 2021). To ensure participants met the study's criteria, screening questions were incorporated into the research instrument. The sample size was determined using Cochran's (1977) formula for an unknown population, resulting in a target of 385 respondents. This sample size is considered robust for the planned statistical analyses, including Structural Equation Modelling (SEM) (Kline 2016; Soper 2025).

Data collection was executed via an online questionnaire developed on the Microsoft Forms platform. The instrument was structured into several sections: a Participant Information Sheet and consent form, demographic questions, and multi-item scales measuring the constructs of the integrated theoretical model (drawn from the UTAUT, TTT, SET, and SPT). The scales primarily used Likert-type items, which were treated as interval data for analysis, a practice supported by methodological literature (Carifio and Perla 2008; Norman 2010). The questionnaire was distributed through social media platforms (Facebook, Instagram, and WhatsApp) using a digital flier containing a link and a QR code, leveraging the high internet and social media penetration in South Africa (Kemp 2024).

The data analysis followed a two-stage process. First, data cleaning and preparation was conducted, addressing missing data, outliers, and testing for statistical assumptions such as normality and multicollinearity (Gaskin 2022). Subsequently, the analysis employed both descriptive and inferential statistics. The analytical techniques included Exploratory Factor Analysis (EFA) to assess the underlying structure of the constructs and Structural Equation Modelling (SEM) to test the hypothesised relationships and the overall model fit.

To ensure the rigour and trustworthiness of the findings, the study adhered to established principles of reliability and validity (Fornell and Larcker 1981; Sekaran and Bougie 2016). Reliability was assessed using Cronbach's alpha and composite reliability estimates to confirm the internal consistency of the measurement scales. Validity will be evaluated through content validity, face validity, and construct validity (convergent and discriminant). Furthermore, the research received ethical approval from the university's ethics committee. Ethical principles of informed consent, anonymity, confidentiality, and voluntary participation were strictly maintained throughout the data collection process, in accordance with the Protection of Personal Information Act (POPI Act).

1.9 SUMMARY OF KEY FINDINGS

The analysis of data from 414 South African non-adopters of online FMCG shopping yielded several critical findings. Following rigorous data cleaning and validation procedures, the measurement model demonstrated satisfactory fit indices (CFI = .95, TLI = .94, RMSEA = .038), with composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV), and square root of AVE values all meeting established psychometric thresholds (Bollen and Stine 1992; Fornell and Larcker 1981; Hu and Bentler 1999; Kline 2023). These results confirm adequate construct reliability and validity, with the exception of Poor Promotional Effort, which exhibited insufficient psychometric properties and was subsequently excluded from subsequent analyses. Descriptive statistics revealed pronounced negative perceptions among respondents, with all constructs' mean scores exceeding 3.4 on the five-point scale, surpassing the neutral midpoint threshold and indicating substantive disagreement with e-commerce participation.

The structural model testing, however, provided a more nuanced picture. Contrary to expectations derived from the inverted UTAUT framework, the core constructs of Negative Performance Expectancy, Negative Effort Expectancy, Negative Social Influence, Negative Facilitating Conditions, and Technophobia did not exhibit a statistically significant direct influence on the reluctance to shop online (all *p*-values > .05). Instead, the reluctance was significantly driven by factors related to trust and social exchange. Specifically, Perceived Lack of Reciprocity ($\beta = 0.183$, $p = 0.014$) and Distrust in Online Social Channels ($\beta = 0.368$, $p < .001$) were found to be significant positive predictors of non-adoption intention. Furthermore, the model explained a substantial portion of the variance in Distrust in Online Social Channels ($R^2 = 0.33$), which was itself significantly influenced by Distrust in Online Payment Systems ($\beta = 0.499$, $p < .001$) and a Perceived Lack of Social Presence ($\beta = 0.199$, $p < .001$). Finally, the proposed moderating effect of Digital Illiteracy on the relationships between key predictors and reluctance to shop online was not supported (Hayes, 2022).

These findings shift the explanatory focus from conventional ease-of-use and utility barriers to the more profound roles of distrust in digital intermediaries and disrupted social exchange principles as the primary drivers of online shopping reluctance in the South African FMCG context.

1.10 THESIS STRUCTURE

This thesis is structured into seven distinct but interconnected chapters, each designed to systematically address the research problem and achieve the stated objectives. The organisation of the thesis is as follows:

Chapter One: Overview of the study

This chapter provides a foundational overview of the research. It presents the background to the study, articulates the problem statement, and clearly defines the research questions and objectives. It also outlines the significance of the study, delimits its scope, and includes a condensed methodology overview and a summary of key findings to offer a preliminary insight into the research outcomes.

Chapter Two: Online Shopping Literature Review

This chapter offers a comprehensive and critical examination of existing scholarly work relevant to the study. The review outlines the global and local foundations of online shopping and synthesises these perspectives on online shopping adoption. The chapter further foregrounds the non-adoption phenomenon, which is central to the study.

Chapter Three: Theorising Online Shopping

Building on the literature review, this chapter presents the integrated theoretical framework that guides the research. It elaborates on the constructs drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT), Trust Transfer Theory (TTT), Social Exchange Theory (SET), and Social Presence Theory (SPT). The chapter logically develops the study's hypotheses, outlining the proposed relationships between the independent, dependent, and moderating variables.

Chapter Four: Research Methodology

This chapter details the philosophical and practical design of the research. It justifies the adoption of a post-positivist paradigm and a quantitative, descripto-explanatory approach. The chapter thoroughly describes the research design, including the sampling strategy (convenience and snowball), sample size determination, instrument development, data collection procedures via an online survey, and the planned data analysis techniques, including Structural Equation Modelling (SEM). It also addresses issues of reliability, validity, and ethical considerations.

Chapter Five: Results Presentation and Interpretation

This chapter presents the empirical findings of the study. It begins with data cleaning and preparation, followed by a profile of the sample. The chapter then provides descriptive statistics for all constructs and presents the results of the hypotheses testing through Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). The results are clearly interpreted, stating which hypotheses were supported or rejected.

Chapter Six: Discussion and Key Findings

The chapter discusses the key findings in relation to the existing literature and the study's theoretical framework. It interprets the implications of the results, explaining the drivers of non-adoption identified in the South African context.

Chapter Seven: Conclusions, Contributions and Recommendations

The final chapter concludes by summarising the answer to the research questions, highlighting the theoretical and practical contributions, acknowledging the study's limitations, and proposing actionable recommendations for stakeholders and future research.

1.11 SUMMARY OF THE CHAPTER

This chapter has served as the foundational introduction to the thesis, establishing the research's necessity, direction, and structure. It commenced by contextualising the study within the South African e-commerce landscape, highlighting the paradox of robust digital infrastructure coexisting with the persistent non-adoption of online shopping for FMCG. The Problem Statement formally articulated this issue, identifying a critical gap in the literature: the overwhelming focus on adoption drivers has left the motivations of non-adopters

systematically underexplored. To address this gap, the chapter presented clear Research Objectives and corresponding Research Questions aimed at developing and testing an integrated theoretical model to explain this reluctance.

The scope of the study was delineated, confirming its focus on an integrated framework of inverted technology adoption and social theories within the South African FMCG context. A brief literature review substantiated the theoretical foundation, arguing for a model that combines inverted UTAUT constructs with technophobia, distrust, and a lack of social presence, moderated by digital illiteracy and promotional effort. The Methodology Overview justified the post-positivist, quantitative survey approach, detailing the sampling, data collection, and analysis plans designed to test the proposed model rigorously. A summary of the key findings provided a preliminary insight, indicating that trust and social exchange factors, rather than traditional ease-of-use barriers, are primary drivers of non-adoption. Finally, the chapter concluded with an outline of the thesis structure, guiding the reader through the logical progression of the subsequent chapters. Collectively, this introduction establishes a compelling rationale for the research and a clear roadmap for the inquiry to follow.

CHAPTER TWO
LITERATURE REVIEW

2.1 INTRODUCTION

E-commerce has experienced rapid growth, becoming a transformative force in business, similar to the industrial revolution. Technological advancements, such as improved network bandwidth and the widespread use of digital devices, have fueled this growth, enabling online retail stores to thrive. These advancements have enhanced consumer engagement with e-commerce, expanding opportunities for businesses. Online retail, characterised by diverse business models like subscriptions and pay-per-product, offers increased sales, broader market reach, and reduced operational inefficiencies, enabling cost-effective competition. The global rise in online transactions is evident, with e-commerce outperforming traditional retail growth.

The growth of online retail is also notable in the South African market, which is seeing a shift in consumer behaviour towards online shopping. Despite this, there are challenges hindering widespread adoption, particularly in the context of FMCG. Chapter one of the study provided an overview of the topic and frames the research questions. This chapter builds on existing literature, exploring the barriers to FMCG online shopping in South Africa, identifying gaps in current knowledge. By delving into these challenges, the chapter aims to offer insights to foster the adoption of online shopping and contribute to the ongoing discourse on e-commerce in the South African market.

Figure 2.1 provides a graphical presentation of the chapter structure for ease of reference. The chapter begins by foregrounding online shopping as a paradigm shift in consumer behaviour, and then critically reviews the literature to expound the concepts relevant to the research questions presented in chapter one.

Figure 2.1: Chapter Structure

Source: Researcher 2025

2.2 TRADITIONAL SHOPPING

Traditional stores commonly known as brick-and-mortar retail stores refer to the customary way of purchasing and selling of both tangible and intangible products through direct, physical interactions in shops, markets, and other face-to-face settings (Hansen 2021). For years, this model has played a vital role in the development of economies and societies (Banaji 2020). Grounded in personal interactions, human relationships, and the physical buying and selling of goods, traditional commerce provides a rich and engaging experience that continues to hold significance in the modern era (Khan, Hollebeek, Fatma, Islam, and Riivits-Arkonsuo 2020).

One of its defining features is the face-to-face engagement between consumers and businesses, fostering trust and familiarity that can be difficult to achieve in other forms of commerce. This personal connection is fundamental to the overall experience, creating a level of trust and familiarity that is often challenging to replicate in other forms of commerce.

Customers also benefit from the ability to physically inspect and experience products by seeing, touching, or trying them before purchasing (Pino, Amatulli, Nataraajan, De Angelis, Peluso, and Guido 2020). This hands-on interaction helps consumers make better-informed decisions based on their direct experience with the products (Khan et al. 2020).

The social aspect of traditional commerce significantly contributes to its enduring appeal (Zafar, Qiu, Shahzad, Shen, Bhutto, and Irfan 2021). Shopping in physical spaces is often a communal activity, where people come together to interact, share experiences, and exchange ideas (Pino et al. 2020). Markets, malls, and retail stores serve as social hubs that strengthen community ties and enhance the shopping experience through personal interaction (Misra and Verma 2023). For many consumers, the act of shopping extends beyond purchasing goods it represents a social activity that fosters connection and a sense of belonging (Ameen, Tarhini, Shah, and Madichie 2021).

In contrast to open-air markets, shopping malls provide a more controlled, comfortable, and climate-regulated environment designed to elevate the overall customer experience. This evolution highlights how traditional retail has adapted to meet shifting consumer expectations offering not only products but also integrated experiences such as dining and entertainment to attract and retain shoppers in a highly competitive landscape (Isharyani, Sopha, Wibisono, and Tjahjono 2024).

Another defining component of traditional commerce is customer service (Lee and Lee 2020). Within brick-and-mortar settings, the attentiveness and professionalism of sales staff play a vital role in shaping customer satisfaction (Teixeira, Duarte, Macau, and de Oliveira 2022). The ability to seek advice, ask questions, and receive personalised recommendations from knowledgeable employees adds value to the shopping experience and often influences purchasing choices (Hansen 2021). High-quality customer service fosters customer loyalty, encourages repeat business, and drives positive word-of-mouth—key factors in the long-term success of physical retail establishments (Cuesta-Valino, Gutiérrez-Rodríguez, and García-Henche 2022).

Moreover, traditional commerce is essential to sustaining local economies. Independent retailers, small businesses, and community markets form the backbone of this system, strengthening local economic resilience (Song, Escobar, Arzubiaga, and De Massis 2022).

These businesses often source their goods locally, fostering a mutually beneficial relationship between producers and retailers that strengthens the local economy (Isharyani, Sopha, Wibisono and Tjahjono 2024). Furthermore, traditional commerce generates employment opportunities, from retail staff to supply chain workers, further supporting the economic structure of communities (Watson 2023).

However, traditional commerce faces several challenges. The costs of operating physical stores, such as rent, utilities, and staffing, can be substantial (Gauri, Jindal, Ratchford, Fox, Bhatnagar, Pandey, Navallo, Fogarty, Carr and Howerton 2021). Businesses must also navigate varying foot traffic, which can be affected by factors like location, weather, and the overall economy (Khan, Hassan, Fahad and Naushad 2020). Competition among retailers in highly populated regions is often fierce, compelling businesses to differentiate themselves through distinctive product selections, superior customer service, or attractive pricing strategies (Gauri et al. 2021).

Nevertheless, traditional commerce continues to demonstrate resilience and adaptability as a business model. Many retailers have adopted innovative strategies to elevate the in-store experience, such as introducing experiential shopping opportunities where customers can engage in interactive activities or attend events within the store (Bonfanti, Vigolo, Vannucci, and Brunetti 2023). In addition, businesses are increasingly investing in visually appealing and welcoming store designs to create enjoyable environments that encourage customers to linger and enhance their overall shopping satisfaction (Hagtvedt and Chandukala 2023).

2.2.1. Brick-and-Mortar Retailing

In-store traditional retailing serves as the foundation of traditional commerce (Song et al. 2022). It is characterised by direct, physical interactions that allow consumers to view, handle, and evaluate products before making a purchase (Bourg, Chatzidimitris, Chatzigiannakis, Gavalas, Giannakopoulou, Kasapakis, Konstantopoulos, Kypriadis, Pantziou, and Zaroliagis 2023). Gaining insight into the various types of retailers is essential for understanding the broader retail environment, including consumer behaviour patterns, market developments, and competitive dynamics (Desmichel and Kocher 2020).

Retailers are generally divided into two principal categories: **merchandise retailers** and **food retailers**. Table 2.1 provides an overview of these two traditional retail types, with particular emphasis on the different subcategories of merchandise retailers.

Table 2.1: Types of merchandise retailers

General merchandise retailers	Food retailers
Department stores are retail establishments that offer a wide variety of products, systematically arranged into separate departments under one roof (Sharma and Chadha 2020). Each department typically specialises in a particular product category, such as apparel, electronics, household items, or cosmetics (Desmichel and Kocher 2020).	**Full-service supermarkets** are big retail outlets that provide a broad assortment of food and non-food products (Tlapana 2020). They generally carry groceries, fresh fruits and vegetables, meats, packaged foods, dairy items, and household essentials, and often include specialised sections such as a bakery, deli, or pharmacy (Musasa and Tlapana 2023). These supermarkets focus on delivering variety, convenience, and high-quality offerings, frequently enhancing the shopping experience with features like self-checkout systems, loyalty programs, and various in-store services (Kim, Rangel, and Colabianchi 2024).
Discount stores are retail outlets that sell products at prices lower than those of other stores (Yoo, Welden, Hewett and Haenlein 2023). They are able to offer these reduced prices by employing strategies such as buying in bulk, securing favourable terms from suppliers, and minimising additional services (Terblanche, Beneke, Bruwer, Corbishley, Frazer, Pentz and Venter. 2016.).	**Hypermarkets** are a combination of both supermarkets and department stores (Tlapana 2020). They usually provide a vast selection of products, including food items, household essentials, clothing, electronics, furniture, appliances, and outdoor equipment. Designed to function as a one-stop destination for shoppers, hypermarkets cater to a wide variety of consumer needs while offering products at competitive prices (Musasa and Tlapana 2023).
Specialty retailers focus on particular product categories or niche markets within the retail sector (Sharma and Chadha 2020). Unlike general merchandise stores, they provide a narrower but more in-depth range of products within their area of specialisation (Ariffin et al. 2020). These retailers are designed to meet the distinct preferences and requirements of a specific target customer group (Terblanche et al. 2016).	**Warehouse clubs**, also known as **membership warehouses** or **wholesale clubs**, are retail establishments that sell bulk products at discounted prices to customers who hold a paid membership (Tlapana 2020). These outlets typically carry a limited selection of items, focusing mainly on essential goods such as groceries, household supplies, and electronics (Musasa and Tlapana 2023). Members benefit from reduced prices and the cost savings that come with purchasing in large quantities (Kim, Rangel, and Colabianchi 2024).
Category specialists are retailers that concentrate on specific product categories within the broader retail market (Sharma and Chadha 2020). In contrast to specialty retailers, which often focus on a single niche, category specialists provide a broad assortment of products within their chosen category and offer customers detailed expertise and guidance (Yoo et al. 2023).	**Convenience stores** are compact retail outlets designed to offer quick access to a limited selection of products for immediate or everyday use (Tlapana 2020). They commonly stock essential groceries, snacks, drinks, tobacco products, and newspapers (Musasa and Tlapana 2023). Renowned for their extended hours, accessible locations, and speedy service, these stores serve customers seeking fast, grab-and-go purchases without the need for a full shopping trip (Kim, Rangel, and Colabianchi 2024).

Off-price retailers offer branded products at prices lower than those found in conventional retail stores (terblanche et al. 2016). They source merchandise such as excess stock, clearance items, out-of-season goods, or discontinued products from manufacturers and other retailers, and sell them at reduced prices (terblanche et al. 2016).	

2.2.2 The Size and Status of Brick-and-Mortar Retailing Worldwide

In recent years, the global retail industry has witnessed substantial expansion, growing from **\$28,846.57 billion in 2023 to \$31,310.6 billion in 2024**, reflecting a **compound annual growth rate (CAGR) of 8.5%** (Dai, Stephens, and Si 2024). This upward trend has been fueled by rapid economic growth in developing economies, increasing urbanisation (Mawejje 2024), and the rising prevalence of franchise-based business models. The growing demand for hypermarkets, supermarkets, discount chains, and out-of-town retail complexes—along with easier access to retail financing has further accelerated this expansion (Chibvura, Doba, and Mupamhanga 2023).

Figure 2.2 illustrates global brick-and-mortar revenue patterns since 2015, showing a pronounced upward trajectory over time. Projections suggest that this momentum will continue, with double-digit growth expected by 2026. A significant portion of this progress is attributed to the **U.S. retail sector**, which encompasses more than **1.067 million physical stores** nationwide. In 2023, the country recorded a **net increase of 1,820 new stores**, although this represented a **70.6% decline** compared with the net number of store openings in 2022.

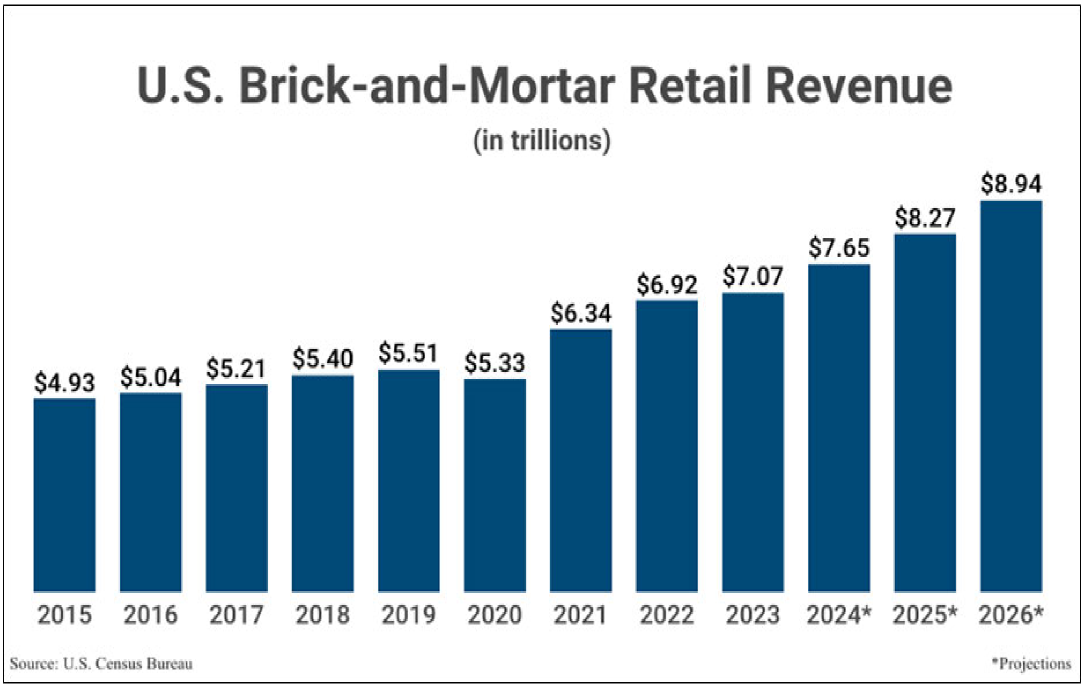


Figure 2.2: USA Brick-and-Mortar Retail Revenue
Source: Pozzi 2013

According to a study by Capital One Shopping Research in 2022, most consumers in the USA visit brick-and-mortar stores at least once a week, with 45% primarily shopping in physical locations instead of online. Notably, 62% of consumers mainly purchase groceries in-store, and 50% prefer physical stores for personal care and beauty products. Apparel and footwear are also commonly bought in person, with 40% of consumers favouring brick-and-mortar shops for these items. Furthermore, 28% of shoppers primarily purchase home goods in physical stores.

This study, however, focuses on online shopping behaviour concerning FMCG within South Africa, with a particular focus on identifying the key factors contributing to the non-adoption of online shopping among South African consumers. Despite substantial investments in online infrastructure by retailers, especially in the wake of the COVID-19 pandemic, there remains a notable reluctance among consumers to embrace this mode of shopping. The next section highlights online shopping: a paradigm shift.

2.3 ONLINE SHOPPING: A PARADIGM SHIFT

Online shopping has become a significant development for many industries, including retail, especially for FMCG. It is the demand side aspect of e-commerce, which Chaffey and Ellis (2019) defined as selling or purchasing products online backed by advanced information and communication technologies (ICT). Online shopping is the purchasing part of e-commerce. It can be through mobile technology (m-shopping/commerce), online stores (websites) or social media sites (social commerce), and now in the metaverse. This shift has been driven by numerous factors, from consumer behavioural shifts such as the technophilia, pursuit of convenience, seeking access to a variety of products, and the ability to compare prices easily (Martínez-Córcoles *et al*. 2017; Ronit 2011).

Technophilia is the strong attraction and enthusiasm that individuals have for activities involving advanced technologies and is expressed by the easy adaptation to the social changes brought by technological innovations (Osiceanu 2015). Ronit (2011) posited that this enthusiasm and attraction to use technology is linked to the rewards for technology adoption. In line with this conceptualisation, technophiles portray positive orientation toward online shopping and feel good when they adopt new online shopping technologies. Another factor driving this shift in consumer behaviour is the pursuit of convenience. This is one of the key factors motivating the increasing adoption of online shopping (Law, Kwok and Ng 2016). Besides being the culture of some online shoppers (Dang and Pham 2018), convenience is crucial because it brings them efficiency (Asiedu and Dube 2020). In online shopping, customers can conveniently compare prices and merchandise, place their orders, pay for the orders, and get the product delivered to them (Nguyen, De Leeuw, Dullaert. and Foubert. 2019).

Also, others point to the generational cohort shift, with more Gen Ys and Gen Zs joining the mainstream economic active citizenry (Eger, Komárková, Egerová, and Mičík 2021; Marjanen, Kohijoki, Saastamoinen and Engblom 2019; Munsch 2018). A new generational cohort, the Gen Alpha, born from 2010 to 2024, is said to be the most influential generation (McCrindle and Fell 2020). Prensky (2001) first coined the phrase ‘digital natives’ to describe those who grew up in a digital world, in comparison with ‘digital immigrants’ who only began to engage with technology at a later stage of life.

Hence, it is not surprising that the newer generations have a greater affinity towards online shopping. Their influence is already felt in many markets, including FMCG (Stahl and Literat 2023). Generally, they are technophiles who enjoy improved access to the internet and various technologies, such as mobile devices and technologies by individuals (Lee and Lee 2020), as well as e-commerce

infrastructure by supply organisations (Nigatu and Atsbeha 2021). Fast Moving Consumer Goods businesses are among the frontrunners in adopting online business, enabling their customers to buy products conveniently without visiting the brick-and-mortar stores.

Furthermore, e-commerce has made it convenient for consumers to access a wide variety of products and compare prices without visiting multiple brick and mortar establishments (Bulacan, Milan and Fernandez 2022). For instance, a person who comes home tired from work may opt not to cook and instead order a takeaway. This individual can simply search for "dinner takeaway for one near me" and receive a list of restaurants and fast-food outlets offering a range of food options to compare and choose from, all without having to leave their home. They can further refine their search based on criteria such as price, delivery time, and special dietary requirements. Additionally, the emergence of the COVID-19 pandemic is touted as the accelerator for consumer adoption of online shopping globally (Guo *et al.* 2020; Moon, Choe and Song 2021; Pantano *et al.* 2020; Raza and Khan 2022). Understanding consumer attitudes and behaviour towards online shopping is crucial for FMCG businesses to market their products effectively. Fast Moving Consumer Goods companies must continuously monitor the changing consumer behaviours and adjust their marketing strategies accordingly.

2.4 GLOBAL HISTORICAL OVERVIEW OF ONLINE SHOPPING

Depicted in Figure 2.3 is the history of online shopping, a form of e-commerce. E-commerce has its origins in the late 1970s and is attributed to Michael Aldrich, an English inventor (Angamuthu 2020; Laliberte 2023), who connected a television (TV) to a telephone line (Ang 2021). This period is widely recognised as the first generation of e-commerce. However, Tian and Stewart (2008) argued that the development of electronic data interchange (EDI), rooted in the 1960s when some transport and retail businesses aimed to create "paperless offices," should actually be credited for the e-commerce business. The first e-shopping business was launched in 1982, around the same time that Internet Protocol (IP) was approved for transmitting data on the net in 1983, enabling computers to exchange information (Tian and Stewart 2008).

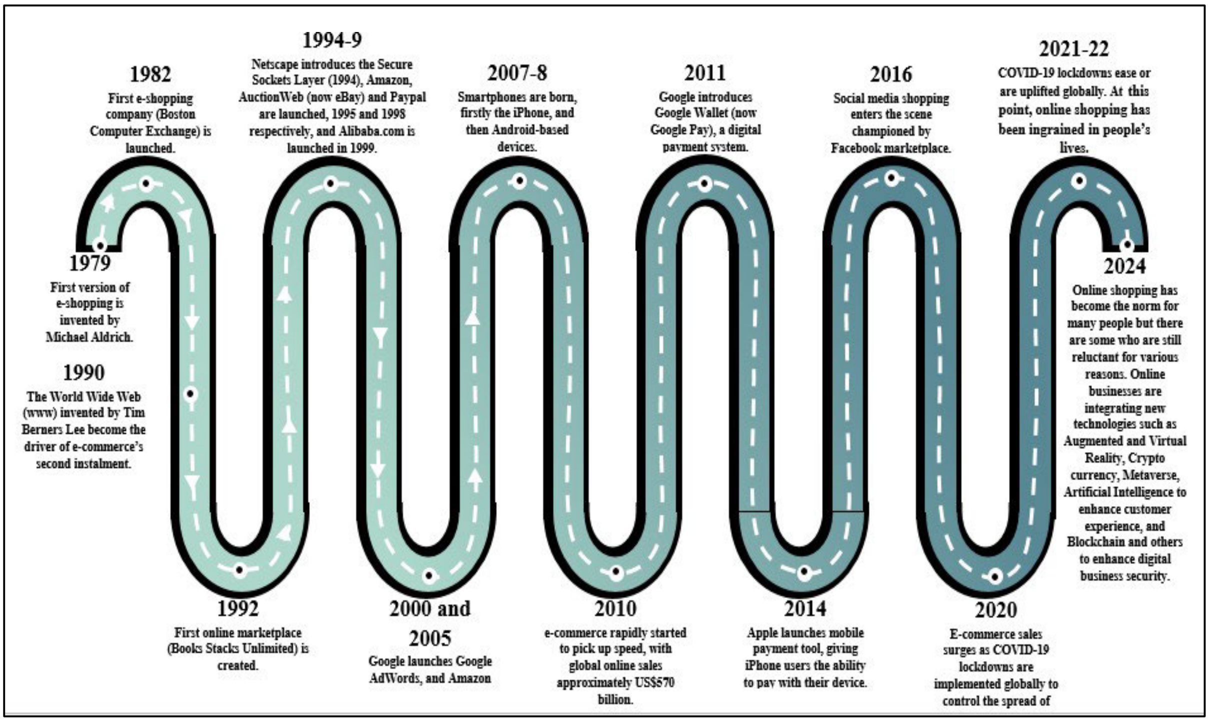


Figure 2.3: The history of online shopping
Sources: Angamuthu 2020; Laliberte 2023

The World Wide Web invented by Tim Berners-Lee in 1990 is widely acknowledged for playing a significant role in driving the second generation of e-commerce. This information comes from multiple sources (Aaronson and Struett 2020; Ang 2021; Laliberte 2023; Roper 2023; Tian and Stewart 2008). The same year, McGill University in Montreal, Canada, launched Archie, the first search engine (Oldest.org. 2023). The period from 1990 to 2000 was a time of great activity and monumental progress for second-generation e-commerce. Tian and Stewart (2008) asserted that the commercialisation of the internet by the America Government Agency (NSFNET) in 1991 was the most significant milestone for e-commerce. In 1992, Book Stacks Unlimited was created as the first online marketplace (Ang 2021). Following Archie, several search engines entered the market, including Veronica in 1992; Aliweb in 1993; Galaxy/eiNet, Lycos, WebCrawler, and Yahoo in 1994; AltaVista, Excite, Infoseek, and MetaCrawler in 1995; Ask Jeeves (now Ask.com) and HotBot in 1996; Northern Light (now SinglePoint) in 1997; and Google Search, MSN Search, and Yahooligans (for children) in 1998 (Oldest.org, 2023). Six of these search engines are no longer active, and only Google Search is popular in South Africa.

Amid search engine launches, Netscape introduced the Secure Sockets Layer (SSL) in 1994, a crucial security feature for e-commerce businesses. In the same year, the first secure online transaction took place when American Phil Brandenberger bought a Sting album (Aaronson and Struett 2020; Roper 2023). Jeff Bezos' Amazon launched in 1995, followed by AuctionWeb (now eBay) in 1998. In 1996, Dell Computers started selling computers to customers online and in 1997, the dotcom (.com) was launched as a commercial domain, allowing more business to have websites to start selling online (Kim 1998). ECash became the first online payment system in 1997, followed by Paypal in 1998. Alibaba.com, Napster, and Boo.com marked the digital milestones of the 1990s, launching in 1999. At that point, global online sales exceeded US$1 billion (Ang 2021; Roper 2023).

In 2000, businesses began to concentrate on monetising their platforms and expanding the services to global markets. For instance, Google launched AdWords, which introduced the well-known pay-per-click (PPC) model, a crucial concept in digital marketing to this day. Sellers (individuals and corporates) were then able to advertise their products on Google Search (Laliberte 2023). In 2004, Mark Zuckerberg's Facebook was launched, spelling the genesis of what we now refer to as social shopping. Amazon also introduced its Prime membership package in 2005, which charged members an annual fee in exchange for perks such as free rapid shipping and exclusive discounts (Ang 2021). The launch of smartphones (iPhone in 2007 and Android devices in 2008) played a significant role in the growth of mobile commerce (Roper 2023).

2.4.1 Online shopping sales growth globally.

Online shopping sales have been growing exponentially over the past few years and this has been accelerated by the increasing use of technology in commercial shopping (Nanda, Xu and Zhang 2021). Figure 2.4 shows the projected growth of global retail e-commerce sales from October 2021 to April 2027. In October 2021, sales amounted to $5.3 trillion, and by October 2023, this figure increased to $5.8 trillion. This steady growth reflects the ongoing shift toward online shopping as more consumers adopt digital platforms for their purchases. The early phase of this period shows strong and gradual momentum in e-commerce, with a consistent upward trend in global sales. The most significant expansion was predicted to occur between 2024 and 2027. By October 2024, global e-commerce sales were projected to reach $6.3 trillion, with further growth to $6.9 trillion by October 2025. This period highlights a faster acceleration in online retail, demonstrating the growing size of the digital marketplace and increasing consumer reliance on e-commerce for both every day and discretionary items.

The upward trajectory is expected to continue in 2026, with global e-commerce sales predicted to hit $7.4 trillion by October and approximately $7.9 trillion by April 2027. This sustained growth underscores the strength and long-term expansion of the e-commerce industry. Projections suggest that the shift towards online retail will persist, fuelled by ongoing technological advancement and evolving consumer behaviour.

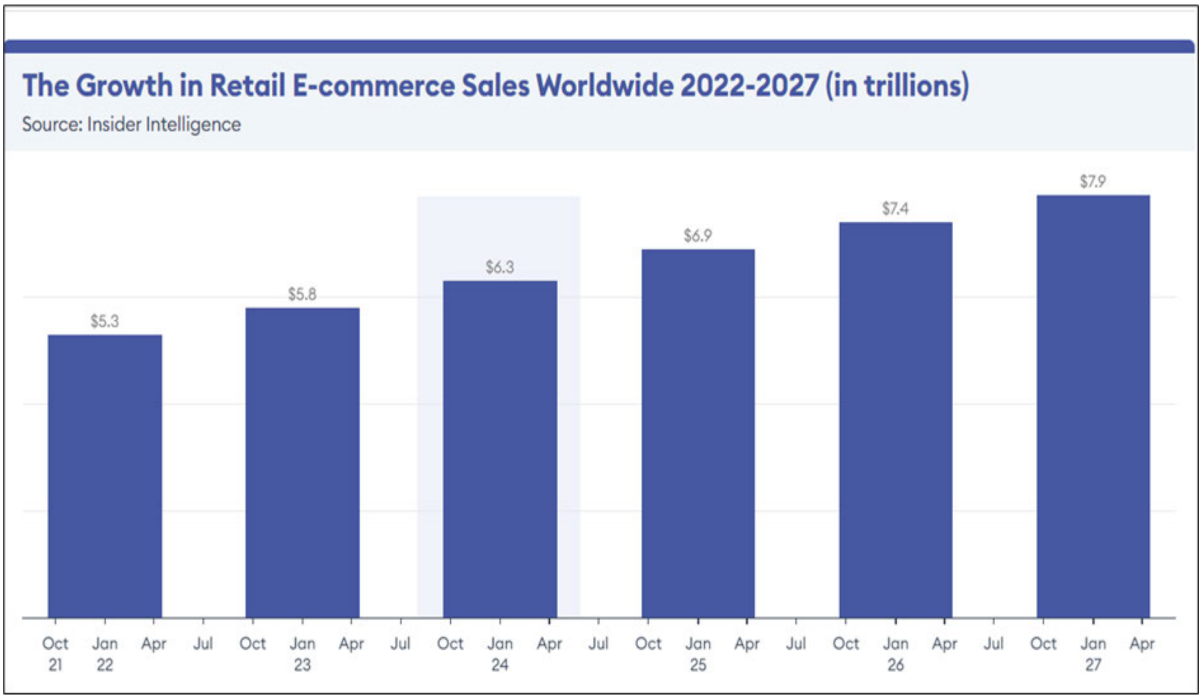


Figure 2.4: E-commerce sales

Source: Ecommerce statistics 2024

In 2022, social media played a critical role in global e-commerce, with consumers spending an impressive $992 billion on purchases made directly through social platforms. This considerable figure highlighted the increasing significance of social media as a commercial channel, as more users engage with these platforms. Notably, this trend is particularly prominent in Thailand, where 90% of internet users have made purchases via social media, and in India, where 86% of online users have engaged in social commerce. These statistics showcase the expanding influence of social media on consumer behaviour and buying decisions.

Figure 2.5: E-commerce sales

Source: Ecommerce statistics 2024

Figure 2.5 illustrates the percentage of individuals who made purchases through different social media platforms. The data shows that Facebook led the way in social media shopping, with 50.7% of respondents reporting that they have made purchases through this platform. This indicated that Facebook continues to be a dominant player in social commerce, leveraging its large user base and integrated shopping tools to drive consumer transactions.

Instagram followed closely as the second most popular platform for social media purchases, with 47.4% of users making transactions. The platform's visually oriented design, combined with features like shoppable posts and stories, likely contributes to its strong performance in social commerce. YouTube is another significant platform, with 33.9% of users engaging in social shopping, showcasing the platform's growing influence through content such as product reviews, unboxing videos, and sponsored content.

Meanwhile, platforms like TikTok (23.9%), Snapchat (18.8%), and Twitter (18.5%) show smaller percentages of purchases. While these platforms play an important role in brand visibility and engagement, they haven't yet reached the same level of success in converting users into buyers as Facebook and Instagram. Overall, the data highlights the varying degrees of influence different social media platforms have on consumer purchasing behaviour, with Facebook and Instagram leading in social commerce.

2.5 UNDERSTANDING ONLINE SHOPPING IN SOUTH AFRICA

While the history of the Internet in South Africa dates to the early 1970s, where it revolutionised the printing industry (Tankard 1998), its adoption into E-Commerce only came about in the 1990s (Cloete, Courtney and Fintz 2002) and was already projected to generate slightly over US$1 billion by 1999 (Mann 2000). The adoption is affirmed by a sudden proliferation of research studies from the late 1990s to early 2000s, which could be termed as the genesis of scholarly interests in the concept of conducting business over the internet. Since then, the adoption of e-commerce has tremendously grown to a multi-billion Rand industry.

According to Goga, Paelo and Nyamwena (2019), general retail trade was estimated to be ZAR1 trillion in 2017, accounting for 1% of the entire retail market (StatsSA 2017). With the scope broadened to include education, travel and downloadable entertainment, e-commerce revenue ballooned to an estimated R37 billion in the same year (Smith 2017). During the same period, online imports also seemed to pick up, with the South African Post Office (SAPO 2017) reporting a 20% increase in parcels coming into South Africa by air compared to the previous year. Most of the cross-border online purchases are from the United States and Europe (International Trade Administration; ITA 2024). By 2021, the estimated revenue generated through online retail had grown to around R200 billion and estimated to reach ZAR400 billion by 2025 (BusinessTech 2022). The sudden spike of online sales, a 66% in 2020 compared to the previous year (ITA 2024), is attributed to the COVID-19 pandemic forced restrictions on access to traditional retail stores (Kibuacha 2021).

According to Ndlovu (2024), more recent statistics show that South Africa's e-commerce sector is experiencing remarkable growth, reaching an unprecedented R71 billion in sales value in 2023. This marks a significant 29% increase from R55 billion in 2022, indicating a robust expansion within the industry. As of 2023, online retail now accounts for 6% of the total retail sector, which itself generated R1.1 trillion in sales. These insights are drawn from the "Online Retail in South Africa 2024" report, compiled by World Wide Worx (2024). The continued growth of e-commerce highlights the sector's increasing importance within the broader retail landscape.

Clothing continues to dominate South Africa's online shopping market, contributing about 30% to the sales basket, a trend consistent with previous years. The FMCG segment, however, has seen significant growth, rising from 17% in 2022 to 22.3% in 2023. This surge can be attributed to the expansion of on-demand delivery services such as Pick ‘n Pay’s Asap! and Checkers Sixty60, which have made online grocery shopping more accessible and convenient. Despite a slight decline in its share, the electronics category remains a significant part of the online retail landscape, with 12.7% of total sales volumes in 2023. The entry of Amazon into the South African market is expected to bolster this category, potentially restoring it to a 15% share by the end of the year.

The report also highlights the factors driving success in South Africa’s online retail market. Notably, education levels are strongly correlated with online shopping participation, with nearly 37% of online shoppers residing in cities and towns and over half possessing post-matric qualifications. Customer service emerged as the most critical factor for success in online retail, with 73% of surveyed retailers emphasising its importance over other factors such as stock availability, product quality and range, and competitive pricing. Furthermore, the majority of retailers adopted a hybrid business model, where online sales complement their physical store operations, reflecting a strategic approach to capturing a broader customer base in an increasingly digital market.

2.5.1 Facilitators of Online Shopping in South Africa

While the exponential growth in online shoppers for period 2020 to 2022 can be attributed to the COVID-19 pandemic, technological innovations have been the catalyst for e-commerce adoption over the period from the 1990s to date. As previously noted, the internet is the bedrock of e-commerce, and by extension, online shopping. It is the springboard for the other e-commerce innovations that have become the backbone of online shopping, such as the social media, mobile commerce technology and digital payment systems. By January 2024, South Africa had about 46 million active internet users (Kemp 2024), which indicated a 74.7% internet penetration rate. Digital literacy was on average at 90% for people aged 15 years and above. Internet connection speeds have been increasing on a year-to-year basis, with downloads and upload speeds increasing by 35.4% and 16.8% respectively, with a latency of - 4%[1]. Furthermore, reduced data prices following the Competition Commission’s ruling in 2019 also contributed to e-commerce adoption rates.

Following the internet, mobile technological advancements have taken over from traditional computer systems in catalysing e-commerce. Even within computer systems, we have seen a migration from desktops and laptops to newer versions with wireless network connection features (mobile laptop technologies) to enable mobility. Thus, some describe laptops as a form of mobile technology and include it in mobile commerce (m-commerce) definitions (Humphreys, 2013; Omonedo and Bocij, 2014; Puiu, Demyen, Tănase, Vărzaru and Bocean 2022; Schwiderski-Grosche and Knospe 2002). However, it is noteworthy that smartphones enjoy a portability advantage over laptops, with 77% indicating they use their phones to purchase online (Cowling 2024). M-commerce refers to e-commerce conducted over mobile devices such as smartphones, tablets, personal digital assistants (PDA) and laptops/notebooks that can connect to the internet wirelessly. It is a subset of e-commerce (Schwiderski-Grosche and Knospe 2002).

The development, affordability and ubiquity of smartphones and other smart devices has pushed the boundaries of traditional e-commerce, prompting the invention of other technological innovations that support mobility such as mobile banking and payments, mobile applications (famously known as apps), mobi-sites and geo-marketing. All these innovations do not only replace traditional brick and mortar business interactions but also eliminate time and geographical barriers (Puiu et al., 2022). As a result, m-commerce has widened consumers' access to numerous products at any time and location, including the FMCG. Mobile statistics provided by DataReportal's Digital 2024: Global Overview Report (Kemp 2024), indicate the pervasiveness of mobile devices. For instance, in South Africa, mobile connections are almost two times the population and smartphones device ownership is almost 100%, and 98.7% of those who access internet, do so through their smartphones. Furthermore, mobile technological advancements have also become the backbone of social media consumption, as most people access it through their mobile devices.

Table 2.2 presents an overview of notable social media platforms that operate(d) in South Africa. As the name suggests, social media started off as platforms for social connections for friends and relatives but grew to become a cornerstone of modern marketing. Terms such as social media marketing or social commerce have emerged to describe how businesses and consumers engage in relationships and transactions. In South Africa, social media use has grown in leaps and bounds in line with internet penetration rates. As of January 2024, more than half (57.3%) of individuals with access to internet had one or more social media accounts, with WhatsApp, Facebook and Tiktok being the three mostly used platforms, respectively (Kemp 2024).

Admittedly, defining what is or is not social media is becoming very difficult as platforms proliferate and there's increasing convergence in the platform business sector. Lüders (2008) explains this difficulty as a result of the accelerated integration of social media tools/features into platforms that were not traditionally regarded as social media. Also, social media platforms, in pursuit of competitiveness and aligning with the dictates of omni-channel marketing, are incorporating non-social aspects, for example, traditional e-commerce features. While individuals sign up on social media platforms primarily for socialising, a study by GWI cited in Kemp (2024) revealed that a third of South Africans also use social media to access content by their favourite brands and to find products to purchase.

Table 2.2: Social Media Platforms in South Africa

Name of Social Media Site	Date Launched Globally	Date Launched in South Africa	Date Exited South Africa	Overview and E-commerce Usage
MXit	-	2005	October 2015	MXit was a South African-born mobile social network that was extremely popular among the youth for sending messages and sharing content. It allowed users to chat, play games, and use chat rooms. E-commerce was integrated through Mxit Money, enabling users to purchase airtime and other services and the Tradepost which helped consumers discover products and competitions (Duffet 2015). Business such as the Engen Car Magazine leveraged MXit as a marketing communications tool (du Plessis 2010).
Facebook	February 2004	2006	-	Facebook is the most popular social media platform in South Africa with a significant user base. It's used for personal networking as well as e-commerce, with businesses leveraging Facebook Marketplace for ads to reach customers and relationship building in Pages and Messenger. Consumers can purchase on marketplace. While Facebook also uses paid advertising, which is a digital version of traditional commercials, it has entrenched social network advertisements (SNA), which thrive on social context, and user-generated content (UGC) to drive organic impression (Wiese, Martínez-Climent, C. and Botella-Carrubi 2020).
WhatsApp	January 2009	-	-	WhatsApp is the most used messaging app in South Africa (Kemp 2024). It's also used for business communications and has features like WhatsApp Business for e-commerce purposes, which enables the integration of digital payment systems for consumers to purchase products. WhatsApp has been instrumental in the success of informal and small businesses, but of late, even big corporations have realised the relationship (brand) building value of including it into digital media mix for relationship (brand) building, customer engagement and care, concierge services and advertising (broadcasting messages) (Modak and Mupepi 2017).

Instagram	October 2010	-	-	Instagram has seen significant growth in South Africa, especially among younger demographics. A photo and video sharing social network. It's highly visual and used extensively for brand marketing. Instagram Shopping allows businesses to tag products in posts and stories, facilitating direct sales. This platform is central to the development of the influencer marketing, until the arrival of Tiktok. It has become a vital cog in marketing destination and accommodation services (Tobias-Mamina, Kempen, Chinomona, and Sly 2020).
LinkedIn	May 2003	-	-	LinkedIn has a growing user base in South Africa, but primarily for professional networking; hence it is useful for recruiting. It has also been utilised for B2B e-commerce, and B2C when the target audience is professional.
Twitter (now X)	March 2006	-	-	Twitter's growth in South Africa has been moderate. It's used for public discourse and news, as well as a platform for brands to engage with customers. This platform has enabled businesses, especially big ones to climb down from the corporate stature and humanise their customer engagement. For example, Nandos SA has carved out a humanly brand over the years that thrives on cheeky satire and people love it. Twitter can be powerful for brand building, but it has to be used with extreme care (Snyman and Mulder 2014).
TikTok	September 2016	-	-	Globally, TikTok has rapidly grown in popularity, especially during the lockdown period, prompting marketers to use is as a marketing communication tool. It's used for creative content, viral challenges, and influencer marketing; hence a good tool to drive digital work of mouth, brand visibility and awareness creation. TikTok for Business provides advertising solutions and shopping features integrated into the platform.
Snapchat	July 2011	-	-	Snapchat is a multimedia messaging app popular among younger audiences. In South Africa, it's used for sharing moments and has potential for e-commerce through promotional offers and exclusive discounts1234.

WeChat	January 2011	-	-	WeChat is a Chinese multi-purpose messaging and social media app. It offers a variety of services including instant messaging and digital payments, and it's used for e-commerce in South Africa.
Reddit	June 2005	-	-	Reddit is a network of communities based on people's interests. It's a platform for discussions and content sharing. In South Africa, it's also used for sharing insights on e-commerce platforms and strategies.
MySpace	2003	2005	2011	An early social networking site focused on music and entertainment. MySpace allowed for custom profiles and was used by artists for promotion. Its e-commerce use was limited compared to later platforms.
Telegram	August 2013	-	-	Telegram is a cloud-based instant messaging system. It's known for its security and speed, and while not primarily an e-commerce platform, it can be used for business communications in South Africa.
Pinterest	March 2010	-	-	Pinterest is a visual discovery engine for finding ideas like recipes, home and style inspiration. It's used in South Africa to drive e-commerce by showcasing products and ideas.
Google+	2011	2012	2019	Google's social networking project, integrated with other Google services. It saw limited e-commerce use but was utilised for brand engagement and SEO benefits before its shutdown.

2.5.2 E-commerce Sectors and Platforms in South Africa

E-commerce in South Africa has experienced substantial growth over the past decade (Goga, Paelo and Nyamwena 2019), driven by increasing internet penetration, mobile connectivity, and changing consumer preferences (Cowling 2024; Kemp 2024; Makhitha, Van Scheers and Mogashoa 2019; Worku and Muchie 2019). However, it is still a promising concept, and its adoption is effectively low (Goga, Paelo and Nyamwena 2019). The e-commerce market encompasses a variety of sectors, each contributing to the overall digital economy. Prominent sectors that have considerably adopted e-commerce include retail, fashion, electronics, groceries, and services.

According to a Statista (2025) report, e-commerce has become an integral element of the retail sector in South Africa (Cowling, 2024), and Goga, Paelo and Nyamwena (2019) affirmed that the sector has seen a significant surge in online shopping, with leading traditional brick-and-mortar retailers establishing strong online presence and numerous digital-native brands have emerged. For example, Pick 'n' Pay/Checkers and Woolworths have capitalised on this trend, providing convenient and efficient delivery services through their Sixty60 and Woolworths Online, respectively. The fashion and apparel sector also boasts a robust online presence, with traditional brick and mortar brands such as Mr Price, Spree, HandM, Cape Union Mart, and OneDayOnly to digital fashion brands such as Zando, RunwaySale, Zaful, and Superbalist joining the online business craze. The electronics and appliances sectors are also increasingly turning to online stores for competitive pricing and wide product selections, notably with brands such as Yuppiechef, The Gadget Shop, HiFi Corp, Game, and Makro. Clicks and Dischem have also embraced e-commerce to allow their consumers to shop for consumer goods such as personal care and home hygiene products, healthy and pharmacy products, and 'Mom and Baby' products. There are also some platforms such as Takealot, Bobshop (formerly Bidorbuy), Loot, and the recent market entrant (Amazon), that are not sector specific, but rather carry a range of products across different sectors.

While e-commerce comprises a suite of various technologies (Lipka, Wiards, Markgraf, Zukowski and Sonde 2024), e-marketing practitioners are currently seized with the integration of technologies such as artificial intelligence (AI), mixed (augmented and virtual) reality and blockchain as the backbone of their digital marketing strategies. Artificial intelligence is transformative technology which has become an essential tool for e-commerce platforms (Gupta, Kumar and Khurana 2024). AI-driven algorithms' ability to analyse vast amounts of data enables e-commerce businesses to understand customer behaviour, create tailored marketing strategies, and enhance overall user experience (Kakkar and Monga 2017; Lari, Vaishnava and Manu 2022), ultimately increasing customer engagement and sales. Artificial Intelligence also optimises supply chain management, inventory control, and customer service, driving efficiency and reducing operational costs.

One of the primary applications of AI in e-commerce is the development of intelligent personal assistants and chatbots. These AI-powered agents can provide seamless customer support, quickly respond to enquiries, and even assist in the purchasing process — enabling e-commerce businesses to deliver high quality services and achieve cost-effective service excellence (CESE) (Wirtz, Hofmeister, Chew and Ding 2023; Wirtz and Pitardi, 2023). Artificial Intelligence has also become critical in powering recommender systems (RS), which are becoming increasingly popular in e-commerce, employing statistical techniques and AI to predict user preferences (Necula and Păvăloaia 2023). Traditionally, e-commerce businesses employ RS for personalising marketing offerings, including content. In addition, the advantages of AI-based recommender systems for e-commerce are manifold, encompassing enhanced decision-making, decreased shopping duration and effort, improved sales, and the capability to address data sparsity and cold-start issues (Necula and Păvăloaia 2023).

Beyond customer service and personalisation, increased efficiency and reduced costs, AI has also been instrumental in optimising e-commerce logistics and supply chain management (Ping, Hussin and Ali 2019). Of late, extant operations management and e-commerce literature revealed a dominance of studies on the integration of technology in optimising logistics and supply chain management (LSCM). One of the topical issues refers to the integration of AI into LSCM to improve operational outcomes. Logistics is a key element of e-commerce, particularly the fulfilment process. For instance, e-commerce businesses such as Alibaba, eBay and Amazon have long been trying to optimise their fulfilment processes through AI-driven smart warehouses (Mahroof 2019; Zhang, Pee and Cui 2021). Artificial Intelligence can significantly assist in optimising and innovating various aspects of LSCM, including the fulfilment process, thus exponentially improving overall efficiency, which can be passed on to the customer through prices.

The other application of AI in e-commerce is further exemplified by the use of intelligent pricing strategies. AI-powered systems can dynamically adjust prices based on market trends, competitor prices, and customer behaviour, ensuring that e-commerce businesses remain competitive and maximise their profits (Chen and Zhang 2015). Erdmann, Yazdani, Mas

Iglesias and Marin Palacios (2024: 7) categorises AI-supported pricing functions (AISPF) as "forecasting tools in form of AI-based price prediction models" and "price optimisation tools in form of AI-based pricing strategies based on market conditions." However, it is crucial to note that while the integration of AI in e-commerce has brought about numerous benefits, the ethical considerations surrounding its use have become a subject of increasing scrutiny.

Another emerging technology with significant implications for the e-commerce landscape is mixed reality, which encompasses both virtual reality and augmented reality (Khan and Nikov 2011; Steinicke and Wolf 2020). Mixed reality technologies have the potential to revolutionise the online shopping experience by providing more immersive and interactive product exploration (Farshid, Paschen, Eriksson and Kietzmann 2018; Kim, Kim, Park and Yoo 2023). For instance, an early study explored the application of virtual reality technology in e-commerce, conceiving a 3D web-based shopping mall and describing the supporting web technologies at the time (Yu and Pan 2012). More recent research has shown interest in the metaverse, which leverages augmented reality (AR) and virtual reality (VR). Metaverse marketing is a virtual marketing world where digital and physical realms converge, allowing marketers to innovatively present products to target markets and consumers immersive shopping experiences. While South Africa's underlying macro-environmental factors such as increasing internet and smartphone penetration provides good foundation for metaverse marketing adoption (Statista 2024), its adoption is not yet broad-based online shopping.

While e-commerce affords businesses and consumers to conveniently interact, and sell or purchase products, it faces security concerns for both parties. Blockchain technology, "a secure distributed database that preserves ordered lists of records, known as blocks, which cannot be changed" has brough relief for some of these concerns (Bulsara and Vaghela 2020: 3794). For e-commerce, blockchain benefits include reduced cost of transactions, securing payments and data, including reward schemes (loyalty programmes), warranties, guarantees, and personalised promotion, and addressing the lack of transparency faced by e-commerce firms (Xuan, Alrashdan, Al-Maatouk and Alrashdan 2020).

2.6 ONLINE SHOPPING BEHAVIOUR – PREVIOUS STUDIES

There has been some heightened research interest in online shopping, pervading beyond developed economies into developing economies like South Africa. The growth of online shopping is facilitated by technological advancements and affordability. Extant literature investigating the factors influencing online shopping behaviour can be put into three categories. The first consists of studies that adopted established theoretical frameworks such as the

UTAUT (Venkatesh *et al*. 2003), the TAM (Davis 1989), the TPB (Ajzen, 1991), and the SOR model (Mehrabian and Russell 1974) to explain online shopping. Such studies tested factors hypothesised as positively influencing the intention to shop online and actual online shopping behaviour. The second category comprises studies that modified/extended the established models, and the third category consists of studies that tested the influence of novel predictors. Table 2.3 provides an indication of some studies that have investigated factors influencing online shopping.

The sample of studies in Table 2.3 clearly shows that numerous factors influence online shopping behaviour. The influence of these factors varies from one context to another. Also, most studies on online shopping seek to explain what drives people to (or want to) shop online, leaving a paucity of explanations of why some people do not. This study aims to bridge this gap by inverting UTAUT, the TTT, SET and the SPT models, Chapter 3 presents a more detailed discussion of these models and how they underpin the study.

Table 2.3: Factors Influencing the online shopping.

Study - Author (s)	**Summary of the article (context and theoretical/conceptual model)**	**Identified Online Shopping Behaviour Predictors**
Daroch Nagrath and Gupta (2021)	The study investigated factors that influenced customers not to prefer online shopping. It is an exploratory study with a sample limited to the education sector in India.	They identified six factors (*Fear of bank transactions and no faith*, *Traditional shopping being more convenient than online shopping*, *Reputation and service provided*, *Bad experience*, *Insecurity and insufficient product information*, and *Lack of trust*). However, they did not test the predictive power of these factors.
Mofokeng (2021)	This study focused on the impact of online shopping factors on customer satisfaction and loyalty in South Africa. The study was a category three - it did not use or modify any established theoretical model.	The study identified *Information quality*, *Product delivery*, *Product variety*, *Perceived security*, and *Privacy concerns* as attributes of online shopping behaviour. It tested their predictive value for customer satisfaction and loyalty, indicating the continuation of online shopping behaviour. Only Privacy concerns were found to be a not significant predictor of satisfaction.
Moon, Choe and Song (2021)	The study analysed the determinants used to select either online or offline shopping channels after the pandemic in South Korea. These determinants were drawn from Ajzen's (1991) TPB and Rogers' (1975) Protection Motivation Theory (PMT).	The study tested the predictive power of *Attitudes*, *Subjective norms* and *Perceived behavioural control* (from TPB), and *Severity*, *Vulnerability*, *Response efficacy*, *Self-efficacy*, *Social distancing*, *Knowledge of COVID-19*, and *Recognition of government policy* (from the expanded PMT) and found that all were significant predictors of intention to shop online.
Pentz, Du Preez and Swiegers (2020)	The authors assessed the impact of perceived risk (Jacoby and Kaplan, 1972) on intention to shop for books and clothing online, comparing the experienced and inexperienced online consumer groups. The study was conducted in South Africa	They tested the influence of *Financial, Psychological*, *Performance*, *Time*, and *social risks* on the (re)purchase intention of the two groups. The experienced group's psychological and social risks (*Retailer reputation* and *Social influences*) were significantly related to the intention to shop for books and clothing online.

	and a sample of Generation Y university students was used.	The psychological risk and social influence risk negatively influenced intention. For the inexperienced group, only financial and social (retailer reputation) risks had a significant relationship with the intention to shop online for books and clothing. The former had a negative relationship, while the latter had a positive influence.

Abu-AlSondos *et al.* (2023)	The authors conducted a systematic literature review to investigate the significant elements that impact customer attitudes regarding online shopping in Jordan.	They found *Trust*, *Cultural hurdles such as Uncertainty avoidance and a Lack of understanding*, *Security*, *Perceived ease-of-use*, *and Perceived utility* as the most prominent factors influencing online shopping behaviour.
Moeti, Mokwena and Malebana (2021)	This study investigated the factors that affect consumers' acceptance and use of online shopping in Limpopo province, South Africa. The Diffusion of Innovation Theory (Rogers 1983; 1995) was employed to identify patterns and rates of how consumers accept or reject online shopping.	The study assessed the influence of *Relative advantage*, *Compatibility*, *Complexity*, *Trialability* and *Observability* on the acceptance and use of online shopping. Only Triability was found to be a significant predictor of online shopping behaviour.
Pillay and Mayayise (2021)	The authors combined constructs from the TAM and UTAUT2 model to investigate the factors influencing consumer intention to purchase online in South Africa. COVID-19 was added as a situational factor.	In this study, *Perceived ease of use* and *COVID-19* were significant positive influencers of online purchase intention. The direct effects of *Trust*, *Perceived risk*, *Price value*, *Perceived usefulness*, and *Facilitating conditions* were not significant. The moderating effect of COVID-19 on the relationships between the independent variables (Trust, Perceived usefulness, perceived ease of use, Price value and Perceived risk) and online purchase intention was significant.
Albugami and Zaheer (2023: 705)	This study combined the modified UTAUT and e-SERVQUAL (Parasuraman, Zeithaml and Malhotra 2005)	Through an Exploratory Factor Analysis, the study confirmed that the UTAUT constructs (*Performance expectancy*, *Effort expectancy*, and *Social influence*) and

	"to observe the influence of these two variables on buyers' intention to adopt internet shopping" in Saudi Arabia.	e-SERVQUAL constructs (*Assurance*, *Reliability*, *Website design*, and *Customer service*) significantly influence online shopping adoption.

Asiedu and Dube (2020)	The study drew its independent variables from the TAM and UTAUT and added novel variables essential to explaining online shopping behaviour in Suzhou, China.	The study's findings show that of the three independent variables (*Convenience*, *Perceived Usefulness*, and *Perceived ease of use*), only Convenience has a significant positive relationship with *Attitudes* towards online shopping. Also, *Social influence* and *Online shopping experience* were found to have positive relationships with *Sentiment* about online shopping, while *Price promotion* was not significant. Sentiment has a significant positive relationship with attitudes. Lastly, attitudes were the only variable that predicted online shopping behaviour.
Batada (2021: 46)	This case study "explores the impact that organisational readiness (ORD), data and payment security (DPS), user satisfaction (USAT), user-friendliness (UFR), and competition (COMP) have on the use of the online platform (UTIL)" during the COVID-19 pandemic in Pakistan. The study also sought to determine the satisfaction levels of online shoppers. The Technology-Organisation-Environment (TOE) framework was used to model the study.	The finding showed that all the independent variables (*Organisational readiness*, *Data and payment security*, *User satisfaction*, *User-friendliness and Competition*) significantly positively impact the use of the online platform, herein referred to as online shopping.
Eniezan *et al.* (2022)	This study examines the factors influencing adults' acceptance of online shopping during the pandemic in Jordan. The authors extended the UTAUT model by adding COVID-19 Fear as a new construct.	All the independent variables (*Performance expectancy*, *Effort expectancy*, *Social influence*, *Facilitating conditions* and *COVID-19 Fear*) were significant predictors of online shopping behaviour, with Social influence exhibiting the greatest impact.

Johnson and Ramirez (2020)	This study approached online shopping from an Omnichannel marketing perspective. Consumers now engage in showrooming (researching in-store before purchasing online). The study sought to determine the moderating and interaction effects of the Millennial generational cohort and Showrooming in predicting online shopping intention.	The independent variables were risk factors (*Financial*, *Product* and *Time/Convenience* risks), while the *Millennial generational cohort* and *Showrooming* were moderators. The findings indicated significant cohort differences for financial and time/convenience risks.
Makhitha. Van Scheers and Mogashoa (2019: 312)	The paper set out "to determine the consumer attributes that influence online shopping behaviour of South African consumers".	Using a factor analysis, the authors identified three constructs (*Convenience*, *Perceived usefulness*, and *Security risk*), which were found to have a significant relationship with online shopping behaviour.
Mokhtar *et al.* (2020)	The study investigated the attributes that influence young adults in Malaysia.	The study identified four attributes (*Convenience*, *Perceived risk*, *Customer satisfaction* and *Price level*) and hypothesised that they influence online shopping behaviour. The findings confirmed the hypotheses, with convenience and price having a positive influence while perceived risk had a negative influence. Surprisingly, customer satisfaction did not have a significant influence.

2.7 ONLINE SHOPPING USAGE PRE AND DURING COVID-19

Before the COVID-19 pandemic struck, online shopping was already steadily becoming popular due to the sudden growth of e-commerce globally (OECD 2020a), underpinned by the explosion of the fourth industrial revolution (Dang, Bao and Cho 2023). The pandemic forced or accelerated the adoption of e-commerce as people were confined to their homes (national lockdowns), meaning they could not go to the brick-and-mortar shops to buy products. Even though FMCG retailers and fast-food shops were regarded as essential services and were allowed to operate during the pandemic, the stringent regulations and general fear of catching the virus meant that only a few went to the physical shops, with many others forced into online shopping.

The lockdowns brought about significant changes in consumer behaviour (Mehta, Saxena and Purohit 2020; Tinonetsana and Msosa 2023). The lockdowns forced numerous businesses, including FMCG providers, to quickly adopt e-commerce, adding to a few that already had some online presence. In South Africa, companies such as Takealot, Zandos, Superbalist, Checkers, Makro and Game already dominated the online business market. During the pandemic, the authorities (World Health Organisation and Government) actively encouraged e-commerce to mitigate the spread of the virus (Beaunoyer, Dupéré and Guitton 2020). The resultant structural market change triggered a surge in online purchases and ingrained behavioural changes, some of which were assumed to last beyond the pandemic (OECD 2020b; The Economist 2020). Essentially, consumers who were not fond of online shopping, especially the not-so-tech-savvy ones, were trapped in online shopping. However, some still did not participate, which can be explained by digital inequalities (Beaunoyer, Dupéré and Guitton 2020), digital literacy or technophobia. While digital literacy can be easily mapped to Prensky's (2001) notions of digital natives and immigrants, digital inequality extends beyond this dichotomic categorisation to include the socio-economic and demographic factors of accessing and using technology (Yates, Kirby and Lockley 2015; Zhang 2015).

In 2020, during the first year of the COVID-19 forced shutdowns, numerous developed economies where e-commerce was already in traction witnessed a slump in e-commerce revenue for the first few months. However, in the second quarter of 2020, sales peaked in these economies and surged substantially. For example, the United States saw 16.1%, the United Kingdom 31.3%, and 24.6% for China (OECD 2020b). For African economies, a precedented growth in digitalisation was recorded (United Nations Economic Commission for Africa and

African Development Bank. 2022). In South Africa, e-commerce sales spiked as more joined the e-commerce bandwagon, but there were some misfortunes; for instance, some people lost jobs and had income and savings reduced, affecting their spending power (McKinsey and Company 2020; Statistics South Africa 2020). While the online business growth projections promised an overshoot beyond the pandemic, it is reported that most people in South Africa reverted to traditional ways of shopping as soon as COVID-19 regulations were eased (Dludla 2020; Tinonetsana and Msosa 2023).

2.8 ONLINE SHOPPING USAGE POST-COVID-19

The global COVID-19 pandemic significantly accelerated the growth of FMCG e-commerce, a trend reflected in a recent Mastercard study highlighting the increased prevalence of online shopping among South African consumers. According to the survey, 68% of South African consumers are engaging in online shopping more frequently than they did prior to the pandemic (Mtotywa and Kekana 2023). This shift is particularly evident in specific categories, with 81% of consumers purchasing data and airtime online, 56% shopping for clothing, 54% for groceries, and 51% for beauty and haircare products (Mtotywa and Kekana 2023). The expansion of e-commerce has also extended to other facets of financial management, as 76% of respondents indicated they had acquired the skills to bank online during this period. Furthermore, there has been a notable rise in support for local small businesses, with 63% of consumers consciously opting to shop at these enterprises through online platforms (Mtotywa and Kekana 2023).

Social media has also emerged as a key driver of online consumer behaviours, with 64% and 41% of respondents discovering new sellers via Facebook and Instagram, respectively. These findings suggested that online shopping in South Africa has experienced significant growth since the onset of COVID-19, with e-commerce becoming an integral part of consumers' daily routines. This is evident from a study conducted by Katrodia (2023), who studied the trend of online shopping in South Africa on different categories of products pre, during and post COVID-19.

Figure 2.6 reveals a slow increase in online shopping across various FMCG categories in South Africa, particularly before, during, and after the COVID-19 pandemic. For instance, groceries, a key FMCG category, experienced a gradual increase from 3% pre-COVID-19 to 6% post-COVID-19, reflecting a growing trend of consumers purchasing daily essentials online. Similarly, categories like beauty and hygiene (5% pre-COVID-19 to 13% post-COVID-19), and small appliances (10% pre-COVID-19 to 22% post-COVID-19), also saw significant increases, showing that consumers have increasingly embraced online channels for a broader range of essential and discretionary products. This shift aligns with the broader trend of e-commerce growth, indicating that online shopping in South Africa continues to rise, even beyond the lockdown period.

Category	Pre-COVID	COVID lockdown	Post-COVID
Consumer Electronics	17%	21%	24%
Groceries	3%	4%	6%
IT	17%	31%	26%
Beauty & hygiene	5%	11%	13%
Small appliances	10%	20%	22%
Fashion	11%	21%	17%
Mobile phones	14%	17%	20%
DIY	8%	12%	15%

Figure 2.6: E-commerce sales

Source: Thompson 2020

2.9 NON-ADOPTION OF ONLINE SHOPPING IN SOUTH AFRICA

Online shopping has become increasingly popular in South Africa in recent years, albeit slowly (Pentz, du Preez and Swiegers 2020), or as Pillay and Mayayise (2021) noted, the concept is still in its infancy, especially compared to developed economies. According to Mofokeng (2021: 1), South Africa is ranked as the 37th largest market for e-commerce, with an annual growth rate (AGR 2021-2025) of 8.16%, or an estimated market volume of US$6,898 m by 2025. Although these figures show promising growth, the performance remains disappointing, considering the high internet and digital penetration in South Africa compared with its African peers. A 2019 South African Digital Consumer Report by Rogerwilco (2019) estimated that more than 24 million e-commerce users would generate about 1.4% of all retail sales in South Africa. Interestingly, the report states that 71% of the people who engage in online shopping abandon the process at the digital checkout point.

While many previous studies have investigated factors that positively influence the adoption of online shopping in South Africa (Hung-Joubert and Erdis 2019; Makhitha, Van Scheers and Mogashoa 2019; Pillay and Mayayise 2021; Moeti, Mokwena and Malebana 2021; Musikavanhu and Musakuro 2023), no study known to the researcher has investigated the reasons for individuals' non-adoption in South Africa. In support of this observation, Nery-da-Silva, de Araujo and de Souza Meirelles (2024) deprecated that "non-shoppers are seldom addressed alone." The closest would be Pentz, du Preez and Swiegers (2020), who investigated perceived risks as barriers to online shopping. However, their sample comprised individuals (experienced and non-experienced) who had shopped online before. As such, their study cannot be said to have investigated the non-adoption of online shopping; instead, it was about repeat online shopping behaviour. Benson and Ndoro (2022) investigated the factors influencing online shopping cart abandonment, which is also about shoppers who would have engaged in the online shopping process but faltered before purchasing. It is worth noting that non-adoption behaviour and adoption of e-commerce are not necessarily the opposites (Richetin, Conner and Perugini, 2011); hence using adoption behaviour findings in reverse may not adequately or appropriately explain non-adoption (Mainardes, de Souza and Correia 2020).

Also, this paucity of studies investigating factors influencing the non-adoption of online shopping extends beyond the South African consumer markets. Bringula (2016), Mainardes, de Souza and Correia (2020), and Nery-da-Silva, de Araujo and de Souza Meirelles (2024) studies are some of the few to have investigated strictly the factors influencing the non-use of online shopping in the Philippines and Brazil, respectively. While Hernández-García, Iglesias Pradas, Chaparro Peláez and Pascual Miguel (2011) and Faqih (2016) concurred with Nery-da-Silva, de Araujo and de Souza Meirelles (2024) that research has neglected the analysis of non-adoption of online shopping, they surprisingly went on and used instruments with items measuring adoption rather than non-adoption.

Bringula's study categorised the factors into three taxa: "Company Domain, Personal Domain, and Technical Domain". Mainardes, de Souza and Correia (2020) used the TPB (Azjen 1991) and added negative word-of-mouth (NWOM) and disinterest to explain non-adoption of e-commerce. Nery-da-Silva, de Araujo and de Souza Meirelles (2024) identified four indicators (disinterest dimension, inability dimension, operational difficulty dimension, and distrust dimension) to explain the non-adoption of online shopping. In another study, Hernández-García, Iglesias-Pradas and Urueña-López (2013: 89), reduced the reasons for not shopping online by a Spanish sample into three dimensions; that is, "absence of physical presence of the goods or channel preference; security concerns and privacy risks; and lack of internet access and/or skills". From these previous studies it is evident that the understanding of online shopping defers amongst consumers. Therefore, it would be beneficial for this study to examine factors influencing consumer non-adoption and E-commerce Non-Users Segment in the south African context.

2.9.1 Factors Influencing Consumer Non-Adoption of Online Shopping

In today's rapidly evolving digital landscape, the phenomenon of consumer non-adoption of online shopping has become a topic of increasing interest and importance. While the convenience and accessibility of e-commerce platforms have transformed the retail landscape (Katta and Patro 2016), there are still segments of the population that have not fully embraced this shift (Mainardes, de Souza and Correia 2020; Nery-da-Silva, de Araujo and de Souza Meirelles 2024). A comprehensive understanding of the factors influencing this non-adoption is crucial for businesses and policymakers to develop strategies that can effectively engage this untapped market.

There are numerous factors of non-adoption of online shopping identified or suggested in literature. Table 2.4 provides a non-exhaustive summary of the reasons why some individuals are not shopping online.

Table 2.4: Factors of non-adoption of online shopping

Factor	Description	How treated in the present study
No perceived utility	Functionality or utility has long been central to understanding consumer. Within the online shopping adoption literature, perceived utility (or lack of) has been identified as a choice factor. As stated by Wu *et al*. (2015), consumers are value-driven. Hsu, Chang and Chuang (2015) term this as perceived value, which relate to consumers' perceptions of the intrinsic and extrinsic benefits that can be derived from using a system. Perceived value is increased when getting product information and/or purchasing products require less effort (Davis 1989). It, therefore, follows that consumers are highly unlikely to adopt online shopping if they believe it would not enhance their shopping outcomes and experiences.	Adapted into "No or negative performance expectance" variable drawn from the UTAUT (Venkatesh *et al.* 2003).
Lack of trust	While numerous studies have investigated the effect of trust on intention to shop online or online shopping behaviour (Hsu, Chang and Chuang 2015; Retnowati and Mardikaningsih 2021), a few have shown distrust in online shopping, including online payment systems which are a central element of online shopping. Distrust in online shopping arises when consumers do not believe that the system will function in a non-prejudicial manner, or an e-commerce business will honour its promise, and is more prominent for first-time purchases (Darke *et al*. 2016). This could be due to past unmet promises (Chen, Wu and Chang 2013), platform security or privacy breaches (Bandara, Fernando and Akter 2020), feeling that an online business is not capable of securing information (Tuteja, Gupta and Garg 2016) or is pretending to care about customers (Chang and Fang 2013) and lack of physical interaction (Darke *et al*. 2016; Nepomuceno, Laroche and Richard 2014). Lack of trust is one of the major barriers of online shopping (Leong, Hew, Ooi and Wei. 2020; Palvia 2009; Rasty *et al*. 2021). It reifies uncertainty and amplifies risks, thus reducing the likelihood of adoption of online shopping (Nery-da-Silva, de Araujo and de Souza	Distrust in online shopping channels.

	Meirelles 2024). It is crucial to note that trust and distrust are not necessarily the opposites. Literature shows that the two concepts can co-exist (Rasty *et al.* 2021), hence both must be prioritised by online businesses.	Distrust in online payment systems.

Perceived risk/insecurity	Perceived risks are inevitable in the adoption of technology (Humbani and Wiese 2019) and are closely related to distrust in online shopping (Tuteja, Gupta and Garg 2016). It is the consumers' insecurities that an e-business cannot control or would not adhere to e-commerce security parameters such as encryption, authentication and non-repudiation, and will not adequately protect customer information from unauthorised access (Tuteja, Gupta and Garg 2016) . In South Africa, online fraud and identity theft are prevalent crimes that make many people uncomfortable with sharing their details online. Wu *et al*. (2015) suggested seven categories of perceived insecurity, i.e. financial risk, social risk, performance risk, time risk, privacy risk, psychological risk and physical risk.	These were incorporated into the "technophobia" variable.
Complexity	Literature on 'user adoption of technology' has long placed emphasis on the simplicity or easy navigability of systems to enhance user experience. The TAM (Davis 1989) and UTAUT (Venkatesh *et al*. 2003) are notable theories that have incorporated ease of use and performance expectancy which have been respectively used to explain the importance of navigability of e-commerce websites or platforms. Navigability, in the context of e-commerce, refers to the ease with which users can locate and access the products, services, and information they seek on websites or platforms. To enhance navigability, research has suggested numerous approaches, with user interface design (UID) touted as the most effective for enhancing the user experience in e-commerce platform (Ekşioğlu, Varol and Duman 2015; Gunawan, Anthony and Anggreainy 2021) and includes adaptability to different devices (Alao *et al*. 2016). A well-designed e-commerce platform is easy to use, visually appealing, interactive and more important, functional (Gunawan, Anthony and	Adapted into "No or negative effort expectance" variable drawn from the UTAUT (Venkatesh *et al*. 2003).

	Anggreainy 2021). Apart from the design elements, navigability or usability can be influenced by prior experience, and digital literacy/efficacy (Nery-da-Silva, de Araujo and de Souza Meirelles 2024), and can also influence trust in an e-commerce platform (do Espírito Santo and Trigo 2020), attitudes towards the platform or online shopping (Djurica and Figl 2017) and strengthen intention to purchase online or the actual purchase behaviour (do Espírito Santo and Trigo 2020).	

Negative influence of important others.	The proliferation of digital technologies, especial in commerce has redefined the role of consumers from passivity to active churning of information about products or brands (Roberts and Dinger 2016), and in the process influencing each other's emotions, attitudes, opinions and purchase decisions. However, early researchers in human behaviour argued that it is not merely the human-to-human influence that is impactful, but that of important referent individuals or groups. The social influence construct was adopted and popularised by the Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975) and the Theory of Planned Behaviour (TPB) (Ajzen 1991), which have been adopted extensively across various research fields. In these theories, the influence of important referents is known as the subjective social norm. Ajzen (2020) splits subjective norm antecedents into injunctive and descriptive normative beliefs. Injunctive beliefs are the likelihood that the important referent would approve or disapprove performance of a behaviour, coupled with the individual's motivation to comply with the referent in question. Descriptive beliefs are convictions that important referents also perform the behaviour. Several previous studies have looked at this construct's impact from an approval of view leaving a gap for the inversed impact. Thus, this present study sought to narrow this gap by looking at the impact of disapproval of a behaviour by important others.	Negative social influence drawn from the UTAUT (Venkatesh *et al*. 2003).

Low perceived behavioural control or operational difficulties	Ajzen (1985) extended the TRA to address its “limitation in dealing with behaviours over which people have incomplete volitional control” by adding perceived behavioural control as the antecedent of behavioural intention. Perceived behavioural conditions (PBC) accounts for the opportunities, conditions and resources that determine the actual control (or lack of) over; hence the (in)ability to perform a behaviour (Ajzen 1991). Accordingly, Ajzen theorised that PBC directly influence intention and actual behaviour. Venkatesh *et al.* (2003) later labelled PBC as the ‘Facilitating Conditions’ in their UTAUT model which consolidated views of eight different theories of technology adoption. One of the constructs retained from a factor analysis by Nery-da-Silva, de Araujo and de Souza Meirelles (2024) was the “operational difficulty dimension”, which had external factors that negatively affected individuals’ perception of successful online shopping, for example, logistical or bureaucratic requirements. Within the realm of online shopping, poor or unfavourable facilitating conditions such as poor/lack of customer support, poor internet connectivity, no access to a compatible device, lack of time and digital illiteracy can explain hesitancy to shop online.	Adapted into “No or negative facilitating conditions” variable drawn from the UTAUT (Venkatesh *et al.* 2003) and “Digital illiteracy”.
Disinterest	Mainardes, de Souza and Correia (2020) extended the TPB by adding two consequent factors to explain the perpetuation of non-adoption of online shopping. The two factors are negative word of mouth and disinterest. While no studies have investigated disinterest in e-commerce, it is dealt with indirectly in innovation resistance studies which looks at barriers such as distrust, perceived value and risks and complexity of e-commerce (Mainardes, de Souza and Correia ; Talwar *et al*. 2020). Disinterest is a form of resistance which can be displayed through opposition (Mani and Chouk 2017), in this case to online shopping.	Not incorporated in the present study as a standalone construct, but under the technophobia variable.

While non-users are labelled differently (semantics) in each of the three studies, there are notable commonalities among certain groups' characteristics based on factors presented in Table 2.4. Common barriers to adoption include the perception that online shopping is complicated, concerns over data privacy and financial security, distrust in online shopping and payment systems, and lack of internet access. Interestingly, many of these groups are on the cusp of adopting online shopping. For instance, fun-seekers and fearful browsers (Swinyard and Smith 2003), as well as the sceptical/distrustful segment (Iglesias-Pradas, Pascual-Miguel, Hernández-García and Chaparro-Peláez 2013), are already frequent internet users who search for product information and engage with digital content. Their hesitance towards online shopping is less about complete aversion and more about perceived risks and uncertainties.

To bridge this gap, online retailers and policymakers must focus on targeted interventions that directly address these concerns. Enhancing consumer trust through robust security measures, transparent privacy policies, and reliable customer support can mitigate fears associated with financial transactions. Additionally, improving user experience by simplifying navigation and enhancing website usability can make online shopping more intuitive.

Another crucial aspect is consumer education emphasising the tangible benefits of online shopping, such as convenience, broader product variety, and potential cost savings. Social proof, in the form of user testimonials, influencer endorsements, and peer reviews, can also play a pivotal role in reassuring hesitant consumers. Ultimately, the conversion of these non-adopters hinges on reducing perceived risks, improving accessibility, and fostering trust, in the digital marketplace. By strategically addressing these barriers, retailers can tap into a significant pool of potential customers who are already engaged with the internet but have yet to take the final step towards e-commerce participation.

2.9.2 E-commerce Non-Users Segmentation

As indicated earlier, scholars studying online shopping are seemingly not interested in the behaviour of non-adopters (Nery-da-Silva, de Araujo and de Souza Meirelles 2024) leading to inaccurate strategic approaches to convert them to online shopping. Segmentation, targeting and positioning are the bedrock of any marketing strategy, including strategies for non-adopters. E-commerce non-users can be categorised into various groups, for example, based on computer literacy (Swinyard and Smith 2004). While there has been so much interest in understanding online shopper segments (e.g., Prashar, Sai Vijay and Parsad 2016; Zhou, Wei and Xu 2021), slow research traction is observed when it comes to segmenting those who are hesitant of shopping online.

Unlike the Nery-da-Silva, de Araujo and de Souza Meirelles (2024) study that exclusively segmented online non-shoppers, other studies such as Abad, Jiménez and González (2022); Iglesias-Pradas *et al*. (2013); and Swinyard and Smith (2003) included both online shoppers and non-online shoppers. Abad, Jiménez and González (2022) surveyed 405 seniors (60 – 75 years) from Spain, comprising of e-commerce users and nonusers. For nonusers, the study identified seven groups of nonusers using a K-means clustering – the indifferent, reluctant, practical, optimistic, convenient, novice and enthusiastic. Also from a Spanish sample, Iglesias-Pradas *et al*. (2013) identified four groups of nonusers of online shopping — the sceptical/distrustful, infrastructure-conditioned, product-conditioned and others using a latent class analysis (LCA) approach. Swinyard and Smith (2003) also identified four groups of online non-shoppers (the fearful browsers, shopping avoiders, technology muddlers and fun-seekers), albeit from an American sample.

2.10 SUMMARY OF THE CHAPTER

The chapter provided a comprehensive review of literature on online shopping behaviour, with a specific focus on the South African e-commerce market. It began by outlining the purpose of the literature review, identifying key gaps in existing knowledge, and contributing to the broader discourse on online shopping. A notable gap highlighted was the prevailing research bias towards factors influencing adoption, while limited attention has been given to understanding the reasons behind consumers' reluctance or refusal to engage in online shopping. The discussion positioned online shopping as a major paradigm shift in consumer behaviour driven by advancements in information and communication technologies (ICT). Factors such as technophilia, convenience, and generational influences were explored as key drivers of this shift, alongside the transformative impact of e-commerce on the retailing of FMCG, enabling price comparisons, wider product access, and enhanced convenience.

The chapter also traced the historical evolution of online shopping from the late 1970s to the present, outlining milestones such as the development of the World Wide Web (WWW), the introduction of secure payment systems, and the rise of mobile and social commerce. It further analysed global and South African online shopping behaviour, identifying both drivers and barriers to adoption. The influence of the COVID-19 pandemic in accelerating online shopping due to restricted access to traditional retail channels was also highlighted. The final sections focused on the often-overlooked perspective of non-adopters, emphasizing the importance of segmenting this group to improve marketing effectiveness. The chapter concluded by setting the stage for Chapter 3, which builds on these insights by presenting the theoretical foundations and conceptual framework of the study.

CHAPTER THREE

GROUNDING THEORIES AND EMPIRICAL LITERATURE

3.1 INTRODUCTION

This chapter builds upon the foundation laid in the previous chapter by focusing on the theoretical relationships among various factors that contribute to the non-adoption of online shopping. The aim is to explore and understand the underlying reasons for individuals' reluctance or lack of intention to engage in online shopping, as outlined through the five specific research questions that drive this study. By delving into these questions, the chapter offers a detailed examination of the factors that influence consumer behaviour in the context of e-commerce adoption. To guide this exploration, a conceptual framework is presented, synthesising key insights drawn from a range of theoretical frameworks. This framework highlights the interconnections between individual, technological, and environmental variables that may shape consumers' attitudes and behaviours toward online shopping. The hypotheses within this framework were specifically formulated to address the various aspects of reluctance toward online shopping, aiming to test how different factors such as perceived risk, trust issues, and technological barriers affect the decision to avoid or delay adoption. Through this conceptual model, the study seeks to contribute to the growing body of literature on e-commerce adoption, offering valuable insights for both researchers and practitioners aiming to reduce barriers to online shopping. This chapter thus sets the stage for further empirical testing, which will provide a clearer understanding of the dynamics at play in the reluctance to shop online

3.2 RESEARCH QUESTIONS (RQ)

As stated in Chapter 1, this study sought to determine factors that influence customer non-adoption of FMCG online shopping post-COVID-19 in South Africa. The following six research questions were raised to operationalise the objectives of the present study:

1. Do the inverted UTAUT factors explain the reluctance to shop online?
2. Does technophobia, lack of reciprocity and distrust in online shopping channels influence the reluctance to shop online?

3. What is the relationship between (i) lack of reciprocity, (ii) distrust in online payment systems, and (iii) lack of social presence, and the distrust in online shopping channels?
4. Does poor promotional effort moderate the effect of (i) negative performance expectancy (ii) technophobia, and (iii) the effect of distrust in online shopping systems on the lack of reluctance to shop online?
5. Does poor promotional effort moderate the effect of distrust in online payment systems on distrust of online shopping channels?
6. Does digital illiteracy moderate the effect of (i) negative performance expectancy, (ii) negative effort expectancy, and (iii) technophobia on the reluctance to shop online?

3.3 CONCEPTUAL FRAMEWORK OF THE STUDY

To answer the above research questions, this study drew from three established theoretical frameworks: The Unified Theory of Acceptance and Use of Technology (UTAUT), the Trust Transfer Theory (TTT), the Social Exchange Theory (SET), and the Social Presence Theory (SPT), which are discussed in Subsections 3.3.1 to 3.3.4.

3.3.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT was developed by Venkatesh *et al.* (2003) to synthesise the earlier models of technology acceptance to have "a unified view of user acceptance". The eight models unified into UTAUT are the Theory of Reason Action (TRA) (Fishbein and Ajzen 1975; Ajzen and Fishbein 1980), the Technology Acceptance Model (TAM) (Davis 1989), the Theory of Planned Behaviour (TPB) (Ajzen 1991), the Motivational Model (Davis, Bagozzi and Warshaw 1992), the Combined TAM-TPB Model (Taylor and Todd 1995), the Model of PC Utilisation (Thompson, Higgins and Howell 1991), the Innovation Diffusion Theory (IDT) (Rogers 1983; 1995), and the Social Cognitive Theory (SCT) (Bandura 1999).

Since its origination, the UTAUT has been applied in numerous studies across various sectors beyond the information systems context, with some modifying the model by adding new variables. These studies have confirmed the improved variance explained and envisaged by Venkatesh and his colleagues. Attuquayefio and Addo (2014) applied the UTAUT to analyse students' ICT adoption in Ghana, and the model explained 70% of the variation in technology acceptance. Abrahão Moriguchi and Andrade (2016) employed the UTAUT model to evaluate mobile baking adoption in Brazil, with the model explaining 76% of the behavioural intention. The authors added perceived Cost and perceived Risk to UTAUT's performance expectancy, effort expectancy and social influence as predictors of behavioural intention. Ayaz and

Yanartaş (2016) applied a reduced UTAUT version, with performance expectancy, effort expectancy and social influence as independent variables. The model explained 61% of the variation of the intention to accept the electronic document management system.

The original UTAUT (Venkatesh *et al.* 2003) proposed four predictors of behavioural intention (BI) and, ultimately, actual behaviour; namely, performance expectancy (PE), effort expectancy (EE), and social influence (SI). The facilitating conditions (FC) variable was hypothesised to directly predict actual behaviour. The Gender variable was hypothesised as moderating the relationships between PE, EE and SI with BI, while Age was a moderator for the influence of all the four predictors. The model also hypothesised that Experience moderated the influence of EE and SI on BI and FC on actual behaviour. Lastly, the voluntariness of use was added as a moderator of the impact of SI on BI. The original model is depicted in Figure 3.1.

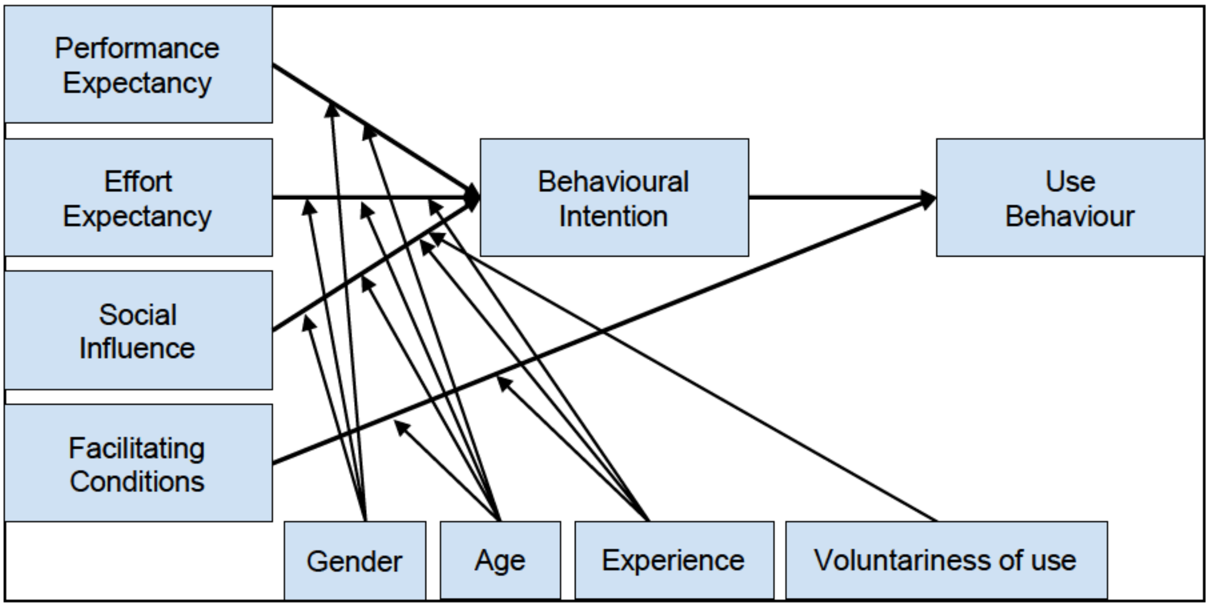


Figure 3.1: Original UTAUT Model

Source: Venkatesh *et al.* 2003

After nearly a decade of UTAUT, Venkatesh and colleagues extended the original model, which primarily focused on the organisational context, to UTAUT2, consistent with the consumer context (Venkatesh, Thong and Zu 2012). The extended model incorporated three new predictors (hedonic motivation, price value, and habit). The researchers proposed new moderation effects of gender, age, experience, and voluntariness of use variables. Notably, the facilitating conditions variable was added as a predictor of behavioural intentions. The

UTAUT2 showed some improvement in explaining the variance in consumers' behavioural intention and actual technology use (Venkatesh *et al.* 2012).

3.3.1.1 Advantages of UTAUT

Using the UTAUT in a study on the non-adoption of technology in FMCG offers several advantages:

UTAUT stands out as a comprehensive framework because it synthesises key constructs from eight established models, including the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Diffusion of Innovations (DOI), and others (Venkatesh *et al.* 2003). This integration ensures that UTAUT captures a broader range of factors influencing technology adoption and non-adoption (Venkatesh *et al.* 2003). For example, while TAM focuses primarily on perceived usefulness and ease of use, UTAUT incorporates additional dimensions such as social influence and facilitating conditions, which are critical for understanding barriers in specific contexts such as non-adoption of online FMCG shopping.

UTAUT acknowledges external factors, such as cultural norms, infrastructure limitations, and user diversity, which are often overlooked in other models (Sharma and Ghosh 2021). This holistic perspective makes UTAUT particularly effective for analysing complex adoption environments where multiple variables interact, such as in the FMCG sector, where consumer behaviour, technological infrastructure, and socio-economic factors are tightly interwoven (Liu and Li 2020). As a result, researchers and practitioners can gain deeper insights into both the drivers and inhibitors of technology usage, facilitating targeted strategies to address non-adoption.

The predictive power of UTAUT lies in its ability to effectively identify and quantify the factors that drive or inhibit technology usage intentions and behaviours. The model systematically evaluates why certain individuals or groups resist or fail to adopt technology (Venkatesh *et al.* 2003). In the context of FMCG, where technology platforms like e-commerce websites or mobile apps are becoming critical channels, UTAUT's predictive capabilities are invaluable for pinpointing specific barriers, such as perceived lack of benefit, complexity, or inadequate support systems.

The applicability of UTAUT has been proven across diverse industries, user groups, and geographical contexts such as South Korea (Jin and Liu 2020), Bangladesh (Hossain and Quaddus 2012) and Saudi Arabia (Al-Gahtani and Al-Salman 2021); establishing it as a vigorous framework for studying technology adoption and non-adoption. In sectors ranging from healthcare to education, and in both developed and developing markets, UTAUT has consistently demonstrated its ability to adapt to unique challenges and variables (Venkatesh, Thong and Xu 2012). This flexibility is particularly relevant to the FMCG sector, where consumer demographics and behaviour are highly diverse.

UTAUT's constructs allow for an exploration of cultural and socio-economic factors, such as income disparities and digital literacy gaps, which are often pivotal in FMCG markets with limited technological integration (Rana and Dwivedi 2015). This adaptability ensures that UTAUT provides actionable insights tailored to the unique dynamics of the FMCG sector, enabling businesses to address resistance and foster wider acceptance of technology among diverse consumer groups.

3.3.1.2 Application of the UTAUT Model in the Online Shopping Context

The UTAUT model has been extensively applied in its various conceptualisations (original, extended or integrated) to explain the acceptance and adoption of online shopping. For example, a Boolean search in Google Scholar and Semantic Scholar for studies that applied the UTAUT showed that most either extended or integrated the model. The search words used were "Unified Theory of Acceptance and Use of Technology" or "UTAUT" and "Online shopping." Hungilo and Setyohadi (2020) extended the UTAUT2 by adding personal innovativeness, perceived risk and trust to explain consumer intention to shop online in Tanzania. The study's results showed that only effort expectancy, price value and trust were the significant predictors of intention to shop online. Celik (2016) added the anxiety variable to the original UTAUT to test whether it inhibited "customer outcome beliefs" (e.g. performance expectancy and effort expectancy) and usage intentions of online shopping. Celik (2016) further expanded on the original UTAUT model by introducing the anxiety variable to examine its impact on customer outcome beliefs (performance expectancy and effort expectancy) and the usage through intentions to shop online. Performance expectancy and social influence were found to significantly predict intention to shop online while effort expectancy and facilitating conditions were not. The negative effect of anxiety on the intention to shop online was confirmed.

Some studies integrated the UTAUT with other models. For example, Chang, Fu and Jain (2016) combined the UTAUT with the innovation diffusion theory (IDT) to show how virtual community building, website performance expectancy, effort expectancy, trialability, and two mediators (familiarity and perceived risk) interact and affect online shopping intention. The findings of this study revealed that UTAUT (performance and effort) constructs have a significant positive effect on website familiarity. However, their hypothesised negative effect on perceived Risk was not significant. The IDT constructs (virtual community building and trialability) have a significant positive effect on product familiarity and a not significant adverse effect on perceived risk. All three mediators significantly affect intentions; product familiarity and website familiarity have a positive effect, while perceived risk has a negative effect).

It is, however, noteworthy that studies employing the UTAUT do so to explain people's intention to shop online and pro-online shopping behaviour. To this end, no study known to the researcher has adopted UTAUT to explain why people do not accept or adopt online shopping. Thus, this study employs an inverted UTAUT, using negative statements for the five constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intentions). The study excluded actual behaviour (non-adoption) due to the time lag needed for data collection, as behavioural intentions indicate the extent to which an individual is willing to perform in the future (Ajzen, 1991). Hence, a two-phase approach must be adopted to capture use behaviour accurately. The first phase would collect behavioural intention data, with the second phase conducted to collect data on actual behaviour a few months after the first phase. For the present study, such would elongate the timeframe of the study. The present relied on Fishbein and Ajzen's (1975) suggestion that behavioural intention is a suitable proxy for actual behaviour. Several previous studies have adopted the suggestion (Bianchi and Andrews 2012; Hernández and Sánchez-Mangas 2011; Koch Frommeyer and Schewe 2020).

3.3.2 Trust Transfer Theory (TTT)

Trust Transfer Theory (TTT) explains how trust established in one context or entity can be transferred to another related context or entity (Putri, Prasetya, Handayani and Fitriani 2024). Originally conceptualised in the fields of psychology and marketing, TTT is widely applied in e-commerce, digital platforms, and inter-organisational relationships (Çevik and Koç 2022). The theory posits that when individuals lack direct experience with a particular entity, trust becomes the cornerstone of human interactions with other humans or entities such as organisations, animals, and machines (Kaplan Kessler and Hancock 2020). Trust represents a conviction that the other party will uphold their obligation. According to Mou, Shin and Cohen (2017), this conviction stems from one's knowledge and beliefs about the other party's honesty, integrity, benevolence, and competence, making fulfilment predictable. In a trust transfer process, there are three parties: the trustor, the trustee and the third party (Putri *et al.* 2024;

Sim, Loh, Wong, and Choong 2021). The trustor (e.g., customer) evaluates and judges the trustee (e.g. retailer). The third-party (online platform), also known as the broker, must have a strong connection with the trustee (Chen Huang, Davison, and Hua 2015; Stewart 2003) to enjoy the positive spinoffs of the trust on the trustee.

Numerous studies in the relationship marketing field have applied trust to explain consumer behaviour (Deng Su, Zhang and Tan 2021; Karunasingha and Abeysekera 2022; Leong and Meng 2022; Liao, Hsieh and Kumar 2023). Lack of trust has been cited as to why people do not buy or opt out of relationships (Oliveira, Alhinho, Rita and Dhillon 2017; Stewart 2003). According to Stewart (2003), trust is transferable and can be divided into intra-channel and inter-channel (online or offline). Intra-channel trust transfer describes how trust built through previous positive channel experiences is transferred to future interactions. For example, persistent positive interactions and experiences in an online shopping platform like Takealot can bring about trust for the platform, positively influencing a customer's future purchase decisions. On the other hand, inter-channel trust transfer is the transference of trust from one context to another, influencing individual or group perceptions, attitudes, and behaviour in a different context. For example, a retailer's positive offline reputation influences consumers' trust in their online business.

3.3.2.1 Advantages of TTT

The TTT is widespread in consumer behaviour studies when multiple retail channels coexist and has proven to offer various advantages (Deng *et al.* 2021), for example:

i. TTT emphasises how trust is transferred from a familiar, trusted entity (e.g., a physicalFMCG store) to a new, unfamiliar entity (e.g., an online grocery platform) (Suh and Han 2003). This focus on trust is particularly relevant for understanding non-adoption, as distrust in technology or digital platforms is often a major barrier in FMCG.

ii. The theory helps explore why consumers might resist adopting technology due to distrust in online platforms, such as concerns about data privacy, payment security, or the reliability of digital services and provides a structured way to assess how these factors influence non-adoption (Behera, Bala and Rana 2023).

iii. Fast Moving Consumer Good retailers often operate in both brick-and-mortar and online spaces. The Trust Transfer Theory explains how trust in traditional stores (e.g., Shoprite or Spar) might not immediately transfer to their online platforms, highlighting areas where non-adoption stems from a lack of perceived continuity or authenticity (Saprikis and Avlogiaris 2021).

iv. Trust transfer is influenced by cultural norms and consumer behaviours, making the TTT highly adaptable to studying diverse FMCG markets (del Río and Arroyo 2024.). For instance, in South African context, TTT can explore how urban consumers' trust in local retail brands influences their willingness (or unwillingness) to use those brands' digital platforms.

3.3.2.2 Application of the TTT in Online Shopping Context

Stewart (2003) conducted a study using the TTT as a theoretical grounding to explore "how consumers' initial trust judgments about organisations they encounter on the Web may be influenced by hypertext links from trusted websites and associations with the more trust-inducing traditional retail channel." In the study, Stewart found that the hypertext links from one credible website to another instilled a belief that the two organisations have a business relationship, hence the transfer of trust from the credible to the target organisation. Also, trust from physical shopping channels influences trust on the web and the intention to shop from the firm's online store. Since the publication of the TTT, several studies have adopted the theory to explain online shopping behaviour.

Cui, Mou, Liu and Kurcz (2018) investigated trust transfer from domestic m-commerce to cross-border m-commerce. They confirmed the concept, including that trust is an important factor for online search intention. In the study conducted by Zhang and Wang (2021), trust transfer was confirmed from online-to-offline (O2O) platforms to offline merchants, affirming the assertion that positive experiences with a platform (e.g., Instagram) builds trust, which is likely to be transferred to merchants that use that platform (Chen *et al.* 2015). Sim *et al*. (2021) integrated UTAUT with trust-building mechanisms to predict behavioural intention in adopting m-commerce. All five independent predictors in the model (the four original UTAUT variables and Trust in vendor) significantly predicted behavioural intention. More important in illustrating the trust transfer process was the finding of a significant moderating effect of the perceived effectiveness of e-commerce institutional mechanisms (the third party) on the user's intention to adopt m-commerce. In the present study, the trust-transfer theory was inverted to explain how a lack of trust in one context (e.g., an online payment system) can be transferred to a lack of trust in online shopping as a channel, leading to a reluctance to adopt online shopping.

3.3.3 Social Exchange Theory (SET)

The origins of the SET are attributed to Homan's (1958) essay titled "Social Behaviour as Exchange." This theory was developed from behaviourism and microeconomics principles to explain human behaviour. Other sociologists later adopted this theory (Blau 1964; Emerson 1962) to study organisational behaviour. The SET posits that human interactions are premised on a cost-benefit perspective (Leong and Meng 2022; Shiau and Luo 2012), where individuals have expectations and anticipations. From the thoughts of Homans (1958) and others, social exchanges can be negotiated or reciprocal (Urbonavicius *et al.* 2021).

The negotiated exchanges are regulated and formalised, and parties to them are assumed to have prior knowledge of the regulatory framework, benefits, and costs, key aspects of joint decision processes between the parties (Molm 2003). On the other hand, reciprocal exchanges are primarily informal, non-negotiated and unregulated. Such exchanges thrive on reciprocity and trust (Degutis *et al.* 2023; Urbonavicius *et al.* 2021; Zeng, Ye, Li and Yang 2020), which are not guaranteed in advance (Molm, Takahashi and Peterson 2000). It has been shown that despite the legal systems that regulate and structure social exchanges, especially in online shopping situations where individuals must disclose personal information, there is a low willingness to disclose (Barth and De Jong 2017).

Central to reciprocity are three principles – interdependence, belief and moral norm (Gouldner 1960). By interdependence, Gouldner suggested that parties to an exchange must be dependent on each other, that is, each party must hold something of value to the other party; hence look after each other's interest, cooperate and restrain risks (Ahmad, Nawaz, Ishaq, Khan, and Ashraf 2023). The exchange relationship becomes continual when one party initiates and the other reciprocates, which paves the way for the next cycle, and is strengthened by trustworthiness and commitment. According to Gouldner (1960), reciprocity as a belief is linked to cultural orientation, and Luo (2002) likens it to "you get what you deserve" idea of karma. Gouldner further proposed that reciprocation is not simply instrumental, but a "moral norm embedded in humans universally" (Ahmad *et al.* 2023). Explaining reciprocity as a moral norm, Frazier and Rody (1991) interpreted it as *quid pro quo* behaviour.

3.3.3.1 Advantages of SET

Using SET in a study on technology non-adoption in FMCG offers several advantages such as:

i. SET is grounded in the principle that individuals weigh the perceived benefits against the perceived costs before engaging in an exchange or adopting a behaviour

(Cropanzano and Mitchell 2021). In the FMCG context, it helps explore why consumers may feel that the costs (e.g., effort, trust issues, learning curves) of adopting technology outweigh the benefits (e.g., convenience, quality, speed, or discounts).

ii. SET highlights the importance of value perception in decision-making (Kim and Lee 2022). This is particularly relevant in FMCG, where consumers are often highly sensitive to perceived convenience, reliability, and pricing. The theory provides a framework to assess how consumers view the trade-offs between traditional shopping experience and technology-based alternatives like online grocery platforms (Liu and Chen 2023).

iii. Trust is central to SET, as exchanges require a belief in fairness and reliability (Cropanzano and Mitchell 2021**)**. For non-adoption, SET can uncover trust-related barriers, such as concerns about product quality, delivery reliability, or data security in digital FMCG transactions.

iv. SET enables the study to explore a variety of perceived costs not just financial, but also emotional, cognitive, and social (Blau 2020). For example, a consumer might perceive the technology as too complex (cognitive cost) or worry about societal judgment for using online platforms instead of traditional shopping (social cost).

v. The theory considers the expectation of reciprocity, which can explain consumer reluctance if they feel the exchange (e.g., using an app or platform) does not adequately reward their effort or loyalty (Zhang, Wang, Anjum and Mu 2022). In FMCG, this could mean a lack of tangible incentives like discounts or loyalty rewards for adopting the technology.

3.3.3.2 Application of the SET in Online Shopping Context

E-commerce has revolutionised the exchange relationships between businesses and customers. Unlike traditional marketing, e-commerce thrives on the ability to collect and analyse big data about customers in real time, to target and customise market offerings. This reliance on micro data about customers has brought privacy and data safety concerns to the fore, notably with the prevalence of fraud and identity theft in South Africa. Traditionally, the exchange relationship between the two parties would be premised on sales (income) for the seller and product for the customer, whereas in e-commerce, the benefits also include privacy and personal data protection. Thus, the benefits can be outweighed by privacy and data protect concerns, which explains the unwillingness to share personal information or accept website cookies tracking functionalities (Giese and Stabauer, 2022; Urbonavicius *et al.* 2021).

The application of SET is not new in marketing, including in studies within the online shopping (e-commerce) discourse, and particularly in studies investigating the willingness to disclose personal information in online shopping channel or payment systems (Degutis *et al.* 2023; Urbonavicius *et al.* 2021; Zeng *et al.* 2020), and the acceptance of website cookies (Giese and Stabauer 2022) due to privacy concerns (Luo 2002). The theory's central elements trust and reciprocity are key factors in e-commerce. Often e-commerce providers (e-tailers) require personal information to precisely segment and target customers in real-time. They either request such information from customers, for example, personal details for e-commerce through registrations and banking details for online payment. They also use cookies (not anymore without consent) to track customers' online footprint, the sites one visits, what they click on, time taken per page and much rich information (Schiefermair and Stabauer 2020).

The disclosure of personal information, general knowledge sharing, and acceptance of cookies is based on the belief that the online platform or seller will reciprocate through targeted value propositions (Degutis *et al.* 2023; Urbonavicius *et al.* 2021; Zeng *et al.* 2020). Similarly, banking and financial details are shared based on mutual trust that data will be protected and only utilised solely for the intended purpose. Customers get value in different ways; successive exchanges between these parties, for example an e-tailer and online shopper, will be driven by either interdependence, beliefs or moral norms (Gouldner 1960). The relationship and continuity of the exchanges will apart from the parties' dyadic efforts be sustained by the perceived reputation of the e-retailer, based on their interaction and social presence in online communities (Leong and Meng 2022; Shiau and Luo 2012), which can influence the trustor's (customer) beliefs. In essence, reciprocity and trust goes hand in glove in e-commerce relationships (Yang 2019).

While previous studies have done tremendously well in applying the SET to explain online positive consumer behaviour, its application in investigating lack of intention to shop and/or purchase online is still under-researched. In the present study, perceived lack of reciprocity is used to explain why some consumers do not intend to shop online and, by extension, not adopt online shopping.

3.3.4 Social Presence Theory (SPT)

Social Presence Theory (SPT) explores the degree to which individuals perceive a sense of connection, warmth, and human interaction in mediated communication. Developed by Short, Williams and Christie (1976), the theory posits that different communication channels vary in their ability to convey social presence, influencing how users engage with and interpret messages. Traditionally, shopping is a social activity, with consumers' decision making often influenced by their interactions with others (Lu, Fan and Zhou 2016). Often, the interaction would be physical, person-to-person; for example, with other customers or store assistants. However, the emergence of e-commerce, celebrated for transforming how companies engage with customers in the digital age, has significantly impacted such traditional social interactions. It has diminished the capacity to convey nonverbal cues, such as gaze, tone of voice, and facial expressions. These cues are crucial for establishing a strong sense of social presence, driving motivation, and fostering mutual understanding.

Short, Williams and Christie (1976) proposed the SPT to explain the centrality of social presence in human decision-making process. Several scholars (Jiang, Rashid and Wang 2019; Lu, Fan and Zhou 2016; Osei-Frimpong and McLean 2018; Yeboah, Agyekum, Owusu-Prempeh and Prempeh 2023) have acclaimed SPT as the ideal theoretical framework for understanding social context in e-commerce, especially the psychological and physiological media immersion, and corresponding behaviour (Johnson and Hong 2023). At the core of the theory lies the concept of social presence, which Short, Williams and Christie (1976) defined as the significance of the other in mediated communication and the resulting importance of their interpersonal interactions. It is the extent of perceived presence of other, especially in technology-mediated situations (Biocca, Harms and Burgoon 2003; Gunawardena 1995). To this end, Short, Willimas and Christie (1976) suggested that social presence is strongly linked to intimacy and psychological closeness. It is often quantified as perceived warmth, which conveys a sense of human contact, sociability, and sensitivity within a medium (Rice and Case 1983).

3.3.4.1. Advantages of SPT

Using SPT in a study on technology non-adoption in FMCG offers several advantages, particularly in understanding how the lack of human interaction in digital platforms may influence consumer behaviours. The following are the key advantages of SPT:

i. The SPT emphasises the importance of perceived human presence in communication and interactions. In the context of FMCG technology non-adoption, it helps explain how the absence of social cues, personal engagement, or real-time assistance on digital platforms can create a sense of detachment, leading to resistance or mistrust (Joubert and Maritz 2022).

ii. Many FMCG consumers are accustomed to face-to-face interactions such as seeking assistance from store employees or engaging in social shopping experiences. SPT provides a framework to examine how the lack of social presence in online supermarket platforms or mobile apps can deter adoption, especially for users unfamiliar with self-service digital environments (Lu, Fan, and Zhou 2016).

ii. Trust is closely linked to social presence. SPT can uncover how the absence of perceived social presence in technology (Joubert and Maritz 2022) (e.g., chatbots or automated systems lacking human-like responses)

iv. The SPT emphasises the role of emotional connection and warmth in communication (Felix, Rauschnabel and Hinsch 2017). In FMCG, where consumer loyalty is often built on relationships and personalised experiences, the inability of technology to replicate these elements can lead to dissatisfaction or hesitation in adoption.

3.3.4.2 Application of the SPT in Online Shopping Context

Social presence has been applied and researched extensively, including in marketing (Chen, Chen and Chen 2023), particularly in developed economies where e-commerce and, more recently, social commerce, are prevalent. Yet in South Africa, where e-commerce adoption has been steadily growing (Goga, Paelo and Nyamwena 2019), scholars are yet to show interest in applying social presence to explain or predict consumer behaviour. Social presence has become synonymous with social commerce, described as the as a new evolution of e-commerce (Hew, Lee, Ooi and Lin 2016; Huang and Benyoucef 2013).

Liang and Turban (2011) defined social commerce (s-commerce) as business activities and transactions conducted through social media, substantially changing the business environment and customers' mindset (Felix, Rauschnabel and Hinsch 2017; Kumar, Bezawada, Rishika, Janakiraman and Kannan 2016). In addition to interactivity, social media communication promotes participation, collaboration, individualised attention, and is communal (Osei-Frimpong and McLean 2018). These affordances provide social presence and a way for firms to engage with customers and create lasting relationships through social commerce. Essentially, social commerce offers multimedia content, chat or message boards, virtual agents, online forums, and socially rich text (Gefen and Straub 2004), allowing customers to not feel alone in their decision-making journeys. The impact of social commerce is underscored by the intensive integration of social networking functionalities across all digital platforms.

Marketing scholars have shown considerable interest in using social presence to explain consumer behaviour under e-commerce and s-commerce contexts. Aditionally, Leong and Meng (2022) investigated the impact of social presence, electronic word-of-mouth (eWOM) and logistics service quality on trust in social retailers and how such trust influences the intention to shop online. All the direct and indirect relationships hypothesised were significant save for eWOM. In another study, a multi-variable research model (Lu, Fan and Zhou 2016), social presence was hypothesised to positively impact on trust in online sellers. Results revealed that all three dimensions of social presence showed a positive and significant impact on trust in online sellers.

Despite the evidence that social presence is a key explainer of consumer behaviour in computer-mediated marketing of products, coupled with the steady growth of e-commerce in South Africa, the concept of social presence has still not received the attention of marketing scholars in this context. In this study, perceived lack of social presence is applied to explain the reluctance to shop online by some individuals.

3.4 INTEGRATED CONCEPTUAL FRAMEWORK

The present study integrates the four models discussed in Sections 3.3.1 to 3.3.4. While these models have independently explained over 50% of the variation in the outcome variables (e.g., willingness to share, behavioural intention and actual behaviour), in most studies, this research was motivated by the possibility of improving the variation explained by the integrated model as seen in other studies; for example, Venkatesh *et al*. (2003), Fortes and Rita (2016) and Fishbein and Ajzen (2010). The integrated model presented in Figure 3.2 includes the four independent variables of the UTAUT model, technophobia, perceived lack of reciprocity from the SET, the two trust variables from the TTT, and perceived lack of social presence from the SPT to explain the reluctance to shop online. Each of these variables are discussed and corresponding hypotheses developed under subsections 3.4.1 to 3.4.11.

3.4.1 Negative Performance Expectancy

Venkatesh *et al.* (2003:447) defined performance expectancy as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance”. In the context of online shopping, performance expectancy can be defined as the extent to which an individual believes they will benefit from shopping online. Online shopping brings convenience and efficiency; people shop in the comfort of their homes, offices, or on the go and take less time performing shopping tasks. Hence, people will accept and adopt online shopping if they perceive it to be valuable and beneficial (Erjavec and Manfreda 2021; Lian and Yen 2014).

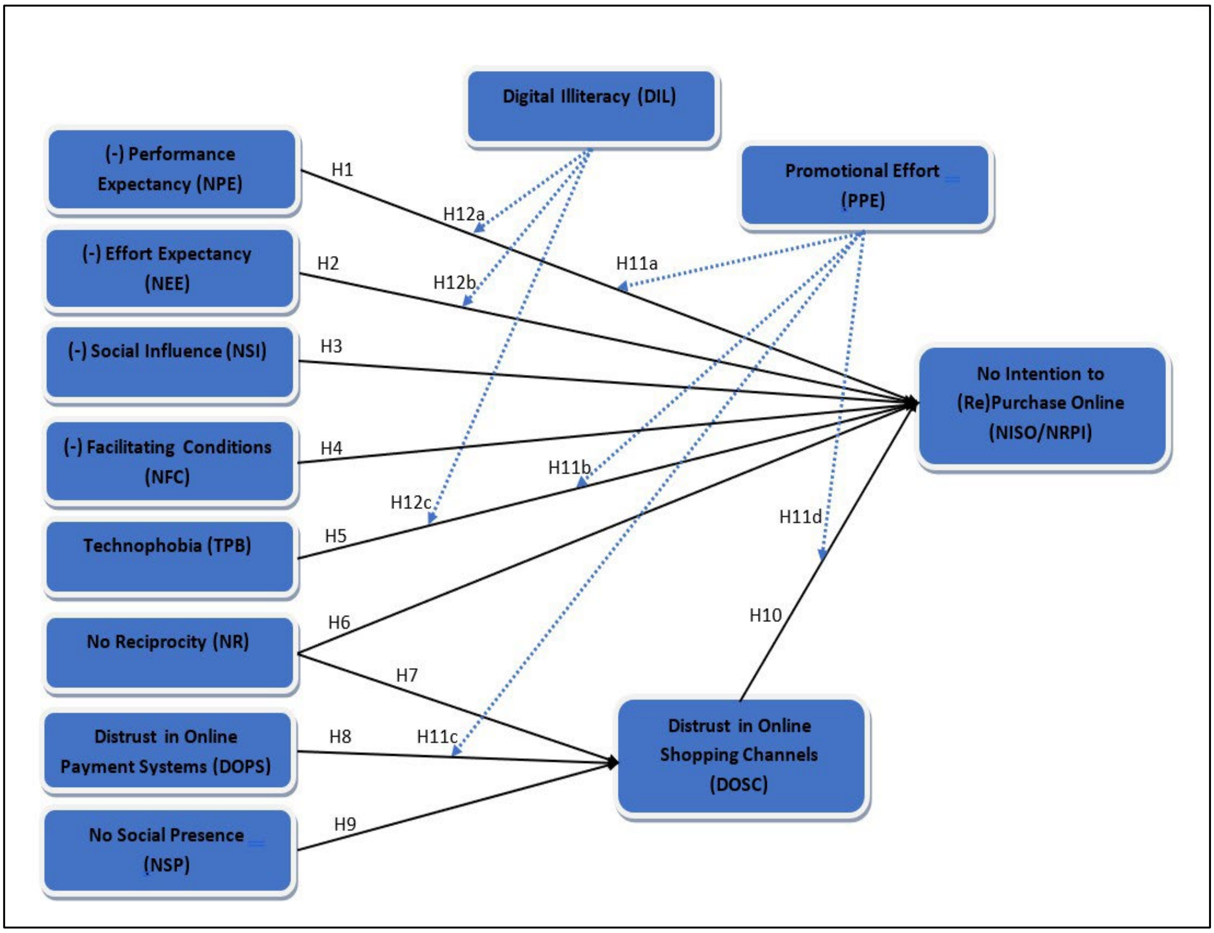


Figure 3.2: Integrated Conceptual Framework

Source: Researcher, 2025

Previous research has shown that older adults are more likely to use and accept online technologies when they perceive their usefulness and benefits, such as in health services (Hoque and Sorwar 2017) or online shopping (Lian and Yen 2014). This effect, particularly strong among older adults (Yan *et al.* 2020), was established in pre-pandemic times. However, during the pandemic, limited access to brick-and-mortar stores due to lockdowns could have further strengthened this effect, making online shopping even more beneficial for older adults compared to non-pandemic circumstances. Therefore, as indicated above in Subsection 3.3.1.1, this present study inverted the original performance expectancy measures to examine whether the disbelief that online shopping brings convenience and efficiency benefits (herein referred to as the negative performance expectance) predicts the reluctance to shop online. Thus, it is hypothesised that:

H1: Negative performance expectancy significantly predicts reluctance to shop online.

3.4.2 Negative Effort Expectancy

"Effort expectancy is the degree of ease associated with use" (Venkatesh *et al.* 2003; 2012). Consequently, people are more likely to accept and adopt a system if they believe it requires less effort to use. While many assume that young and tech-savvy people (Generation Ys, Zs and Alphas) find it easy to use technology; therefore, show an affinity for online shopping (Copeland *et al.* 2023; Hassan Rashid and Li 2015; Nur and Gosal, 2021); Erjavec and Manfreda (2021) argued that the use of digital technologies underlying online shopping channels can be challenging for adults who are not tech-savvy. Thus, there is still a lot of people who are reluctant to shop online.

Contemporary user interface design for online shopping aims to simplify the shopping experience and reduce user irritation (Hasan 2016). Under non-pandemic conditions, effort expectancy positively impacts older adults' intention to use online technologies in certain contexts, such as health services (Hoque and Sorwar 2017). However, this effect does not hold in other contexts, such as online shopping (Lian and Yen 2014; Yan *et al.* 2020). In this study, the original elements measuring effort expectancy are negated to explain why some people are reluctant to shop online. The inverted effort expectancy items are herein referred to as the negative effort expectancy. In line with this, it is hypothesised that:

H2: Negative effort expectancy significantly predicts reluctance to shop online.

3.4.3 Negative Social Influences

As individuals, we have people we deem very important (in-group) to us, such as spouses, children, relatives, friends, and colleagues. Such people have either direct or indirect influence on our decision-making. Accordingly, Venkatesh *et al*. (2003) defined social influence as "the degree to which an individual perceives that referent others believe he or she should use the new system." Social influence within UTAUT heavily depends on the subjective norm (Venkatesh, Thong and Zu 2012). It suggests that individuals are influenced by a smaller circle of close connections who may not have adopted the technology but can form opinions about it and assess the potential adopter's actions in relation to the technology (Sun 2013). Social influence has been shown to positively impact older adults' intention to shop online (Lian and Yen 2014; Yan *et al.* 2020).

Even though online shopping remains a voluntary decision, it is still susceptible to the influence of referent others (Celik 2016), due to internalisation and identification (Venkatesh *et al.* 2003). Individual decisions to adopt online shopping may be influenced by the acceptance and adoption of online shopping by important others (descriptive norms) or by the perception that important others approve of the adoption of online shopping (injunctive norms). Likewise, in the present study, the original measures of social influence items were inverted. They are referred to as negative social influence, where the descriptive and/or injunctive normative pressure discourages the adoption of online shopping. Hence, the hypothesis is:

H3: Negative social influence significantly predicts reluctance to shop online.

3.4.4 Negative Facilitating Conditions

Facilitating conditions entail consumer perceptions of the availability of resources and support to perform a behaviour (Erjavec and Manfreda 2021; Venkatesh, Thong and Zu *et al.* 2012). Several previous studies have claimed that facilitating conditions do not have a positive impact on older adults' intention to use online technologies (Chayomchai *et al.* 2020; Hoque and Sorwar 2017; Lian and Yen 2014). However, because digital literacy among older adults is increasing (Oh *et al.* 2021), with the increased availability of digital resources (Kuoppam¨aki *et al.* 2017), the positive effect of facilitating conditions might become prevalent in the future. However, Yan *et al.* (2020) found a positive relationship between facilitating conditions and older adults' perceptions, acceptance and willingness toward shopping online.

While Venkatesh *et al*. (2003) suggested that facilitating conditions directly influence actual behaviour rather than behavioural intentions, Venkatesh, Thong and Zu (2012) modified the UTAUT and added a hypothesis of the mediated influence of facilitating conditions through behavioural intentions. Therefore, this variable is relevant to the present study because the outcome variable (lack of intention) is seen as a proxy for (non-)adoption, hence a suitable mediator for the influence of the facilitating conditions variable on adoption behaviour. In this study, the original facilitating conditions measures were flipped to portray a perception of the unavailability of resources and support (hereafter referred to as negative facilitating conditions). The following hypothesis was formulated for testing.

H4: Negative facilitating conditions significantly predict reluctance to shop online.

3.4.5 Technophobia and Online Shopping Reluctance

While technophobia is as old as technology itself, little research has been done into its effect on consumer behaviour, especially the adoption or non-adoption of innovations. Technophobia has increasingly become topical as technological innovations become pervasive in people's everyday lives. It is defined as the exaggerated and unjustified fear, discomfort or anxiety of interacting or using technology (Nimrod 2018; Osiceanu 2015), prompting disaffection towards technology in general.

Technophobia is described in the literature as one of the obstacles to technology adoption (Subero-Navarro, Pelegrín-Borondo, Reinares-Lara and Olarte-Pascual 2022; Talukder, Sorwar, Bao, Ahmed and Palash 2020). Even for those who would have adopted technology, Higueras-Castillo *et al.* (2023) found technophobia to be highly influential in limiting e-commerce continuance. Martínez-Córcoles *et al*. (2017) described technophobia as a significant problem in modern society, with many people maintaining negative sentiments toward new technology and purposefully refraining from utilising it, despite its pervasiveness in people's lives. In Subero-Navarro, Pelegrín-Borondo, Reinares-Lara and Olarte-Pascual (2022), technophobia negatively correlated with and had a negative direct effect on the intention to use social robots.

Research highlights that older adults and individuals with lower levels of digital literacy are more likely to experience technophobia, which can lead to a perception that online shopping is overly complex or intimidating (Erjavec and Manfreda 2022). For example, studies show that many older consumers avoid online shopping because they feel the potential benefits are outweighed by the perceived effort or skill required to navigate the platforms (Erjavec and Manfreda 2022) . Additionally, technophobia is linked to heightened concerns about privacy and security, further exacerbating reluctance to adopt online shopping. Such fears, combined with a lack of familiarity or confidence in using digital tools, contribute to a persistent barrier to online consumer behaviour. Thus, the present study argues that technophobia positively influences the lack of intention to shop online among some fast-moving consumer goods markets. The study hypothesises that:

H5: Technophobia significantly predicts reluctance to shop online.

3.4.6 Perceived Lack of Reciprocity

The concept of reciprocity is deeply rooted in SET and intertwined with the personalisation-privacy paradox and self-disclosure discourse (Degutis *et al.* 2023; Lee and Cranage 2011; Leong and Meng 2022; Shiau and Luo 2012; Zeng *et al.* 2021). Reciprocity is the belief that an equal favour will be returned for whatever you give (*quid pro quo*). In an online marketing context, consumers trade off their personal information through self-disclosure if they believe there will be reciprocal benefits from the online businesses concerned. For example, consumers can benefit through the personalisation of products, deals and communications (Degutis *et al.* 2023), hence improving the overall experience. Accordingly, these benefits increase willingness to further share personal information and make purchases (Lee and Cranage 2011).

However, while consumers are keen to share their personal information for positive outcomes, they also have privacy concerns, which online businesses must assuage to create, build and maintain the relationship (Degutis *et al.* 2023; Lee and Cranage 2011). The ability to pacify consumer privacy concerns depends on an online business's integrity and can strengthen consumer trust in that business. Shiau and Luo's (2012) findings suggest that reciprocity predicts the intention to buy online. In an online shopping context, the present study argues that if consumers perceive that personal information disclosure will not be reciprocated and privacy assurance is not provided, they will display reluctance to shop online. Thus, it is hypothesised that:

H6: Perceived lack of reciprocity significantly predicts reluctance to shop online.

In addition to the SET view, the present study draws from the tenets of the TTT to explain that perceived lack of reciprocity. The interplay between these two theories is the concept of reciprocal trust. Sztompka (1999: 28) defined reciprocal trust as "belief that the other person will reciprocate with trust toward ourselves," which can be transferred down online shopping channels (Stewart 2003). Therefore, a perceived deficit of reciprocal trust negates the relationship among the trust triad parties (trustor, broker and trustee). As such, the present study argues that a perceived lack of reciprocal trust can lead to a distrust of online shopping and hypothesises that:

H7: Perceived lack of reciprocity significantly influences distrust in online shopping channels.

3.4.7 Distrust of Online Payment Systems

There has been considerable research on the effect of consumer trust on the adoption of e-commerce. While e-commerce innovation brings substantial consumer benefits, it is also burdened with trust issues about privacy and security concerns. Other than business reputation, some businesses go the extra mile to attenuate the perceived risks by providing privacy and security assurances, displaying online payment security symbols (e.g., Verified by Visa and SecureCode by MasterCard), and allowing for easy opt-out pathways (Lee and Cranage 2011). Despite all these efforts, South Africans wake up to media reports about increasing digital payment fraud (Ozow n.d.; Ramalepe 2023), which erodes their trust in the system. Also, research has highlighted the effect of trust on the acceptance and adoption of online/digital payment systems in South Africa (Maluleke *et al.* 2021; Motseki and Tseko 2022) and elsewhere.

Based on the negatives associated with online payment systems, the present study draws from the TTT to explain how the distrust (described above) is transferred to the general online shopping context. Thus, it is hypothesised that:

H8: Distrust in online payment systems significantly influences distrust in online shopping channels.

3.4.8 Lack of Social Presence

Social presence (SP) is a multi-dimensional construct "SP of the web, perception of others, and SP of interaction with sellers" (Lu, Fan and Zhou 2016: 227). These dimensions have been examined individually, and as a whole in previous studies. For example, Chen, Chen and Chen (2023) combined the three dimensions into one SP variable and tested if it positively influenced consumer identification and purchase intention. The results confirmed their hypotheses. In contrast, Lu, Fan and Zhou (2016) treated them separately, hypothesising that each of them positively impacts trust in online sellers. Likewise, they were found to significantly predict trust in online sellers. Leong and Meng's (2022) findings also confirmed social presence has an indirect positive influence on purchase intention, mediated by trust.

In online shopping, where there are no proxemics (Mehrabian 1968) and hence no physical interactions, social presence assuages proximity concerns and offers psychological intimacy crucial for sustaining online relationships (Rashid, Pitafi, Qureshi and Sharma 2022; Fan, Zhou, Yang, Li and Xiang 2019). Social presence also leans on the principles of reciprocity in that the voluntary exchange of information in online communities is done in anticipation of benefits. Through active and timely responses to consumer and general social engagement, consumers feel supported by the online business, and, together with other users, a wealth of information pertinent to the relationship with an online business is curated and determines consumer perceptions.

Therefore, when an online business lacks social presence, consumers become apprehensive about its reliability and reputation (Leong and Meng 2022), and develop distrust that leads to avoiding creating or maintaining a relationship with it. Thus, the present study argues that lack of social presence positively influences distrust, becoming a barrier to online shopping (Al-Adwan 2019). Considering this, it is hypothesised that:

H9: Perceived lack of social presence significantly influences distrust in online shopping channels.

3.4.9 Distrust of Online Shopping Channels

Likewise, several studies have investigated the impact of trust in online shopping channels on the intention to shop online or actual online shopping behaviour. Deng *et al.* (2016) investigated the effect of channel trust, perceived benefits and switching costs on online purchase intention mediated by online search intention. All the independent variables were found to positively influence online search and purchase intentions, with channel trust being the main factor explaining the search intention and the second most influential factor on online purchase intention. In a comprehensive research model, Oliveira *et al*. (2017) tested the impact of consumer trust dimensions (also influenced by consumer and firm characteristics, web infrastructure and interactions) on overall trust, influencing intention to purchase. The results of the trust hypotheses indicated that the consumer trust dimensions (competence, integrity and benevolence) positively impacted overall trust, explaining 74.5% of the variation. Also, overall trust positively influenced the intention to purchase online, with a 57.5% variance explained.

With the above indications, the present study argues that a lack of trust in online shopping channels predicts a lack of intention to shop online. Thus, it is hypothesised that:

H10: Distrust of online shopping channels significantly predicts a lack of intention to shop online.

3.4.10 Promotional Effort

Yohn (2019) asserted that “marketing has never been more important or more pervasive than it is today”. Through marketing communications (promotional effort), organisations can reach out to markets, providing them with information that would influence consumer behaviour towards the organisation and its products. In online shopping, promotional effort is also crucial for assuring and educating consumers about online channels, their benefits, privacy and security features.

In the 21st- century, an integrated approach to marketing communications has been emphasised in the marketing literature (Yohn 2019; Clow and Baak 2021; Kitchen and Tourky 2021) and has also been adopted by e-commerce businesses to encourage consumers to adopt their online shopping. Through promotional efforts, e-commerce businesses can highlight the usefulness of online shopping systems, enlighten consumers about online shopping technology to attenuate technophobia and assuage the perceived privacy and security risks. Alternatively, the present study contends that poor or ineffective promotional efforts do not help lessen the impact of unappreciation of the usefulness of online shopping, technophobia, distrust of online payment and shopping systems on the reluctance to shop online. Thus, it is hypothesised that:

H11a: Poor promotional effort positively moderates the effect of negative performance expectancy on the lack of intention to shop online.

H11b: Poor promotional effort positively moderates the effect of technophobia on the lack of intention to shop online.

H11c: Poor promotional effort positively moderates the effect of distrust in online payment systems on distrust of online shopping channels.

H11d: Poor promotional effort positively moderates the effect of distrust in online shopping systems on the lack of intention to shop online.

3.4.11 Digital Illiteracy

Several studies have investigated the effect of digital literacy on technology adoption and have found that it directly influences intention to use or actual usage (Nikou and Aavakare 2021; Yu Lin and Liao 2017) and specifically purchase intention (Made and Nyoman 2023; Nazzal, Thoyib, Zain and Hussein. 2022). Few other studies have tested its (digital literacy) moderating effect on the relationships between technology adoption factors (independent variables) and behavioural intention, especially on the acceptance and adoption of online shopping or e-commerce. However, no study known to the researcher has investigated the effect of digital illiteracy on online shopping reluctance, and the present study addresses that gap.

While different scholars have defined digital literacy differently, this study draws from Ng's (2012) digital literacy framework and incorporates OEDCD's (2015) definition to conceptualise digital literacy. Hence, it is defined as an individual's capability to competently and confidently use technology, including the ability to search, evaluate and use product information strewn over the internet using technological devices to shop online. Digital illiteracy is the lack of skills, competencies, and ability to use technology effectively (Fernando and Jain 2022). The present study is interested in the moderating effect of lack of digital literacy. As such, it is hypothesised that:

H12a: Lack of digital literacy positively moderates the effect of negative performance expectancy on the lack of intention to shop online.

H12b: Lack of digital literacy positively moderates the effect of negative effort expectancy on the lack of intention to shop online.

H12c: Lack of digital literacy positively moderates the effect of technophobia on the lack of intention to shop online.

3.5 SUMMARY OF THE CHAPTER

This chapter sought to establish a conceptual understanding of the relationships among the key concepts derived from the research questions of the study, offering a framework to explain online non-adoption behaviour. The core of this conceptualisation lies in identifying the critical variables that influence whether consumers decide to engage with or avoid online platforms. These variables, drawn from established and widely recognised theories, were discussed in depth to provide a comprehensive picture of the factors that impact technology adoption and non-adoption behaviours. The theories referenced include the UTAUT, SET, TTT, and SPT.

By blending these theoretical frameworks, this chapter has outlined how each theory contributes to explaining the reluctance or failure to adopt online shopping. The Unified Theory of Acceptance and Use of Technology (UTAUT), for instance, focuses on factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which are critical to understanding how external and internal variables shape consumer perceptions of technology. Social Exchange Theory (SET) adds a layer of complexity by emphasising the perceived benefits and costs in an exchange, providing insight into why consumers might resist online shopping if they perceive the perceived costs outweigh the benefits. Trust Transfer Theory (TTT) offers an additional perspective by explaining how trust, which is vital for online transactions, is transferred from familiar offline entities to new online platforms. Social Presence Theory (SPT) contributes to this discussion by highlighting the importance of emotional connection and human presence in online interactions, illustrating that a lack of these social cues can contribute to reluctance in adopting digital platforms.

Together, these theories create a comprehensive framework for understanding the multifaceted nature of online non-adoption behaviour. Through this conceptual framework, the chapter also sets the tone for the research methodology that follows. The theoretical grounding helps identify key variables for empirical testing, offering a clear rationale for the hypotheses to be explored. Furthermore, the conceptual discussion provides a foundation for the methodological approach chosen in the study, ensuring that the research is informed by established theoretical perspectives.

The next chapter will build upon this conceptualisation by outlining the methodological choices that were made to explore these variables in depth.

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 INTRODUCTION

Research methodology refers to the overarching strategy and rationale that guides the entire research process (Collis and Hussey, 2021; Saunders, Lewis and Thornhill 2019). It frames the paradigmatic approach, which includes the theoretical and philosophical assumptions about the nature of reality (ontology) and knowledge (epistemology) that influence research design, as well as the selection of specific methods suitable for answering the research questions. Therefore, it lays out the "why" behind the selection of research strategies, the rationale for adopting a particular approach to study a research problem and plays a significant role in defining how closely the study meets the standards of science.

This chapter describes the methodological decisions and procedures used in the current study to answer the research questions. The chapter begins with a general discussion of the research paradigms and explains the hierarchical relationships between their elements. After the general paradigmatic discourse, the onto-epistemological views and the methodological approach that underlie or operationalise the study are outlined and justified. The accompanying research design and methods, including the population examined in this study, are then presented. The chapter also describes the analytical framework and thus lays the foundation for the following chapter on data analysis, presentation and interpretation. The chapter then concludes with an explanation of the reliability and validity concepts and a presentation of the researcher's ethical considerations following the principles of research ethics and integrity.

4.2 RESEARCH PARADIGMS

The concept of research paradigms was popularised by Thomas Kuhn through his seminal work titled "The Structure of Scientific Revolutions". Kuhn (1962: viii) defined research paradigms as "universally recognised scientific achievements that for a time provide model problems and solutions to a community of practitioners." While Kuhn's initial premise of a research paradigm was embedded in the natural sciences, he was later exposed to social scientists, where he was struck by the "overt disagreements between social scientists about the nature of legitimate scientific problems and methods" (Kuhn 1997: x). Before this exposure, Kuhn's reference to scientific achievements was only steeped in the natural sciences field (Collis and

Hussey 2021). As such, social sciences provided the second source of Kuhn's concept of research paradigms. A key part of Kuhn's theory of research paradigms is his openness to the emergence of new paradigms, which accounts for the wide variety of research paradigms presented in the literature.

After Kuhn's seminal work, several scholars have built on his definition to apply the concept in research across different fields, such as education (Kivunja and Kuyini 2017; Rehman and Alharthi 2016), business research (Antwi and Hamza 2015; Liana and Noermijati 2024), information research (Kankam 2019) and marketing (Boateng and Boateng 2014; Möller and Halinen 2022). Various scholars concurred with Kuhn's view of communities and how it shapes the way in which researchers approach and solve research problems differently due to their philosophical assumptions about the development of knowledge. A research paradigm is therefore characterised by a specific community of scholars' philosophical views or beliefs about the nature of reality (ontology), what they value as knowledge or truth and how it can be known (epistemology), their preferred approaches to discovering knowledge (methodology), and the values they attach or prioritise in conducting research (axiology). These elements are illustrated in **Figure** 4.1.

To date, several paradigms have been presented and discussed in literature as underlying research (see Joullié 2016; Lincoln, Lynham and Guba 2011; Rehman and Alharthi 2016; Saunders, Lewis and Thornhill 2019), with a very fine line separating the paradigms (Iofrida *et al.* 2018). To articulate the research paradigm underlying the current study, only the positivism, interpretivism and pragmatism are presented. This choice does not in any way suggest that these are the more valuable ones, but rather that they are the most prominent ones in the social sciences, especially business research literature, with the current study falling under the business research category. Positivism and interpretivism paradigms are believed to sit on the opposite ends of a continuum, with pragmatism featuring as the peacemaker of the purist approach (Fuyane 2021), as shown in **Figure** 4.1.

The selection of a suitable research paradigm is fundamental to the research design as it shapes the researcher's worldview and influences methodological choices (Creswell and Poth 2024; Kivunja and Kuyini 2017). As such, Section 4.3 presents a comprehensive rationale for this paradigmatic choice from ontological, epistemological, methodological, and axiological perspectives.

	Positivism	Pragmatism	Interpretivism
Ontology	• Also known as naive realism. • Reality is seen as external and independent from the researcher. • Believes in objective, singular, discoverable, patterned, and predictable reality. • The world is understood as a product of causality.	• Also known as a 'what works' approach to understanding social phenomena. • Understanding reality is viewed as fundamentally fallible, so knowledge is an open-ended pursuit.	• View the world/reality through humanistic, relativist or idealist lenses. • Believes in multiple realities. • The world as socially constructed, and through the experience individuals create/interpret.
Epistemology	• Objectivist - assumes that the world/reality can be observed and measured through scientific methods. • Deductive – uses law-like (nomothetic) approaches to knowledge discovery and interpretation. • Researcher-researched (reality) independent.	• Values both subjective and objective knowledge. • Intersubjectivity putting emphasis on shared meaning. • Uses abductive reasoning to support knowledge discovery and interpretation in solving problems.	• Subjectivist - accepts multiple narratives, circumstances, perceptions and interpretations in understanding a reality. • Inductive – uses idiographic approaches to knowledge discovery and interpretation. • Researcher-researched (reality) interdependence.
Methodology	• Purely quantitative strategy to enable statistical analysis and validation of cause-effect relationship. • Deductive or nomothetic approach – obsessed with testing of theories. • The aim is to achieve predictive power and generalisation of findings.	• Mixed/multiple methods. research approach to get a rich understanding of reality. • Abductive approach – emphasising practical solutions and outcomes. • Aiming to achieve in-depth understanding by combining quantitative and qualitative research approaches.	• Purely qualitative strategy to account for multiple views, narratives and perceptions. • Inductive or idiographic approach to interpretation of the world. • The aim is to provide an in-depth understanding of phenomenon within specific context.
xiology	• See research as a context- and value-free phenomenon in line with absolutist and dualistic views on knowledge discovery and meaning-making.	• Value-driven research. • Research initiated and sustained by researcher's doubts and beliefs. • Researcher reflexive.	• Research is seen as value-laden and context-bound in line with a relativist view of knowledge.

Figure 4.1: Research Paradigms

Source: Adapted from Collis and Hussey 2021; Fuyane 2021; Iofrida *et al*. 2018; Saunders Lewis and Thornhill 2019; Yilmaz 2013

4.3 RESEARCH PARADIGM FOR THIS STUDY

In his conceptualisation of scientific achievements as paradigms, Kuhn (1962) did not preclude the evolution of these paradigms. Throughout his account, he illustrated the possibility of the emergence of new paradigms. In line with Kuhn's perspective, Bird (2013) asserted that when a paradigm becomes incapable of addressing research issues, it fosters a crisis that ultimately leads to a scientific revolution. Auguste Comte's work, particularly the *Philosophical Considerations on the Sciences and the Scientists (1825)*, provided "the first and classical formulations of the two cornerstones of positivism: the law of the three stages, and the classification of the sciences" (Bourdeau 2022). Thus, Comte is known as the founder of positivism. However, as science evolved, new variations and opposition of Comtean positivism came about in the 20th century, pushing back on the use of scientific method (positivist worldview) to study social and human-related phenomena (Smith and Heshusius 1986).

These dissenting views vary from mild to extreme arguments against positivism, as the dominant worldview to knowledge production, seen as the essence of science (Konakh and Borinshteyn 2019). The positivist research paradigm pursues an objectivist view of reality and promotes prior knowledge as absolute through empiricism and a dualist view between the researcher and reality (Collis and Hussey 2021; Malhotra, Nunan and Birks 2017). Contrary to the Comtean perspective, the extreme voices, for example, Wilhelm Dilthey, advocated for a completely new paradigm – interpretivism, which viewed the world or reality through humanistic, relativist or idealist lenses. Interpretivists believe in subjective multiple realities and the interdependence between the researcher and the researched (Fuyane 2021) and argue that positivism is inappropriate for understanding social reality. According to Smith (1983), Dilthey's interpretive/hermeneutical approach to science emerged as the first serious challenge to positivism. The positivism-interpretivism schism left Auguste Comte (and adherents of logical positivism) and Wilhelm Dilthey's orientation at opposite ends of the continuum.

The mild voices had issues with some, but not all dictates of logical (also known as naïve) positivism, which led to the emergence of post-positivism. Unlike the naïve pursuit of truth by positivists, the post-positivist search for assertability, while retaining the methodological achievements of positivism, addresses its limitations through critical multiplism (Letourneau and Allen 2006). Ontologically, post-positivists are critical realists who believe in one objective reality, but that it cannot be perfectly understood (Iofrida *et al.* 2018; Guba and Lincoln 1994; Strang 2015). They reject absolutism and dualism, and instead see knowledge as justified claims that represent established regularities and probabilities about social and human phenomena, ratherthan rigid universal laws governing behaviour (Guba 1990; Guba and Lincoln 1994).

Thus, the current study, alive to the pitfalls and limitations of naïve positivism, employed a post-positivist paradigm to answer the research questions. The study is a social inquiry into non-adoption of online shopping by some in South Africa, hence the appropriateness of the post positivist worldview. As a reminder, the research objectives driving this study are:

- **RO1:** To examine the extent to which negative performance expectancy, negative effort expectancy, negative social influence, and negative facilitating conditions predict consumers' reluctance to shop for FMCG online.
- **RO2:** To determine the direct influence of technophobia, perceived lack of reciprocity, and distrust in online shopping channels on consumers' reluctance to shop for FMCG online.
- **RO3:** To investigate the relationships between (i) perceived lack of reciprocity, (ii) distrust in online payment systems, and (iii) lack of social presence, and how these factors contribute to the development of distrust in online shopping channels.
- **RO4:** To assess how poor promotional effort moderates the relationship between (i) negative performance expectancy and (ii) technophobia on consumers' reluctance to shop online.
- **RO5:** To evaluate the moderating effect of poor promotional effort on the relationship between distrust in online payment systems and distrust in online shopping channels.
- **RO6:** To explore the extent to which digital illiteracy moderates the relationship between (i) negative performance expectancy, (ii) negative effort expectancy, and (iii) technophobia on consumers' reluctance to shop online.
- **RO7:** To propose a framework to assist retailers in enhancing the adoption of FMCG online shopping.

4.3.1 Onto-epistemological justification

Cope (2003) asserted that ontological and epistemological views are interwoven, with the ontological stance typically shaping epistemological assumptions and overall research orientation. From an onto-epistemological perspective, post-positivism [sometimes] assumes that the nature of reality exists independently of the researcher's perception and can be systematically and objectively measured (Bryman 2016; Saunders, Lewis and Thornhill 2019; Creswell and Creswell 2018), to predict and explain marketing phenomena (Malhotra, Nunan and Birks 2017).

In the context of this study, the factors influencing non-adoption are seen as objective constructs that exist independently of the researcher, ensuring objectivity in data collection, analysis and interpretation. This ontological stance is consistent with the study's focus on examining the contextualised relationships between variables espoused in the research objectives. As Neuman (2014) notes, quantifying these constructs enabled the current study to collect objective, empirical data to generate reliable knowledge and uncover generalisable insights to explain the barriers to online shopping adoption within the South African market. The following subsection articulates and justifies the current study's methodological approach.

4.3.2 Methodological justification

Methodologically, post-positivism advocates for the use of structured and systematic procedures to collect and analyse data, albeit do not follow absolutist and dualist views of pure positivists. Saunders, Lewis and Thornhill (2019) suggested two methodological approaches available to researchers, as depicted in Figure 4.2.

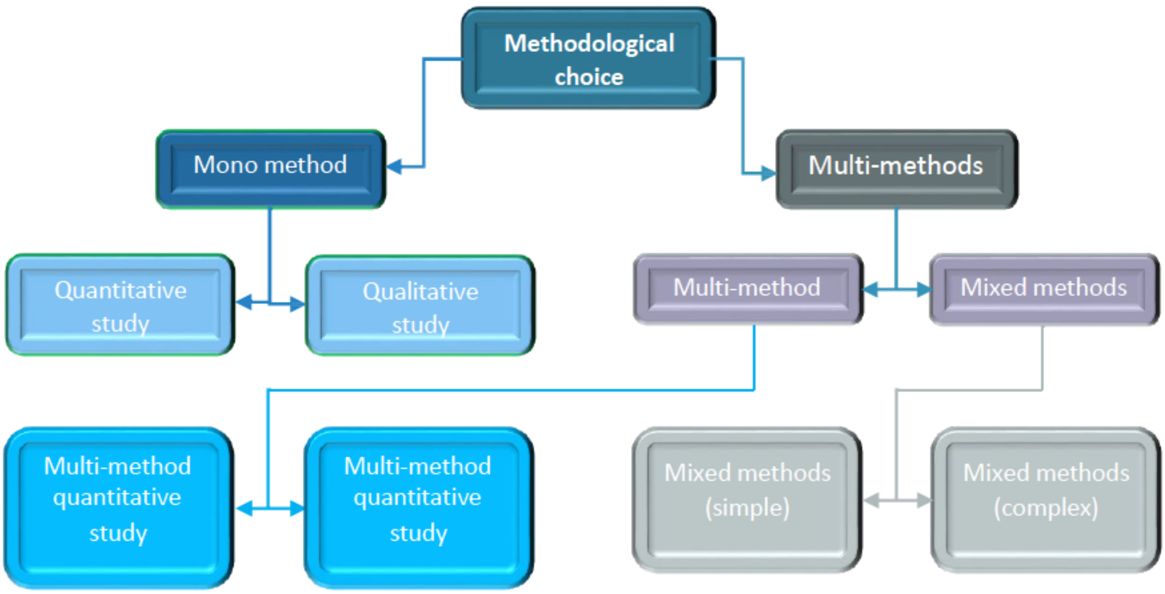


Figure 4.2: Methodological Choices Source:
Saunders, Lewis and Thornhill 2019

The current study adopted a mono quantitative approach to address the research questions. As in its name, this approach quantifies variables to enable statistical analysis of the relationships between or among the variables. Since it is underpinned by an objectivist and nomothetic logic, it uses a structured approach with a predefined purpose, data sources and format, and collects data, often from large samples (Burns, Bush and Veeck 2017). As a result, it emphasises the hallmarks of scientific research purposiveness, rigour, testability, parsimony, precision, confidence, replicability, and objectivity (Sekaran and Bougie 2016). A nomothetic logic was applied in the study to investigate and explain the people's aversion towards online shopping through the quasi-causal effects of the specific factors presented in the integrated framework (Babbie 2020).

An integrated framework was drawn from established theoretical models such as the UTAUT, the TTT, the SET, and the SPT to guide the current study. The post-positivist approach was considered useful in eliminating researcher bias and obtaining an objective perspective of research problem. Surveys and statistical techniques (see Section 4.7) used to test the hypotheses and validate the theoretical framework enabled generalisation of findings within the South African context, in line with post positivist assumptions.

4.3.3 Axiological justification

From an axiological perspective, this study embraces the positivist principle of value-free research, with the researcher maintaining an objective stance throughout the study (Bryman 2016; Guba and Lincoln 1994). This is crucial so that the researcher's biases do not convolute the findings. However, it is conceded that the results of the current study are not exhaustive, and are rather foundational to future research.

4.4 RESEARCH DESIGN

The selection of a research design is a crucial step in the research process, as it operationalises the methodological approach and epistemological views that underpin a study. There is an abundance of research design literature, from peer-reviewed books and journal articles to publicly accessible expert opinions through various formats, such as lecture notes, blogs and videos. While the abundance is welcome, it is also a source of confusion, especially to budding researchers (Abutabenjeh and Jaradat 2018). For instance, a closer inspection of the extant literature shows that there is no consensus on or universal reference to the different terms in the methodological nomenclature.

While the methodology is conceptualised as the praxis of the researcher's worldview in discovering knowledge and solving problems in the research paradigm framework, it remains an abstraction that espouses the type of research, and the logic of theory development and concretises the aim of the study. Hence, methodological choices are operationalised through the research design. However, in the extant literature, some scholars seem to conflate methodology with research methods (Abutabenjeh and Jaradat 2018), using the two terms interchangeably, yet they mean different things (Burns, Bush and Veeck 2017). Also, research design is sometimes defined too broadly; hence overcasting what methodology is. For example, Collis and Hussey (2021) posited that a research design is the choice you will make in terms of the methodology and methods. Such definitions are confusing and usually devoid of the research philosophy underlying the design.

To avoid the definitional ambiguities, the current study views research design as the foremost operational plan of methodological choices; a blueprint guiding how a study will move from the research questions to the outcomes through collecting, measuring, and analysing data (Cooper and Schindler 2013; Sekaran and Bougie 2016). A research design specifies the data sources and the procedures to be followed in collecting, measuring, and analysing data (Abutabenjeh and Jaradat 2018; Bryman and Bell 2015; Malhotra 2015). As with the definitions of research design, there are numerous and sometimes conflicting lists of research designs.

For example, Malhotra, Nunan and Birks (2017) suggested that there are two broad types of research designs namely, exploratory and conclusive designs. Saunders, Lewis and Thornhill (2019) referred to research designs as strategies and outline experiments, and surveys and realist ethnography as quantitative research designs. Saunders and his colleagues also suggested that research designs can be based on the purpose of the research, for example, descriptive, explanatory, evaluative and combined research designs. Collis and Hussey (2021) also mentioned surveys and experiments, but added longitudinal and cross-sectional designs, described as research time horizons by Saunders, Lewis and Thornhill (2019). To attenuate the inconsistent views on research design, the current study follows Sekaran and Bougie's (2016) view, which is rather comprehensive.

Sekaran and Bougie's (2016) view of research design is conceptualised as a combination of various components, that is; a research strategy, the extent of researcher's interference, study setting, unity of analysis, time horizon, data collection techniques, sampling design, measurement and measures, and data analysis methods to answer the research questions. Cooper and Schindler (2013) agree that, although definitions of research design differ, they nevertheless provide the essentials of research design. Figure 4.3 depicts the current study's research design as defined by Sekaran and Bougie (2016).

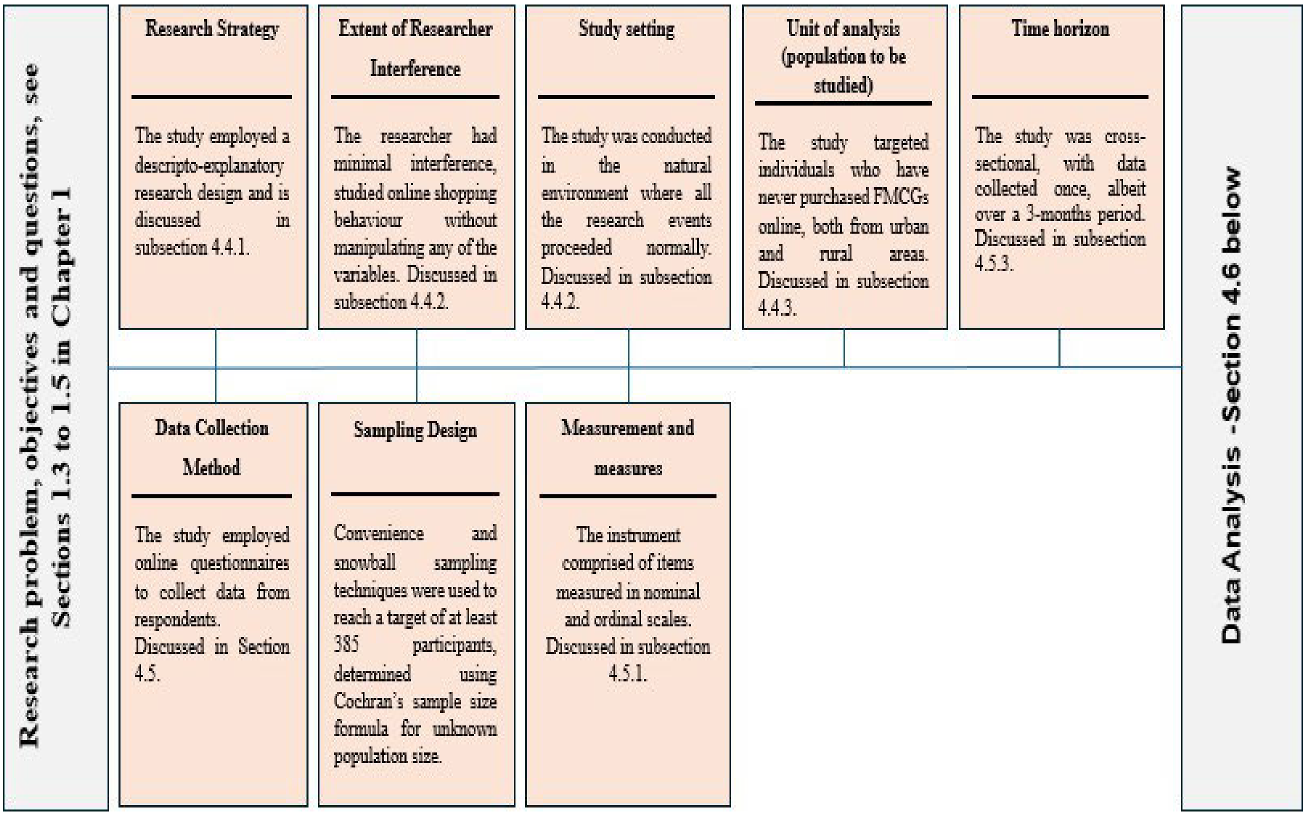


Figure 4.3: The Current Study's Research Design

Source: Sekaran and Bougie 2016

4.4.1 Research strategy

Sekaran and Bougie (2016) defined a research strategy as a means of achieving the research objectives while Saunders, Lewis and Thornhill (2019) posited that different research strategies can be combined to pursue the research objectives. This study adopted a descripto-explanatory strategy, which combines a descriptive and explanatory approach to achieve the research objectives set out in section 4.3. This strategy enables a clear understanding of the "what" and "how" of the population or phenomena and more importantly, its ability to provide a comprehensive understanding of a research problem (Bellamy, 2012; Loeb, Dynarski, McFarland, Morris, Reardon and Reber *et al.* 2017).

In this study, the descriptive research aspect provides a detailed description of the characteristics and behavioural patterns of the sample, laying the foundation for a more in-depth investigation and testing of the hypotheses on the reasons for the reluctance of FMCG consumers to shop online. As such, the explanatory part of the descripto-explanatory approach goes further and seeks to uncover the "why" behind the observed phenomena (Bellamy 2012). In the current study, this involved identifying factors that influence online shopping [reluctance] behaviour and testing the causal relationships to explain the underlying mechanisms driving the observed behaviours.

4.4.2 Researcher Interference and Study Setting

In quantitative research, the extent of interference by the researcher distinguishes between causal (experimental) and non-casual studies. In experimental studies, the researcher manipulates the independent variables or the research setting to determine the effect of such an intervention on the dependent variable (Sekaran and Bougie 2016). The extent of manipulation, including the research settings, varies in natural sciences compared to social and behavioural science studies. In the latter, field experiments are the norm, as opposed to laboratory experiments in natural science studies. The current study falls under the social and behavioural sciences; hence it subscribes to field experiments which are usually conducted in non-contrived settings. In contrast to causal studies, non-causal studies are conducted in non-contrived settings and without researcher interference (Grimshaw, Campbell, Eccles and Steen 2000; Sekaran and Bougie 2016). As a descripto-explanatory study (Saunders, Lewis and Thornhill 2019), the current study was conducted in a natural setting, without any manipulation of the variables or using a control group.

4.4.3 Target population

The target population for this current study comprised individuals aged above 18 years residing in South Africa, who indicated that they have never purchased FMCG online. Respondents were provided with examples of FMCG to ensure a unified understanding and reference of the concept. The research instrument was accessible to people based both in urban and rural areas, with ample access to internet connection and a smartphone. Increasing internet and smartphone penetration is cited in reports (Geopoll 2024; Kemp 2024; Statista 2024; South African News

Agency 2023) and previous studies (Karine 2021; Madhuku and Thusi 2023; Mofokeng 2021) as catalysts to the adoption of e-commerce.

It is estimated that in 2022 there were 42 million people who had access to the internet, , giving it an online penetration rate of 62% and a mobile connection of 108.6 million cellular mobile connections (Nhlapulo and Makhitha 2022). However, despite this growth, data shows that shoppers who are purchasing FMCG online accounts for about 30% of the people who have access to the internet in South Africa (TMO Contributor 2020). Therefore, the estimated population of this study is 29 million people who have internet access in South Africa but do not shop online for FMCG. (Statista 2024, Nhlapulo and Makhitha 2022, Rogerwilco 2019; Sileyew 2019).

This current study notes that there has been a proliferation of studies focusing on the adoption of online shopping in general (for example, Goga, Paelo and Nyamwena 2019; Madhuku and Thusi 2023; Makhitha, van Scheers and Mogashoa 2019; Mofokeng 2021; Pentz, du Preez and Swiegers 2020) and a few specifically focusing on the adoption of online shopping for FMCG (e.g. Cloete 2021; Olutade 2024). While these scholarly works are in tandem with the growing penetration of the online shopping phenomenon, the reluctance to shop online is still an under/unexplored phenomenon. Hence, the current study's focus is on non-adopters to provide a complete picture of online shopping [of FMCG] in South Africa. The following subsections (4.4.4 and 4.4.5) respectively expound on the sampling technique used and the sample size recruited to elicit data for answering the research questions.

4.4.4 Sampling Strategy

Sampling methods describe the approach used by the researcher to draw a sample from the population to answer research questions (Bryman 2016; Collis and Hussey 2021; Saunders, Lewis and Thornhill 2019). A sample is defined as a "process of selecting the right individuals, objects, or events as representatives for the entire population" (Sekaran and Bougie 2016: 235). While there are multiple approaches to sampling, two broad approaches are available to the researcher: namely non-probability and probability sampling (Pace 2021; Shorten and Moorley 2014).

The difference between the two is that in non-probability sampling, population elements do not have an equal chance to be chosen into the sample of the study compared to probability sampling (Leedy and Ormrod 2014; Sekaran and Bougie 2016). While probability sampling is vaunted as most suitable for positivist studies, there are times when it is impossible to do, allowing for the use of non-probability sampling (Saunders, Lewis and Thornhill 2019) or an integration of the two sampling approaches (Wiśniowski, Sakshaug, Perez Ruiz and Blom 2020). Generally, research is viewed through binary lenses, pitting positivist against the interpretivist/constructivist paradigms, explained through the incommensurability or incompatibility thesis (Burrell and Morgan 1979; Kuhn 1962; Howe 1988). This has created a false dichotomy in research for years, with many believing that both traditions cannot be used in the same study (Fuyane 2021), and this is reflected in the adversarial arguments between the two traditions on the ontological, epistemological, methodological and axiological approaches, each claiming primacy and or superiority over the other (Antwi and Hamza 2015; Fuyane 2021).

Onwuegbuzie and Leech (2005), Onwuegbuzie and Collins (2007) and others (e.g., Makrakis and Kostoulas-Makrakis 2016; Walsh 2012; Wood and Welch 2010) noted that the dichotomy manifests incompatibility at a methodological level, resulting in the infamous quantitative-qualitative dichotomy. This methodological dichotomy also spills over to sampling techniques, tribalising probability sampling as a quantitative technique and non-probability as a sampling technique for qualitative research (Onwuegbuzie and Leech 2005). These scholars take a pragmatist view and argued that methodological decisions must primarily be driven by the research questions, rather than the false quantitative-qualitative provinces. They argued that it is possible to use both probability and non-probability techniques without the quantitative-qualitative camps binaries (Collis and Hussey 2021; Onwuegbuzie and Leech 2005) and can be integrated to select a sample for a study (Wiśniowski *et al.* 2020; Yang and Kim 2020).

A post-positivist paradigm, also known as critical multiplism (Guba 1990), which underpins the current study, rejects this binary approach, especially the absolutist tendencies of logical positivists. Post-positivists are aware of the human limitations that may hinder objective observation and apprehension of phenomena, hence incorporate context and the thoughtful use of multiple methods in addressing research problems (Tanlaka, Ewashen and King-Shier 2019). Thus, drawing from the wisdom of these experts (Makrakis and Kostoulas-Makrakis 2016; Onwuegbuzie and Collins 2007; Onwuegbuzie and Leech 2005; Walsh 2012; Wood and Welch 2010; Wiśniowski *et al.* 2020; Yang and Kim 2020), the current study combines convenience sampling and snowball sampling techniques. The two techniques are discussed in depth under the following subsection.

4.4.4.1 Sampling Technique

Convenience sampling entails selecting participants who are easily accessible to the researcher and available for data collection (Collis and Hussey, 2021). While this technique is often criticised for introducing bias and limiting the generalisability of findings, it was considered appropriate for this study due to the hard-to-identify nature of the target population, namely consumers who have never adopted online shopping for FMCG or have never engaged in online shopping at all. Unlike active online shoppers, non-adopters are not readily identifiable through transactional databases or platform records, making probability sampling techniques impractical in this context.

Furthermore, the study specifically sought to capture insights from individuals who are typically underrepresented in e-commerce research, as most prior studies focus on existing users of online platforms. Therefore, accessibility and reach became critical considerations in the sampling design. With the proliferation of social media platforms, convenience sampling has evolved beyond traditional high-traffic physical locations and now enables researchers to access diverse and geographically dispersed populations in a cost-effective and efficient manner (Burns, Veeck, and Bush, 2017). This approach allowed the researcher to reach a broader pool of potential respondents who may not be actively engaged in online commerce but are reachable through digital communication channels.

To complement this approach and improve sample adequacy, a snowball sampling technique was employed. Snowball sampling is particularly useful when studying populations that are difficult to locate or lack a clear sampling frame, as it relies on participant referrals to identify additional respondents within similar networks. In this study, participants within targeted social media groups were encouraged to share the research instrument with others who met the study criteria. This peer-referral mechanism increased the likelihood of reaching individuals who are non-adopters of online FMCG shopping, thereby enhancing the relevance of the sample.

However, it is acknowledged that snowball sampling does not inherently guarantee that all recruited participants belong to the target population. To address this limitation and ensure the integrity of the data, screening (qualifying) questions were incorporated into the questionnaire. These questions were designed to filter respondents and include only those who had never purchased FMCG products online or had never engaged in online shopping altogether. The primary screening question, "Have you ever bought anything online?", served as a critical gateway to identify true non-adopters. This was particularly important given the inherent difficulty in distinguishing between adopters and non-adopters in an online data collection environment.

Collectively, the combined use of convenience and snowball sampling was deemed most appropriate for this study, as it enabled the researcher to effectively access a hidden and under-researched population, while implementing safeguards (through screening mechanisms) to ensure alignment with the study's objectives. Although these non-probability sampling techniques limit statistical generalisation, they are well-suited for exploratory and explanatory research focused on understanding behavioural phenomena such as e-commerce non-adoption

The question had three alternative answers; the "*Yes, I have*", "*No, I haven't, although I have browsed some online shopping platforms*", and "*No, I have neither searched nor bought anything online*." Those who responded "*Yes, I have*", were required to answer a follow up question, which sought to ascertain if they had purchased FMCG. An example of FMCG was provided as a description in the questionnaire and in our alternative answers we included three most common FMCG categories (food items, beauty and personal care products, and home hygiene products) to ensure that only those who had never bought FMCG would be included in the sample. All those who answered the other two alternatives (*No, I …*) qualified for the sample.

4.4.4.2 Sample Size

In addition to sampling methods, sample size has a direct bearing on model fit, the precision and power of parameter estimates, and the suitability of analytical methods to be used; hence the accuracy of sample findings relative to the population of interest (In'nami and Koizumi 2013; Onwuegbuzie and Collins 2007). While the importance of determining an adequate sample size is emphasised in extant literature, there seems to be no consensus on the matter. At best, researchers rely on rules of thumb such as the *n: p* (ratio of subjects to variables), *n: q* (ratio of cases to parameters), or naively following what other previous studies employed. In some studies, sample sizes are arbitrary figures with no reasoning offered for their selection.

Also, Onwuegbuzie and Collins (2007) highlighted that many scholars tend to base their sample size determination on the false dichotomy between the quantitative-qualitative divide, with large samples associated with quantitative research and small samples for qualitative research. Onwuegbuzie and Collins argued that such an approach is more of a fallacy. For the large sample size argument, especially for quantitative research, Kline (2016) raised an important question — 'How large is the large sample size?' In answering this question, different averments and reasoning have been tabled by different scholars, often based on the approaches discussed earlier. For instance, Burns, Bush and Sinha (2014), argued that the acceptable sample size for a quantitative research study ranged from 30 to 500. Culler (2020) suggested that for a population of more than a 1 000 000 a reasonable sample size should be 451. Sekaran and Bougie (2019) stated that a sample of 382 cases is sufficient for a population of between 75 000 and 1 000 000.

Unfortunately, most of the published quantitative studies do not explain how they obtained their sample sizes, but it is suspected that they rely on the established formulas for calculating sample size, for example, the Yamane, Cochran and Slovin formulas. These formulas provide guidelines and certain aspects such as the size of the population, confidence level, margin of error, power and effect size that must be considered when determining sample size (Ahmed 2024; Serdar, Cihan, Yücel and Serdar 2021). Another consideration for sample size is the analytical technique(s) to be used in analysing the data. For instance, extant literature indicates that larger sample sizes are always recommended, especially for statistical techniques such as factor analysis, regression analysis and structural equation modelling (SEM) (Kyriazos 2018; Kline 2016; Brown 2015; Schumacker and Lomax 2016).

For fear of being consumed by the confusion caused by the multiplicity of the rules of thumb, the current study employed Cochran's (1977) formula for calculating sample size for an unknown population. The output of this formula accommodates the expectations of various rules of thumb, such as $n > 100$ (Nunnally 1967; Nunnally and Bernstein 1967), $n = 300$ (Schumacker and Lomax 2016; Tinsley and Tinsley 1987; Tabachnick and Fidell 2014) and Muthén and Muthén's (2002) minimum sample size of 150 for CFA.

$$n = \frac{(t)^2 * pq}{(d)^2}$$

$$= \frac{(1.96)^2 * (0.5)(0.5)}{(0.05)^2}$$

$$= \frac{(3.8416)(0.25)}{0.0025}$$

$$= \frac{0.9604}{0.0025}$$

$$= 384.16$$

$$\boldsymbol{n = 385}$$

Where:

n: is the required sample size

z: is the z-score corresponding to the desired confidence level (e.g., 1.96 for a 95% confidence level)

p: is the estimated proportion of the population with the characteristic of interest (set to 0.5 when the proportion is unknown)

q: is the complement of (1 - p)

e: is the margin of error (the level of acceptable error in the estimate, set at 5%)

Figure 4.4: Sample size calculated using Cochran's formula

Source: Cochran 1977

The sample size determined in Figure 4.4 was checked against Soper's (2025) sample calculator for Structural Equation Modelling (SEM), which is one of the statistical analyses pencilled for the current study. To calculate the minimum sample size for SEM, an anticipated medium effect size of 0.3 (Cohen 1988), recommended statistical power of 0.8 (Hair, Page and Brunsveld 2020), with 12 latent variables (based on the proposed research model in Figure 3.1) and 57 observed variables (see the research instrument in **Appendix One**) and a probability level of 0.05 were inputted into the calculator. The calculator recommended a minimum sample size of 200 cases to detect the effect and for the model structure, making Cochrane's sample size of 385 superior.

4.5 DATA COLLECTION

Data were collected using an online survey method. Online surveys have become an increasingly popular data collection method, offering researchers a range of benefits, albeit with some limitations to consider. One of the primary advantages of online surveys is their ability to reach a wide and diverse audience quickly and cost-effectively (Regmi, Waithaka, Paudyal, Simkhada and Van Teijlingen *et al.* 2017; Putranto 2019). Through some affordances of various online data collection platforms such as Qualtrics, Survey Monkey, Question Pro, Google Forms and Microsoft Forms, laborious data capture associated with the traditional data collection methods can be eliminated; thus, reducing some measurement errors, missing data and transfer of data into analysis platforms, such as Excel and SPSS (Healey, Baron and Ilieva 2002). Also, online data collection affords respondents to complete the survey at their convenience and comfort, eliminating the effect of researcher pressure on respondents, which often leads to socially desirable responses (Callegaro, Manfreda and Vehovar 2015).

Another advantage of an online questionnaire is its shareability over various platforms such as social media, email, websites, discussion forums and a QR code that can be shared in online and offline media with target population members (Regmi *et al.* 2017). However, online surveys also face certain limitations such as sampling and access issues (Wright 2005). Online samples may not represent the general population, as they are restricted to individuals with access to the necessary technologies. Additionally, the quality of data collected through online surveys can be influenced by factors such as participant engagement, attention span, digital literacy or efficacy and the potential for fraudulent responses (Ball 2019; Gunter, Nicholas, Huntington and Williams. 2002).

When considering the use of online surveys, researchers must carefully weigh the strengths and limitations of this data collection method (Regmi *et al.* 2017; Gunter *et al.* 2002). The following two subsections provide further details about the research instrument and measurement decisions made in the current study.

4.5.1 Research Instrument Design and Measurement Scales

The data collection instrument was developed according to the constructs from UTAUT, TTT, SET and SPT. Questionnaire design is a critical aspect of data collection and applies to both online and offline data collections. The design aspect directly affects the appeal and navigability of an instrument and enables the gathering of useful and relevant information (Regmi *et al.* 2017; Roopa and Rani 2012; Song, Son and Oh 2015). Extensive literature exists on questionnaire design principles, providing guidance on construction, wording and ordering of questions (Ball 2019; Bernard 2011), and user-friendly design and layout (Callegaro, Manfreda and Vehovar 2015; Regmi *et al.* 2017), which are all crucial for reliability and validity (Song, Son and Oh 2015).

The researcher drew from extant literature to ensure that the instrument (see **Appendix One**) adequately elicits data from respondents to avert measurement errors and ensure reliability and validity; hence sufficiently answering the research questions. Another crucial aspect during questionnaire development is deciding on the item measurement scales. While metrology, "the study of measurement whose sole purpose is to unify acceptable standards of common understanding and conformity" was introduced in the late 18th century (Allanson and Notar 2020: 377), it is Stevens' (1946) seminal work that is credited for introducing measurement in the quantitative research arena. Stevens founded four classes of measurement scales (nominal, ordinal, interval and ratio) which have become the yardstick of variable labelling and data measurement in quantitative research. In addition to the four scales, Stevens also suggested the appropriate statistical procedures for each scale. The four scales are briefly discussed in the following subsections.

4.5.1.1. Nominal Scale

The nominal scale is one of the qualitative/categorical measures and the most basic level that figuratively labels and classifies variables into mutually exclusive and exhaustive categories without implying any order or magnitude (Collis and Hussey 2021; Flannelly, Flannelly and Jankowski 2014; Malhotra 2015; Margolis 1999). Examples of nominal scale is the classification of gender into male and female, or occupation classified into scholar, employed, unemployed, self-employed and retired. These categories can be numerically coded, for example, 1 for males and 2 for females, but that does not suggest any inherent hierarchy. Researchers can only check for the modal category as a measure of central tendency in nominal data and can also subject it to contingency correlation, percentage difference, Chi-square test of independence, and *Z*-test for proportions (Margolis 1999; Stevens 1946).

4.4.1.2 Ordinal Scale

Like nominal scales, ordinal scales are also categorical measures that divide the judgment of variable characteristics into mutually exclusive and exhaustive categories (Flannelly, Flannelly and Jankowski 2014; Margolis 1999: 216). However, although ordinal scales introduce a sense of natural and theoretical order or ranking to the categories, the intervals between ranks are not necessarily equal (Burns, Bush and Veeck 2017; Collis and Hussey, 2021; Margolis 1999; Mishra Pandey, Singh, and Gupta 2018). An example of an ordinal scale would be the measurement of customer satisfaction as “very dissatisfied”, “dissatisfied”, “neutral”, “satisfied”, or “very satisfied.”

Unlike nominal scales, numerical values assigned to categories of ordinal scale portray hierarchical ordering, which determines whether an object has more or less of a characteristic than some other object (Collis and Hussey 2021; Hair, Page and Brunsveld 2020; Shukla 2023). However, the assigned numbers are mathematically meaningless (Shukla 2023). Also, it does not always follow that larger numbers indicate high values. It is the researcher’s decision (Hair, Page and Brunsveld 2020), for example, one researcher may favour to use 1 for “very dissatisfied”, 2 for “dissatisfied”, 3 for “neutral”, 4 for “satisfied” to 5 for “very dissatisfied”, while another could use the opposite ordering. Mathematically, ordinal data can be subjected to equality test, determination of the median and mode, frequencies, ranges, rank correlations, and Chi-square test of independence (Hair, Page and Brunsveld 2020; Shukla 2023; Stevens 1968).

4.5.1.3 Interval Scale

Unlike the nominal and ordinal scales which are qualitative, interval scales are numerical or as Stevens (1946) asserted; they are quantitative in the ordinary sense of the word. Hence, mathematical operations such as equality test, comparison, addition and subtraction can be performed (Shukla 2023).

While interval scales possess hierarchical ordering like ordinal scales, their difference lies in the points/level descriptors, which are equal (Collis and Hussey 2021; Hair, Page and Brunsveld 2020). For example, the interval between 5 and 19 is the same as in 20 and 25. Also, interval scales have no true zero. For example, 0 degrees Celsius does not mean that there is no temperature.

A long-standing debate exists about whether Likert scales are ordinal or interval (Carifio and Perla 2008; Wu and Leung 2017). On the one hand, are those against the treatment of Likert scales as interval (e.g., Jamieson, 2004; Kuzon, Urbanchek and McCabe, 1996). They primarily based their argument on the fact that the distances between ranks are not equal; hence determining means and standard deviation is meaningless (Sullivan and Artino 2013). For example, what is the average of “Strongly disagree”, “Disagree”, “Agree”, and “Strongly agree” — does it even make sense? They argue that Likert data must be subjected to non-parametric statistical methods (Batterton and Hale 2017).

On the other hand, there are those who view Likert scales as interval scales on which mathematical operations can be performed. These scholars seem to follow Rensis Likert himself, who developed the scale as part of his doctoral studies, where he scored and summed respondents’ attitudes to yield a composite value (Willits, Theodori and Luloff 2016). Numerous scholars, methodologists and statisticians conducted research (e.g., Carifio and Perla 2008; Norman 2010; Wu and Leung 2017) to demonstrate that parametric tests are robust enough to deal with Likert data and still yield relevant results even when their mathematical presumptions are violated. Hence, in the current study, all Likert scale items were assumed to be interval.

4.5.1.4 Ratio Scale

This is the highest level of measurement which allows for all mathematical operations to be performed on data. It is, like the interval scale, a quantitative and continuous measurement and its intervals have equally spaced gradations, but differs in that it has a true, natural or defined zero, which indicates the complete absence of the measured quantity (Collis and Hussey 2021; Flannelly, Flannelly and Jankowski 2014; Malhotra 2015; Shukla 2023). Accordingly, the true zero enables the computation of ratios of points on the scale (Hair, Page and Brunsveld 2020). Table 4.1 presents the instrument structure, items for eliciting responses and the measurement scales used.

Table 4.1: Research Instrument Composition and Structure

Section and Number of items	**Variables/ Items**	**Item discussion and related literature**	**Measurement scale**
Landing page: Participant Information Sheet (PIS) and Consent Form	N/A	The PIS provides detailed information (purpose, methodological procedures of the study, including allaying ethical concerns) about the study. Based on the PIS, respondents declare their consent of wilful participation in the study consent form.	N/A
Filter questions	3	Three filter questions were included to ensure that only those who have purchased FMCG online before were excluded in the study.	Nominal
Section A: Demographic and descriptive information	6	The demographic variables included in this section were gender, ethnicity, age, occupation, income level and education.	Nominal, Ordinal and Ratio
Section B: Access and Connectivity	2	These two items sought to elicit information about how respondents accessed and connected to the internet. Numerous studies and industry reports identified internet access and connectivity, and other supplementary technologies as the mainstay and catalyst for e-commerce (e.g., Makhitha and Dlodlo 2014;	Nominal

		Pentz, Preez and Swiegers 2023; Pérez-Hernández and Sánchez-Mangas 2011).	
Section C: Factors Influencing Non-adoption of Online Shopping	57	As indicated in Chapter 3, the current study employed and integrated model drawn from the UTAUT (Venkatesh *et al.* 2003), SET (Blau 1964; Emerson 1962; Homan 1958), TTT (Oliveira *et al.* 2017; Stewart 2003) and SPT (Short, Williams and Christie 1976) theoretical models. These factors were inverted to capture their influence on the reluctance to shop online.	Assumed interval

4.5.2 Research Instrument Administration

Improved internet penetration and access have become a blessing for researchers, who have grappled with cost and time related challenges, especially during data collection (Innes, Roberts, Preece and Rogers 2016; King, O'Rourke and DeLongis 2014). Internet-based media such as social media, blogs, email systems and websites offer researchers access to a larger group of participants, including the hard-to-reach members of the target population such as individuals living in remote geographical areas (Bender *et al.* 2017; Rueter 2020; Saberi 2020).

Additionally, it enables participants to take part in research interviews or fill out surveys whenever it is convenient. In this study, data were collected using an online questionnaire distributed via a digital flyer containing a survey link and a QR code. The flyer was disseminated across multiple social media platforms, including Facebook, Instagram, and WhatsApp. Participants were approached through both the researcher’s personal networks and targeted online communities, such as WhatsApp groups, Facebook community pages, university student groups, and consumer-focused forums. These platforms were deliberately selected due to their high engagement levels and the diversity of users, which increased the likelihood of reaching individuals who are non-adopters of online FMCG shopping.

The data collection process was conducted over a period of four to six weeks, during which the digital flyer was reposted periodically to enhance visibility and response rates. In addition, participants were encouraged to share the survey link with their contacts, thereby incorporating a snowball sampling approach. This strategy was particularly useful in extending the reach of the study to individuals who may not be directly accessible to the researcher but fall within the target population.

4.6 DATA ANALYSIS

Although each section in this chapter is significant, this one is more so because it serves as a gateway to the following chapter, which presents and interprets the results. Two aspects of data analysis are discussed in this section. The first subsection (4.6.1), describes the procedure for cleaning data and getting it ready for analysis and the second subsection (4.6.2), elucidates the analytical process.

4.6.1 Data Cleaning Process

While emphasis is placed on instrument development to ensure that quality data relevant for answering the research questions is generated (Malhotra, Nunan and Birks 2017), it should be noted that data collected from the respondents is in a raw format, and unsuitable for running various analyses. As a result, data was cleaning is necessary before analysis (Sallis, Gripsrud, Olsson and Silkoset 2021). The current study began with the editing and coding of the data (Malhotra, Nunan and Birks 2017; Sekaran and Bougie 2016), followed James Gaskin's data preparation procedures, which include the checking for missing data, outliers, normality, linearity, homoscedasticity and multicollinearity (Gaskin 2022).

4.6.2 Analytical Framework

Quantitative researchers have an array of analytical techniques or tests to choose from when analysing data to answer the research questions. Generally, in most quantitative studies, both descriptive and inferential statistical analyses are conducted and reported. While descriptive statistics, such as measures of central tendency and dispersion, help us to summarise data and hence gain a better insight of the data, they are not helpful for testing hypothesised relationships (make inferences). To test theory or hypothesised relationships, inferential statistics are used (Vrbin 2022), and the choice of a technique or test is dependent on; first, the measurement scale (Batterton and Hale 2017; Hair, Page and Brunsveld 2020; Margolis, 1999; Sallis *et al.* 2021; Shukla 2023; Stevens 1946; Sullivan and Artino 2013); secondly, data characteristics such as normality, linearity, homoscedasticity and multicollinearity (Gaskin 2022; Hair, Page and Brunsveld 2020; Sallis *et al.* 2021; Sekaran and Bougie 2016); and thirdly, the number of samples (Malhotra, Nunan and Birks 2017).

As indicated in subsections 4.5.1.1 to 4.5.1.4, the four levels of measurement attract different analytical methods. To be specific, qualitative and categorical scales (nominal and ordinal) must be analysed using non-parametric methods, while the quantitative and continuous scales (interval and ratio) can be analysed using parametric methods. However, not all data characteristics determine whether a parametric or non-parametric method is used. Only the assumption of normality is a key determinant of whether a study employs parametric or non-parametric tests, while others determine the suitable estimation methods, for example, in regression and SEM.

Parametric and non-parametric statistical tests may be further classified based on the number of samples in a study (Malhotra, Nunan and Birks 2017). For example, for one sample, the *t*-test and *z*-test would be the appropriate parametric approaches, and the chi-square test, the Kolmogorov–Smirnov test, the runs test and the binomial test would be appropriate non-parametric tests. For two or more samples, statistical techniques can be based on whether it is an independent or a paired sample. For independent samples, the parametric *t*-test becomes the two-group *t*-test and paired *t*-test for paired samples, while the Mann–Whitney *U* test, the median test and the Kolmogorov–Smirnov two-sample tests are non-parametric tests for independent samples, and the Wilcoxon matched-pairs signed-ranks test and McNemar suitable for paired samples (Malhotra, Nunan and Birks 2017). Other popular parametric techniques include linear regression, Pearson correlation, analysis of variance (ANOVA), and Covariance Based SEM (CB-SEM), while other non-parametric methods include Spearman correlation, Kernel regression, and SEM to test the hypothesised relationships.

While the difficulty or near impossibility of selecting analytical techniques before checking the data for statistical assumptions is noted, it is plausible to have an analysis strategy with provisionally earmarked analytical technique(s) to answer the research questions. For the current study, the earmarked techniques were, in addition to descriptive statistics, exploratory factor analysis (EFA) and SEM.

4.7 RELIABILITY AND VALIDITY

Reliability and validity are tests of the goodness of measures (Sekaran and Bougie 2016), which are the bedrock of quantitative research endeavours, ensuring that findings are both replicable and meaningful. They are not just random buzzwords in the research lexicon, but rather fundamental tenets that are central to judgement of research trustworthiness and quality (Saunders, Lewis and Thornhill 2019). Reliability pertains to the replicability and consistency of a measurement instrument. It provides assurance "that transient and situational factors are not interfering" (Cooper and Schindler 2013: 260). Grossoehme (2014) analogises reliability as akin to a scale that faithfully records the same weight every time an individual steps on it.

However, despite being necessary and a contributor to validity, reliability is insufficient for guaranteeing validity, which is the extent to which an instrument measures what it purports to measure (Bagozzi and Yi 2012; Cooper and Schindler 2013; Grossoehme 2014; Saunders, Lewis and Thornhill 2019). A highly reliable instrument that lacks validity merely provides stable yet inaccurate data, leading to spurious conclusions (Sekaran and Bougie 2016). Continuing with Grossoehme's (2014) analogy of a scale, validity would be the correctness or accuracy of the scale.

There are three perspectives on reliability based on the distinction between time and condition; that is, stability, equivalence, and internal consistency (Cooper and Schindler 2013). Stability of the measure implies consistency of results over repeated measurements of the same object using the same instrument, demonstrating that the measure is not subject to situational changes (Sekaran and Bougie 2016). Stability can be assessed using either the test-retest reliability or parallel-form reliability. Equivalence concerns the consistency of a measure across different investigators, samples and forms (e.g., between hardcopy and online, or original and translated) (Heale and Twycross 2015). Internal consistency is the most popular of the three and the one used in the current study. It shows how well the observed items measuring a concept fit together as a whole (Heale and Twycross 2015; Sekaran and Bougie 2016). In this study, reliability was assessed using the classic Cronbach's coefficient alpha (α) and composite reliability estimates.

Like reliability, there are various perspectives or forms of validity that researchers must ensure to enhance the credibility and relevance of their findings. Firstly, validity can be categorised into external and internal validity (Cooper and Schindler 2013). External validity is all about the generalisability of research findings, which might suffer from sampling error. Internal validity, also referred to as measurement validity (Saunders, Lewis and Thornhill 2016) can be further split into face validity, content validity, criterion (predictive and concurrent) validity and construct (convergent and discriminant) validity. All these were adopted to assess if the instrument was able to measure what they purported to measure.

4.8 ETHICAL AND INTEGRITY CONSIDERATIONS

Ethics are "a branch of philosophy which deals with the dynamics of decision making concerning what is right and wrong" (Fouka and Mantzorou 2011: 4). They are the mainstay of any research study, providing guardrails to ensure that researchers do not use research methods and practices that are harmful to human, environment or organisations. Unfortunately, in research, the enforcement of ethics came after cruel treatment of research participants by the Nazi scientists during the Second World War (Ndebele *et al.* 2014), and since then, they have become an integral aspect of research.

Research ethics are underpinned by the beneficence/non-maleficence, voluntariness, respect of anonymity, confidentiality and privacy, vulnerability and researcher'(s') skills and competencies (Fouka and Mantzorou 2011). The current study met all the ethical standards and was granted ethical approval by the researcher's institutional ethics committee (see **Appendix Three**). A participant information sheet detailing the research study was provided as the landing page of the online questionnaire, together with the informed consent form. This was done to ensure that that respondents familiarise themselves with the study, its purpose and objectives, and how anonymity, confidentiality and privacy were enabled and protected. Participation in the study was voluntary, without coercion or deception as the instrument was shared virtually, without any pressure to the participants to participate against their will. There was no deliberate or intent to target vulnerable participants. Also, the researcher adhered to the dictates of the POPI Act.

4.9 SUMMARY OF THE CHAPTER

This chapter outlines the research methodology guiding the study, beginning with a discussion of research paradigms that underpin the ontological, epistemological, and axiological stances. It articulates the rationale for adopting a post-positivist approach and details the methodological justifications, including the quantitative research design, sampling techniques, and sample size determination.

The chapter then describes the research design as a blueprint that operationalises the methodological choices, detailing the procedures for data collection using online surveys, the development and validation of the research instrument, and the various measurement scales employed. Finally, it explains the data cleaning and analysis strategies, while also addressing issues of reliability, validity, and ethical considerations, thereby establishing a robust foundation for the subsequent data analysis chapter.

CHAPTER FIVE

RESULTS PRESENTATION AND INTERPRETATION

5.1 INTRODUCTION

This chapter builds on the previous chapter which outlined the methodological choices made in this study. Before presenting and interpreting the results from rigorous data analysis process, the chapter begins with a section outlining the procedures taken to ensure high-quality data for the analysis. After that, the study's sample is described, followed by descriptive statistics. Then, the main results pertaining to hypotheses testing are presented before closing off the chapter with a chapter summary.

5.2 DATA CLEANING AND PREPARATION

In research, data cleaning is an essential step to avoid the "garbage in, garbage out" phenomenon of research data. Marsden and Pingry (2018: A1) supported this phenomenon when they asserted that even "erudite modelling and estimation can yield no value without quality data inputs." Poor quality data often affects validity, reproducibility and generalisability of findings (Houston, Yu, Martin and Probst 2020; Marsden and Pingry 2018; Saidu, Shagari, Kabir and Abubakar 2023). There is a wide range of techniques for assessing and improving data quality (Batini *et al.* 2009).

Among the many ways of assessing and improving data quality (Hair, Page and Brunsveld*et al.* 2020; Li, Hou and Yu 2019), the researcher followed the data preparation suggested by Gaskin (2022). Gaskin provides a six-step process to ensure that data meets the various assumptions for performing different statistical techniques. For example, normality tests determine whether parametric or nonparametric techniques can be used to analyse the data and answer the research questions. Data with multivariate, linearity, homoscedasticity and multicollinearity issues will throw off regression and SEM analyses. Gaskin's six steps start with identifying and treatment of missing data, followed by identifying univariate and multivariate outlier identification and correction. The third step involves normality testing, followed by testing for deviation from linearity (fourth step), determining if the relationship among variables is homoscedastic (fifth step, and lastly checking for multicollinearity. Subsections 5.2.1 -5.2.6 below details how the researcher applied each of these steps.

5.2.1 Missing Data

Missing data presents a ubiquitous challenge in social and business research, potentially compromising the integrity and generalisability of findings (Mayer, Muche and Hohl 2012; Kang 2013; Newman 2014). The absence of certain data points, whether due to participant attrition, measurement errors, or other unforeseen circumstances, can introduce bias and reduce the statistical power of analyses (Dibal, Okafor and Dallah 2017). Understanding the nature and extent of missing data is crucial for selecting appropriate strategies to mitigate its impact (Kang 2013). In social and business research, missing data frequently occur due to various reasons such as refusal to participate, non-completion, subject attrition, errors in measurement, or communication issues (Liu and De 2015).

Missing data can arise under three different conditions, ranging from missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR) (Little and Rubin 2019; Newman 2014; Rubin 2018). When data are missing completely at random, the probability of missingness is unrelated to both observed and unobserved variables, simplifying the analysis to some extent. Furthermore, the reasons for missingness may be related to the variables being studied, such as participants with lower income being less likely to report their financial information. Ignoring missing data can lead to biased estimates, particularly when the missingness is related to the outcome variable (Cummings 2013).

In the present study, missing data was averted through setting all the items in the online questionnaire as compulsory to ensure that respondents could not leave questions unanswered. Unfortunately, this is thought to be the reason for refusal to participate (14 cases) and no-completion (43 cases). These cases were deleted from the dataset, leaving a sample of 430 observations.

5.2.2 Outliers and Respondent Misconduct

In the second step, data were checked for outliers. While the concept of outliers has been defined by many, sometimes differently and conflicting (Aguinis, Gottfredson and Joo 2013), it remains a difficult and misunderstood concept in research (Leys, Klein, Dominicy and Ley 2018). To avoid the confusion, the present study adopted the all-encompassing definition of the concept, one which recognises that outliers occur at univariate and multivariate levels (Leys, Delacre, Mora, Lakens and Ley 2019). Leys and associates defined outliers as data points with large residual values. Based on this definition, Leys *et al.* (2019), building on

Aguinis, Gottfredson and Joo's (2013) work, proposed three types of outliers, which were considered in the present study – error, interesting and random outliers.

Aguinis, Gottfredson and Joo (2013) recommended a three-step process for identifying and handling outliers. This process starts with identifying error outliers, which are non-legitimate data points that lie distant from other points, possibly as a result of observation, data capture/manipulation, computation or coding errors (Aguinis, Gottfredson and Joo 2013; Leys *et al.* 2019). For example, for a 5-point Likert scale, 55 is punched in instead of 5 as the upper limit. In the present study, no such outliers were identified. Then, after error outliers, the second step is the identification of the interesting outliers, defined as "outlying data points that are accurate", "but not confirmed as actual error outliers" (Aguinis, Gottfredson and Joo 2013; Leys *et al.* 2019). Such outliers can also include respondent idiosyncrasies or misconduct, for example, responses that are contrary to specific theory or unengaged responses. These outlier cases may be of value (Mohrman and Lawler 2012) and the outlyingness must be scrutinised to avoid uninformed exclusion of such cases; hence losing out on a possible theoretical insight (Leys *et al.* 2018).

The last step is of identifying the influential outliers (changed to random outliers; see Leys *et al.* 2019). Aguinis, Gottfredson and Joo (2013) identified two types of influential outliers, that is, model fit outliers and prediction outliers. Aguinis, Gottfredson and Joo (2013:288) defined model fit outliers as "data points whose presence alters the fit of a model, and prediction outliers are data points whose presence alters parameter estimates." However, Leys et al. (2019) argued against this view since all outliers could be influential or not influential at all. Hence, they opted for random outliers, which they defined as "values that just randomly appear out of pure (un)luck" (Leys *et al*. 2019: 2). To practically deploy the three-step outlier identification process discussed above, the present study adopted a twofold approach suggested in literature (Gaskin 2022; Leys *et al.* 2018). First, univariate outlier analysis followed by multivariate analysis.

Univariate outliers are observations that exhibit extreme values on a single variable, while multivariate outliers represent cases with an unusual combination of scores on two or more variables, potentially violating the pattern of multivariate normality (Leys *et al.* 2019; Tabachnick and Fidell 2013). In their study, Aguinis, Gottfredson and Joo (2013) also found that there are numerous approaches for identifying outliers and equally many techniques for handling outliers, further adding to the difficulty and confusion about the concept. In the present study, the univariate outliers were identified using the box plot approach and the identified cases were analysed to determine their outlyingness. All the cases were retained as there was no justification of removing them, as the cases did not even show respondent misconduct (unengaged responses). For multivariate outlier analysis, the probability of Mahalanobis Distance (*p*MAH-1 < .001) was used to eliminate fifteen (15) cases, leaving a sample of 414 cases in the dataset.

5.2.3 Normality Testing

Quantitative researchers must make a choice between adopting parametric and non-parametric analytical techniques for hypothesis testing. However, the choice is not an arbitrary one or dependent on the researcher's liking or ability. It is informed by the type data to be analysed and whether the sample data is drawn from a normally distributed population (Margolis 1999; Tsagris and Pandis 2021). Usually, metric (interval and ratio) data are assumed to follow a normal distribution compared to categorical (nominal and ordinal) data. The distinction between parametric and non-parametric methods is that parametric methods assume that data is normally distributed (Das and Imon 2016), while non-parametric do not. Using parametric techniques to analyse data that violates the assumption of normality may lead to the use of suboptimal estimators, invalid inferential statements and inaccurate predictions (Ahad, Yin, Othman and Yaacob 2011; Das and Imon, 2016; Mishra *et al.* 2019).

Hence, in the present study, normality testing data was subjected to normality testing to guide the analytical choices. Two different tests of data normality were carried out – numerical tests (skewness and kurtosis, and statistical methods – Shapiro-Wilk tests) and graphical methods (histogram and Q-Q plots). The results are presented in Table 5.1 (skewness and kurtosis, and Shapiro-Wilk tests) and in **Figures** 5.1a-l (see histograms and Q-Q plots in **Appendix Five (a)).** Despite the absolute values of all variables' skewness and kurtosis falling within the liberal threshold of ±2.2 (Sposito, Hand and Skarpness, 1983), the standard z-scores ($Z_{skewness}$ and $Z_{kurtosis}$) of most of the variables are way off the ±1.96 threshold. Hence, as anticipated with ordinal-level data, the assumption of normality was violated. The histograms and P-P Plots **Figures** 5.1a-l in **Appendix Five (a)** also confirms. Non-normality influenced the choice of analytical techniques that were adopted in this study.

Table 5.1: Numerical Normality Tests

	Skewness and Kurtosis						Shapiro-Wilk		
Construct	**Skewness Statistic**	**Std Error**	$Z_{skewness}$	**Kurtosis Statistic**	**Std Error**	$Z_{kurtosis}$	**Statistic**	**df**	**Sig.**
NPE	-1.247	0.120	-10.3917	1.416	0.239	5.924686	0.879	414	<.001

NEE	-0.988	0.120	-8.23333	0.98	0.239	4.100418	0.927	414	<.001
NSI	-1.424	0.120	-11.8667	2.161	0.239	9.041841	0.85	414	<.001
NFC	-0.741	0.120	-6.175	0.302	0.239	1.263598	0.932	414	<.001
TPB	-0.703	0.120	-5.85833	0.355	0.239	1.485356	0.951	414	<.001
LRCP	-0.622	0.120	-5.18333	0.116	0.239	0.485356	0.965	414	<.001
DOPS	-0.749	0.120	-6.24167	0.154	0.239	0.644351	0.940	414	<.001
DOSC	-0.747	0.120	-6.225	0.121	0.239	0.506276	0.928	414	<.001
LSP	-0.544	0.120	-4.53333	-0.008	0.239	-0.03347	0.958	414	<.001
NISO	-0.782	0.120	-6.51667	-0.063	0.239	-0.2636	0.885	414	<.001
Dill	-1.133	0.120	-9.44167	1.652	0.239	6.912134	0.889	414	<.001
PPE	-1.51	0.120	-12.5833	3.795	0.239	15.87866	0.863	414	<.001

NPE = Negative performance expectancy, **NEE** = Negative effort expectancy, **NSI** = Negative social influence, **NFC** = Negative facilitating conditions, **TPB** = Technophobia, **LRCP** = Lack of reciprocity, **DOPS** = Distrust in online payment systems, **DOSC** = Distrust in social channels, **LSP** = Lack of social presence, **NISO** = No intention to shop online, **Dill** = Digital illiteracy, and **PPE** = Poor promotion effort.

5.2.4 Testing for Linearity

Linearity represents a fundamental assumption in many statistical techniques, referring to a straight-line relationship between variables where the change in the dependent variable remains proportional to changes in independent variables (Cohen *et al.* 2003). If violated, it can cause problems for regression analysis and SEM (Gaskin 2022). In regression, non-linearity leads to biased coefficient estimates, compromised statistical power, and misrepresentation of relationships, potentially masking true effects or creating spurious ones (Ernst and Albers 2017). In SEM, it can distort estimates, inflate residuals, and undermine model fit, leading to biased conclusions (Hayes 2022; Kline 2023). Thus, data were checked for linearity and the results (see Table 5.2) revealed non-linearity problems between some independent and dependent variables.

Table 5.2: Linearity Checking

Construct	Dev. from Lin. (Sig.) -NISO	Dev. from Lin. (Sig.) -DOSC
Negative performance expectancy (NPE)	0.215	
Negative effort expectancy (NEE)	0.421	
Negative social influence (NSI)	0.183	
Negative facilitating conditions (NFC)	0.217	
Technophobia (TPB)	0.042	
Lack of reciprocity (LRCP)	0.142	0.312
Digital illiteracy (Dill)	0.518	
Poor promotion effort (PPE)	0.755	
Distrust in social channels (DOSC)	<.001	
Distrust in online payment systems (DOPS)		<.001
Lack of social presence (LSP)		0.176

NISO = No intention to shop online, and **DOSC** = Distrust in social channels

Linearity test results in the table above indicate that most of the variables (see column 2) have a linear relationship with NISO. The relationship between NISO and TPB, and NISO and DOSC deviate from linearity, shown by the p-values less than .05. For the relationship between three variables on which DOSC is regressed on, only the relationship with DOPS deviates from linearity. As a result, these variables were transformed using the log transformation technique for the moderated regression analysis and for SEM, robust corrections were applied using the non-parametric Bollen-Stine bootstrap procedure (Bollen and Stine 1992) to estimate corrected Chi-square values to attenuate the effects of non-normality and nonlinearity (Hayes 2022; Kline 2023).

5.2.5 Determining Homoscedasticity

Homoscedasticity refers to the assumption that the variance of residual errors remains constant across all levels of predictor variables, representing an essential condition for valid statistical inference in multivariate analyses (Astivia and Zumbo 2019; Ernest and Albers 2017). When violated, resulting in a condition known as heteroscedasticity (Đalić and Terzić 2021), the variability of residuals differs across levels of prediction, which can lead to inefficient parameter estimates, biased standard errors, and unreliable significance tests (Zambom and Kim 2017; Hayes 2022). In structural equation modelling, heteroscedasticity distorts χ^2 test statistics and inflates Type I error rates for model fit indices, with the CFI and RMSEA being particularly susceptible to misspecification under heteroscedastic conditions (Kline 2023).

In this study, homoscedasticity was assessed by inspecting scatterplots of standardised residuals against predicted values (Astivia and Zumbo 2019; Đalić and Terzić 2021). The results show a moderate random, evenly spread pattern suggesting homoscedasticity. See the scatterplots, **Figures** 5.2a-l in **Appendix Five (b)**.

5.2.6 Checking Multicollinearity

While linearity is a desired assumption for multivariate analysis, multicollinearity, which is the strong overlap or correlation among the independent variables is problematic and must be detected and addressed. Multicollinearity leads to redundancy in the information they provide about the outcome variable (Field 2021). It also causes the inflation of standard errors, and instability in the results such that small changes in sample covariance patterns can generate very different solutions, or analysis failure due to linear dependence (Kline 2023, Shrestha 2020). There are many methods of detecting multicollinearity, among the many, bivariate correlation coefficient, tolerance, and Variance Inflation Factor (VIF) measures have been primary methods for many researchers (Shrestha 2020).

The present study combined the three methods suggested by Shrestha (2020) to check whether multicollinearity among the independent variables existed. The correlation coefficient (r) is a measure of association between two variables. For normal data, Pearson coefficient is used, while for non-normal data, Spearman Rho rank correlation is used as a measure of a monotonic association. A strong correlation coefficient ($.70 \geq r \leq .89$) and an extremely stronger correlation ($> .90$) between two variables indicated the presence of multicollinearity and serious multicollinearity, respectively (Kline, 2023). Based on the results in Table 5.3, there is no multicollinearity issue, as all of the significant Spearman's correlation coefficients are less than the .70 threshold.

After the correlation analysis, tolerance and VIF measures were calculated using IBM SPSS 29.0. Tolerance and the VIF are foundational diagnostic tools for assessing multicollinearity. Tolerance, defined as the proportion of variance in a predictor not accounted for by the other independent variables in the model (Senaviratna and Cooray 2019), is computed as $1 - R^2$, derived from regressing the predictor in question against all other predictors (Menard 2011). A high tolerance value (approaching 1) indicates that the variable shares little variance with others, thus reflecting minimal multicollinearity. In contrast, a low tolerance value, for example, less than 0.1 (Daoud 2017; Tabachnick and Fidell 2018) signals substantial shared variance, suggesting redundancy among predictors and undermining the reliability of individual coefficient estimates (Allison 2012).

The VIF, which is the mathematical inverse of tolerance (i.e., VIF = $\frac{1}{1-R^2}$), offers a more intuitive interpretation by expressing the inflation in the variance of an estimated regression coefficient due to multicollinearity (O'Brien 2007). A VIF value of 1 signifies that there is no multicollinearity, as the variance of the coefficient is not inflated beyond its ideal level.

However, VIF values that rise above conventional thresholds, of 2.5 (Senaviratna and Cooray 2019) and 5 (Shrestha 2020), or indicate multicollinearity concerns with values > 10, show severe enough problems to compromise the precision and validity of parameter estimates (Belinda and Peat, 2014; Kline, 2023). While such thresholds are not absolute, values in this range often justify reconsidering variable inclusion, model respecification, or the adoption of techniques such as principal component regression or ridge regression.

Table 5.3: Spearman's Rho Correlations

	NPE	NEE	NSI	NFC	TPB	LRCP	DOPS	DOSC	LSP	NISO	Dill	PPE
NPE	**1.000**	.320**	.671**	.270**	.244**	-0.080	.154**	.130**	.173**	-0.030	-.127**	.108*
NEE	.320**	**1.000**	.362**	.471**	.220**	0.065	0.016	0.065	.122*	-0.004	.099*	.108*
NSI	.671**	.362**	**1.000**	.317**	.283**	-0.068	.107*	0.030	.140**	-0.045	-0.064	0.057
NFC	.270**	.471**	.317**	**1.000**	.557**	.213**	.111*	0.026	.243**	0.045	.273**	0.034
TPB	.244**	.220**	.283**	.557**	**1.000**	.175**	.174**	0.054	.364**	0.083	.382**	-0.063
LRCP	-0.080	0.065	-0.07	.213**	.175**	**1.000**	.137**	.126*	0.079	.158**	.167**	0.019
DOPS	.154**	0.016	.107*	.111*	.174**	.137**	**1.000**	.450**	.134**	.268**	0.027	-0.053
DOSC	.130**	0.065	0.030	0.026	0.054	.126*	.450**	**1.000**	.215**	.373**	-.102*	-0.050
LSP	.173**	.122*	.140**	.243**	.364**	0.079	.134**	.215**	**1.000**	.127**	.253**	0.006
NISO	-0.030	-0.004	-0.045	0.045	0.083	.158**	.268**	.373**	.127**	**1.000**	.176**	0.029
Dill	-.127**	.099*	-0.064	.273**	.382**	.167**	0.027	-.102*	.253**	.176**	**1.000**	-0.021
PPE	.108*	.108*	0.057	0.034	-0.063	0.019	-0.053	-0.050	0.006	0.029	-0.021	**1.000**

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

According to the results in Table 5.4, tolerance values were all greater than 0.1, and VIFs were all below the 2.5 thresholds, indicating no multicollinearity presence. Critically, reliance on VIF alone is insufficient; its interpretation must be situated within the broader theoretical and empirical context of the model to avoid overcorrecting and inadvertently discarding substantively meaningful predictors.

Table 5.4: Tolerance and VIF values

Model		Collinearity Statistics	
		Tolerance	VIF
1	NPE	0.519	1.926
	NEE	0.733	1.365
	NSI	0.515	1.942
	NFC	0.541	1.848
	TPB	0.582	1.719
	LRCP	0.907	1.102
	DOSC	0.916	1.091
	Dill	0.807	1.239
	PPE	0.976	1.025

a. Dependent Variable: NISO

5.3 SAMPLE PROFILE

The demographic and contextual characteristics of the final sample (*n* = 414) are summarised in Table 5.5 and **Figures** 5.3–5.9. The mean age was 39.72 years (SD = 12.4), suggesting that the sample largely consisted of individuals in the Generation X and Millennial cohorts. This age profile aligns well with past studies on digital adoption, as these cohorts often span both digital natives and migrants (Prensky 2001). As digital natives are often early adopters and frequent users of technology, they are therefore propelled towards adopting e-commerce which is perceived to be very useful (Thangavel and Chandra 2024).

Table 5.5: Measures of Central Tendency and Dispersion (*n* = 414)

	Gender	Ethnicity	Occupation	Income	Education	Device	Connectivity	Age
Mean								39.72
Median	2	1	2	5	3	2	2	
Mode	2	1	2	5	3	1	2	
Std. Deviation								12.400

Figure 5.3 reveals that 51.7% of respondents were females, against 48.3% for male respondents. The split between males and females is indicative of representativity in the sample.

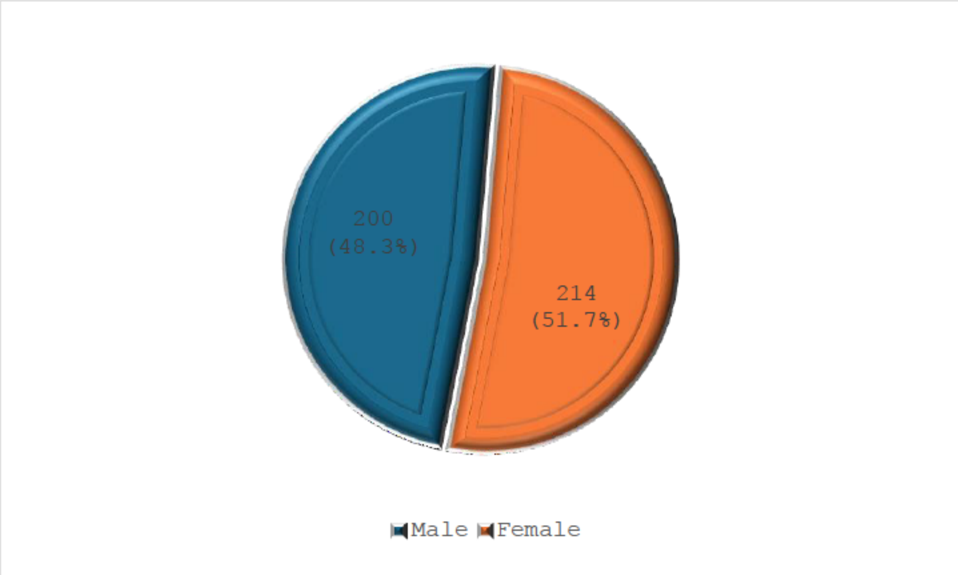


Figure 5.3: Gender (n = 414)

Like gender, the ethnic group variable also shows representativity based on national demographics, where Black Africans are the majority, accounting for approximately 81% of the South African population (Government of South Africa 2025). **Figure** 5.4 shows that the sample comprised 79.2% Black Africans, 7.7% Indians, 7.5% Coloureds and 5.6% Whites. Therefore, the ethnic group spread does not deviate away from the national population profile.

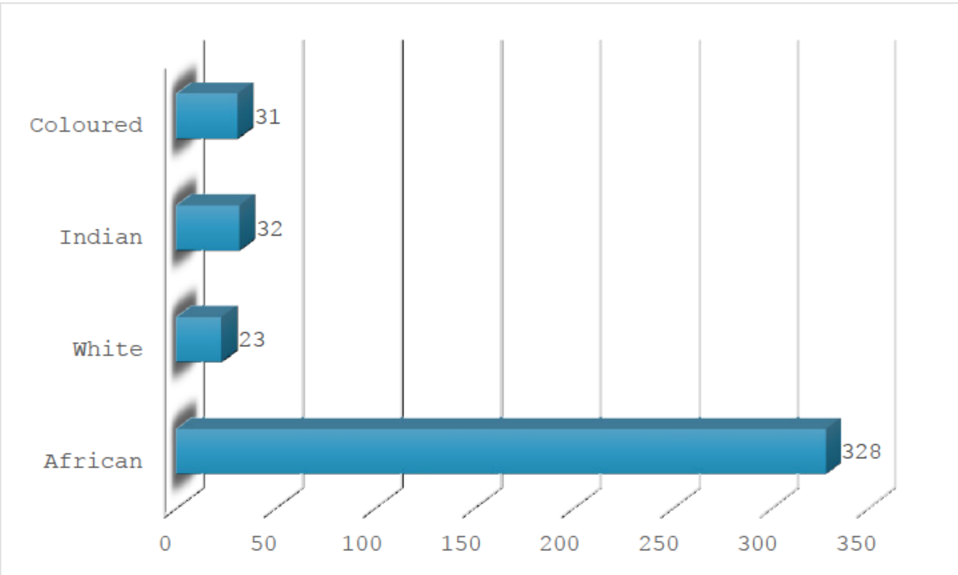


Figure 5.4: Respondents' Ethnic Groups (n = 414)

Figure 5.5 indicates that the majority (45.9%) of respondents were employed, followed by self-employed (22.2%), unemployed (20.5%) and students who constituted 11.4% of the sample. Such a sample is useful in that it accounts for the impact of occupation status. However, there are mixed findings from previous research elsewhere, with some indicating a significant relationship between occupation status and online shopping (Clemes, Gan and Zhang 2014; Imran, Asif and Sajjad 2022), while in other studies (e.g., Deepika 2016), it was found to not be significant.

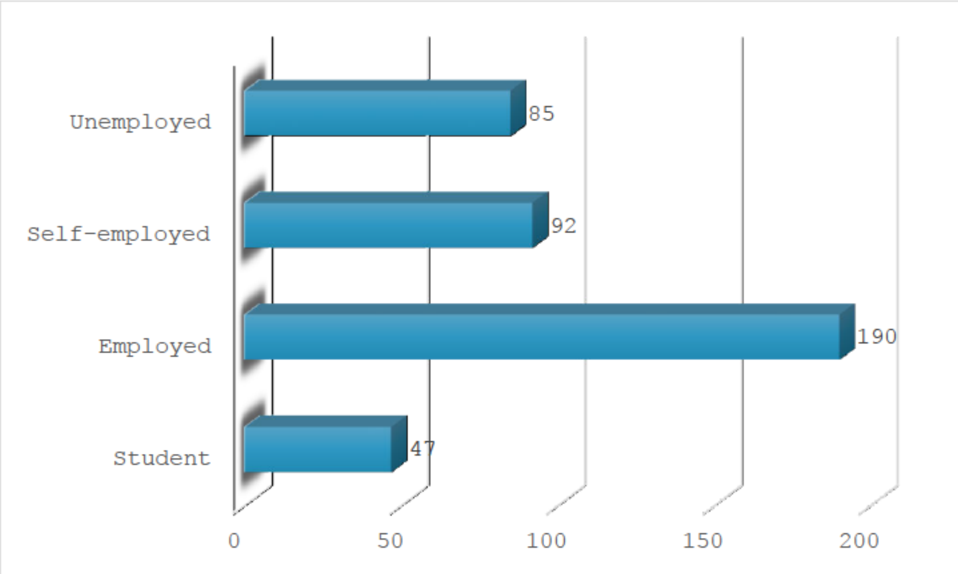


Figure 5.5: Respondents' Occupation (n = 414)

Figure 5.6 shows that most of the respondents earned more than R20,000 per month, constituting 71.3%. After this income bracket is the R10,001–R15,000 income bracket as 9.9% of the sample, then R15,001–R20,000 (8.7%), R5,001–R10,000, and lastly the less than R5,000 income bracket (see Figure 5.6).

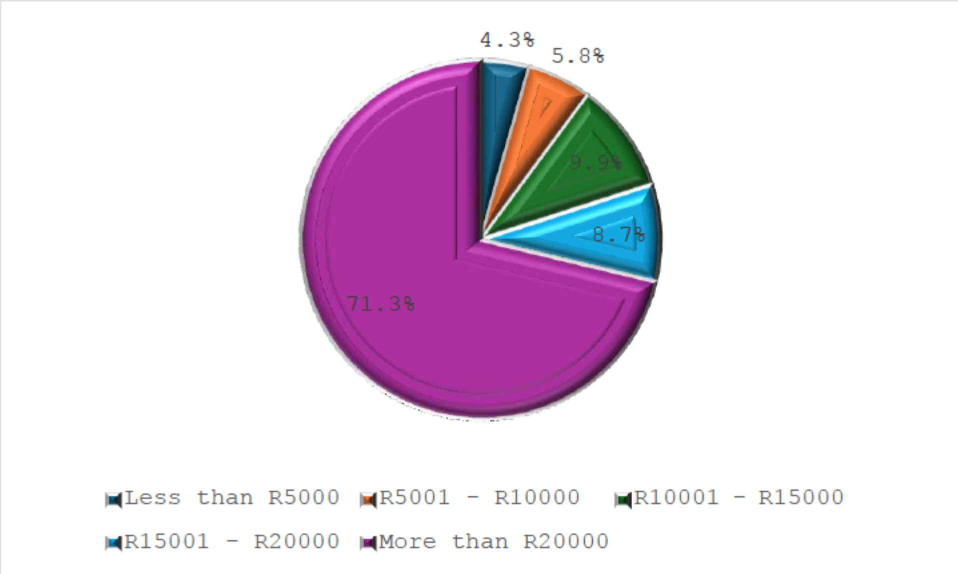


Figure 5.6: Respondents' Income (n = 414)

As shown in **Figure** 5.7, most of the respondents were holders of either a Diploma or an Undergraduate Degree (51.7%), followed by 24.6% with a matric certificate, and 19.1% with a postgraduate qualification. Only 4.6% had no formal qualification.

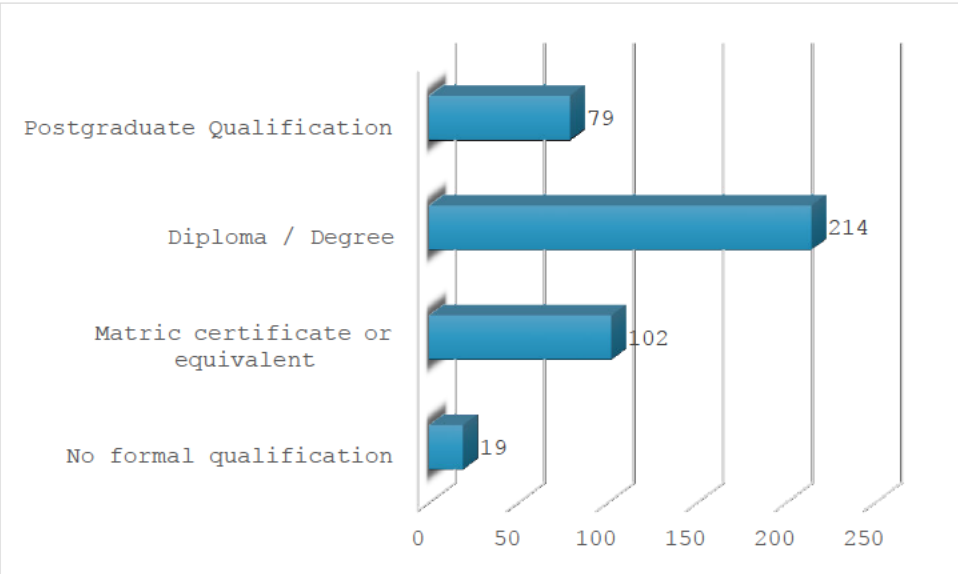


Figure 5.7: Respondents' Levels of Education (n = 414)

Respondents were also asked about the devices they primarily used to connect to the internet, and the results were as expected, with most of the respondents indicating that they used a Smart phone/Tablet (45.9%), followed by Laptop/Desktop (38.6%). Forty-five (10.9%) respondents said they use a smart TV, while 19 (4.6%) said they do not have devices to connect to the internet. **Figure** 5.8 presents the results.

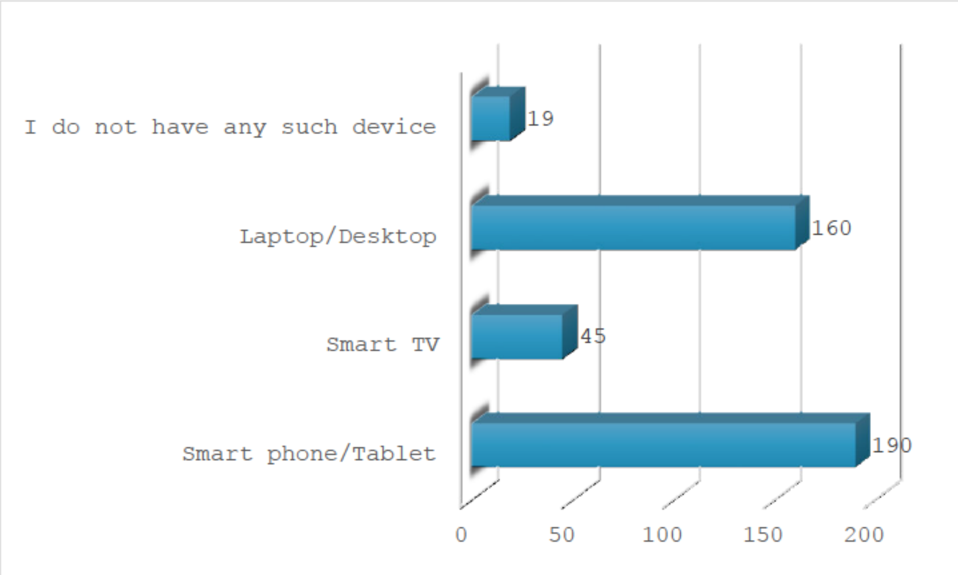


Figure 5.8: Devices Used to Connect to the Internet

To further probe how access to the internet and by extension online shopping platforms, respondents were asked their mode of internet connectivity. Results in **Figure** 5.9 indicate that the majority of respondents use private home internet connections (45.2%), followed by mobile data (36.7%), public Wi-Fi hotspots (9.2%) and work internet connection (8.9%).

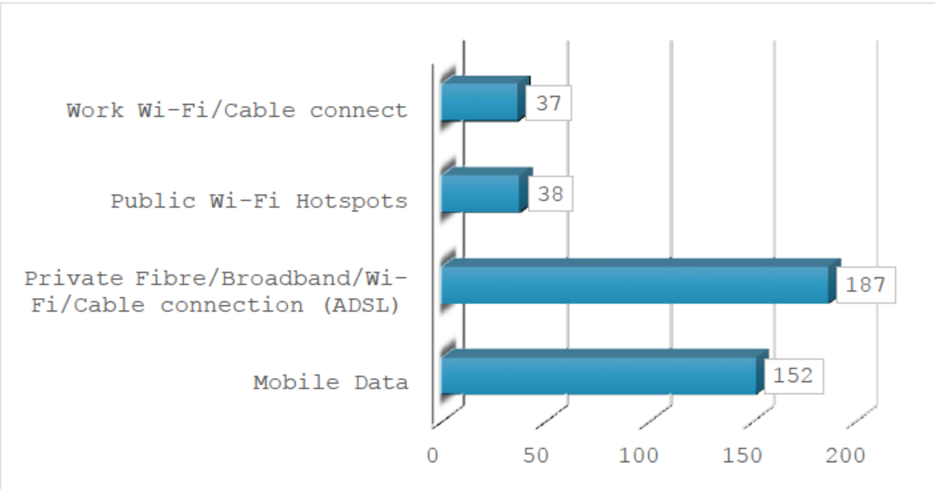


Figure 5.9: Mode of Internet Connection

These results are reflective of improved internet penetration and affordable internet prices in South Africa as reported in the DataReportal's Digital 2024: Global Overview Report (Kemp 2024). Hence, it is not surprising that work internet connectivity is the least used mode of connecting to the internet. The reason work internet connectivity is the least used mode of accessing the internet can be attributed to several factors. Firstly, with improved national internet penetration and declining data costs (Kemp 2024), individuals now have greater access to affordable mobile data and home Wi-Fi, reducing their reliance on workplace networks. Secondly, the widespread use of smartphones and mobile broadband allows users to connect from virtually anywhere, promoting flexibility and convenience compared to the limitations of work-based internet access. Lastly, many employees may reserve work internet usage strictly for professional activities, while preferring personal or mobile connections for private use, especially given increased concerns around privacy and employer monitoring on corporate networks.

5.4 MULTI-ITEM DESCRIPTIVE STATISTICS

This section presents and interprets the multi-item descriptive statistics. As indicated in Appendix One, the twelve constructs had a collective of 52 items measured on a 5-point Likert Scale, from 1 denoting 'Strongly disagree' to 5 denoting 'Strongly agree'. See Appendix One for the wording of the statements. For manageable reporting, composite scores for items per construct were determined, converting the data from being ordinal to metric. Doing so is in line with Harpe's (2015) recommendation that Likert items developed as a group must be analysed as a group, and not an item-to-item analytical approach.

However, the aggregated (mean) scores cannot be sensibly interpreted with the original scale categories. For example, a mean score of 3.57 cannot be interpreted as 'Neutral' since this category was coded as 3, a discreet number. To avert the problem of fictitious interpretation of each construct's mean score, scales ranges were determined and assigned to the five categories of the scale as shown in **Figure** 5.10.

Scale range $= \frac{Maximum\ level - Minimum\ level}{Number\ of\ categories}$

$= \frac{5-1}{5}$

$=$ **0.8**

Then, this was added, starting from the minimum level of the scale up to the maximum level to determine the range for the first category. For each subsequent range, the minimum level was determined by adding 0.1 to the previous range's maximum, and the maximum level was determined by adding 0.8 to the previous range's maximum.

Calculation	**Range**	**Category**
1 + 0.8 = 1.8	1 – 1.8	Strongly disagree
0.1 + 1.8 = 1.9		
0.8 + 1.8 = 2.6	1.9 – 2.6	Disagree
0.1 + 2.6 = 2.7		
0.8 + 2.6 = 3.4	2.7 – 3.4	Neutral
0.1 + 3.4 = 3.5		
0.8 + 3.4 = 4.2	3.5 – 4.2	Agree
0.1 + 4.2 = 4.3		
0.8 + 4.2 = 5	4.3 - 5	Strongly agree

Figure 5.10: Scale Range

After that, composite scores of the constructs were computed, aggregating each construct's multi-items into a single interval variable, and their means determined. Table 5.6 presents the mean scores of the twelve constructs to interpreted using the recalibrated scale ranges.

Table 5.6: Mean Scores for Study's Multi-Item Constructs

	NPE	NEE	NSI	NFC	TPB	LRCP	DOPS	DOSC	LSP	NISO	Dill	PPE
Mean	4.18	3.94	4.14	4.0420	4.02	3.46	3.83	3.82	3.68	4.27	4.04	4.26
Std. Deviation	0.77	0.81	0.88	0.78	0.69	0.84	0.84	0.95	0.90	0.71	0.83	0.62
Minimum	1.20	1.00	1.00	1.20	1.60	1.00	1.00	1.00	1.00	2.00	1.00	1.00
Maximum	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

All the mean scores in Table5.6 are greater than 3.4, which is the maximum level of 'Neutral' range, indicating that majority of the respondents either agreed or strongly agreed with the statements. Further analysis of individual constructs follows.

5.4.1 Negative Performance Expectancy (NPE) Scale

The NPE scale comprised items that were inverses of the original performance expectation (PE) scale introduced in Venkatesh *et al.* (2003) and later applied in various online shopping studies, for example, Erjavec and Manfreda (2022), and Venkatesh, Thong and Xu (2012). Within their seminal work, Venkatesh *et al*. (2003) conceptualised performance expectancy as an individual's belief that employing a specific technology will enhance their job or task performance. The improvement could be time saving, convenience, access to a wider choice, and bargain hunting (Celik 2016). In the present study, PE items were inverted to measure the belief that online shopping does not enhance shopping tasks or experience, and Table 5.7 presents the results.

Table 5.7: Frequencies of Responses to NPE Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	6	1.4	1.4
	Disagree	19	4.6	6.0
	Neutral	45	10.9	16.9
	Agree	124	30.0	46.9
	Strongly agree	220	53.1	100.0
	Total	**414**	**100.0**	

The results in Table 5.7 show that the majority of the responses were split between the 'Agree' and 'Strongly agree' categories, at 30% and 53.1%, respectively. A modest 10.9% of the responses were in the 'Neutral' category, with the remaining meagre responses split into 'Disagree' (4.6%) and 'Strongly disagree' (1.4%). These results tell us that most non-online shoppers do not see online shopping as improving shopping tasks or their shopping experiences. In simple terms, they do not recognise the benefits that online shopping offers.

5.4.2 Negative Effort Expectancy (NEE) Scale

The second construct in the Venkatesh *et al.* (2003: 450) model is effort expectancy (EE), which is the "degree of ease associated with the use of the system [technology]". From an online shopping point of view, EE can be defined as the effortlessness of using online shopping system, primarily platform navigability. In the present study, this wording of statements was flipped to examine if non-online shopping behaviour was due to lack of appreciation of the effortlessness claim. The flipped construct was labelled as the NEE. Table 5.8 presents the results.

Table 5.8: Frequencies of Responses to NEE Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	8	1.9	1.9
	Disagree	27	6.5	8.4
	Neutral	43	10.4	18.8
	Agree	178	43.0	61.8
	Strongly agree	158	38.2	100.0
	Total	**414**	**100.0**	

Table 5.8 shows that majority of the respondents either agree (43%) or strongly agree (38.2%) with statements that portrayed online shopping as complicated, a hassle, needing effort and expertise; hence discouraging. These results tell us that most non-online shoppers do not see the effortlessness found in other studies.

5.4.3 Negative Social Influence (NSI) Scale

Likewise, NSI items in the present study are inverted statements seeking to assess lack of impact of social influence on non-online shopping behaviour. In the original UTAUT, social influence is defined as “the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology” (Venkatesh, Thong and Xu 2012: 159). In the present study, the social influence items were inverted, entailing that non-online shopping behaviour is dissuaded by the descriptive and injunctive norms. The results are presented in Table 5.9.

Table 5.9: Frequencies of Responses to NSI Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	11	2.7	2.7
	Disagree	18	4.3	7
	Neutral	42	10.1	17.1
	Agree	147	35.5	52.6
	Strongly agree	196	47.3	100
	Total	**414**	**100.0**	

The results in the above table show that majority of the responses to NSI items were in the ‘Agree’ (35.3%) and ‘Strongly agree’ (47.3%) categories, with the remaining 17.1% split into ‘Neutral’ (10.1%), ‘Disagree’ (4.3%) and ‘Strongly disagree’ (2.7%). Likewise, these results show that mostly non-online shopping behaviour is influenced by negative social influence.

5.4.4 Negative Facilitating Conditions (NFC) Scale

In the UTAUT model, Venkatesh *et al.* (2003) also included the facilitating conditions (FC) construct, which is defined as "the consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh, Thong and Xu 2012: 159). In the present study, this pertains specifically to non-online shoppers' perceptions of access to resources and support for online shopping behaviour. The results to the aggregated items are shown in Table 5.10. Table 5.10 shows responses to NFC aggregated score, with 83.3% of the respondents agreeing (41.3%) and 42% strongly agreeing. The remainder of the responses are split into 'Neutral', 'Disagree' and 'Strongly agree' categories, at 12.1%, 3.4% and 1.2%, respectively. These results indicate that perceived lack of access to resources and support can explain non-online shopping behaviour (Hossain *et al.* 2017).

Table 5.10: Frequencies of Responses to NFC Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	5	1.2	1.2
	Disagree	14	3.4	4.6
	Neutral	50	12.1	16.7
	Agree	171	41.3	58.0
	Strongly agree	174	42.0	100.0
	Total	**414**	**100.0**	

5.4.5 Technophobia (TPB) Scale

Technophobia, characterised by an exaggerated and unfounded fear, discomfort, or anxiety concerning technology interaction or use (Nimrod 2018; Osiceanu 2015), often culminates in a broader disaffection with various forms of technology (Khasawneh, 2018). In the context of the present study, technophobia can be an important explainer of non-online shopping behaviour. Five items measuring technophobia were aggregated into composite scores. Table 5.11 presents the frequencies to the recalibrated response categories.

Table 5.11: Frequencies of Responses to TPB Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	3	0.7	0.7
	Disagree	13	3.1	3.8
	Neutral	42	10.1	13.9
	Agree	201	48.6	62.5
	Strongly agree	155	37.4	100.0
	Total	**414**	**100.0**	

As presented in Table 5.11, the responses to the technophobia items demonstrate a pronounced agreement among respondents, with 86% answering affirmatively. Specifically, 'Agree' constituted 48.6% of responses, and 'Strongly agree' accounted for 37.4%. Only a small minority were 'Neutral' (10.1%), 'Disagree' (3.1%), or 'Strongly disagree' (0.7%). Such a distribution indicates a considerable level of technophobia and subsequent disaffection toward online shopping among the non-online shopper segment.

5.4.6 Perceived Lack of Reciprocity (LRCP) Scale

The concept of reciprocity as one of the pillars of the SET that leans on the *quid pro quo* principle. In human interactions, reciprocity holds that parties give expecting to receive (transaction), believe in a 'justly world' (idea of karma), and moral norms (Gouldner 1960). Reciprocity is also the bedrock of commercial value exchange situations, especially e-commerce where, on the one hand, businesses require consumers' personal data to better them, so they can tailor-make their marketing activities (Shanahan, Tran and Taylor 2019; Pallant, Pallant, Sands, Ferraro and Afifi 2022). On the other hand, consumers are only willing to release their personal data if they trust that e-commerce businesses would reciprocate by offering them some benefits such enhanced experiences, personalised marketing (deals and communications) (Degutis *et al.* 2023). In the present study, this concept was flipped to perceived lack of reciprocity among non-online shoppers. Table 5.12 presents the response frequencies to the aggregated reciprocity items.

Table 5.12: Frequencies of Responses to LRCP Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	17	4.1	4.1
	Disagree	55	13.3	17.4
	Neutral	114	27.5	44.9
	Agree	168	40.6	85.5
	Strongly agree	60	14.5	100.0
	Total	**414**	**100.0**	

The above table presents a slight shift from the patterns observed in the frequencies presented so far, where high frequencies concentrated around the 'Agree' and 'Strongly agree' response categories. While most of the respondents (40.6%) agreed with the statements suggesting lack of reciprocity in online shopping systems, 27.5% recording a neutral position, 14.5% strongly agreed, 13.3% disagreed, and 4.1% strongly disagreed. When analysed in conjunction with the mean score (M = 3.46) in Table 5.6, these frequencies fall in the bounds of the 'Agree' response category, ranging from 3.4 to 4.2, indicating that respondents moderately perceive a lack of reciprocity.

5.4.7 Distrust in Online Payment Systems (DOPS) Scale

E-commerce typically involves three parties: the buyer, intermediaries, and the seller. Trust is fundamental to the success of e-commerce transactions (Lee *et al.* 2018; Moody, Galletta and Lowry 2014), often playing a more significant role than in traditional in-store transactions. Previous research has demonstrated the impact of trust on individuals' willingness to disclose personal data (Degutis *et al.* 2023), and buy online (Black, 2005). In this context, the buyer serves as the trustor, while the intermediaries act as the trustees. The buyer not only places their trust in these trustees regarding financial transactions but also entrusts them with sensitive personal information, including banking details. Online payment systems are susceptible to data breaches and fraud, which can increase buyer anxiety and erode trust (Lee *et al.* 2018). In the present study DOPS items were used to assess whether individuals have trust issues with online payment systems as the financial intermediaries of e-commerce businesses. The frequency of responses is presented in Table 5.13.

Table 5.13: Frequencies of Responses to DOPS Scale

		Frequency	**Valid Percent**	**Cumulative Percent**
Valid	Strongly disagree	9	2.2	2.2
	Disagree	32	7.7	9.9
	Neutral	68	16.4	26.3
	Agree	181	43.7	73.0
	Strongly agree	124	30.0	100.0
	Total	**414**	**100.0**	

The results in table 5.13 show that most (43.7%) of the respondents selected the 'Agree' response category, followed by 'Strongly agree' (30%), 'Neutral (16.4%), while the remaining

9.9% respondents disagreed with the statements, at 7.7% for 'Disagree' and 2.2% for 'Strongly disagree'. These results, together with the mean score of the aggregated DOPS (M = 3.83) variable indicated that respondents have moderate distrust in online payment systems.

5.4.8 Distrust in Online Social Channels (DOSC) Scale

After the introduction of social media platforms, businesses started embedding their commercial activities in the platforms, paving the way for what has come to be known as social commerce (Zhang and Benyoucef 2016; Zhou, Zhang and Zimmermann 2013). Like online payment systems, online social channels are e-commerce intermediaries, and trust or distrust play an influential role in determining consumers' purchase intentions in a social commerce environment (Wang, Shahzad, Ahmad, Abdullah and Hassan 2022; Zhao, Huang and Su, 2019). In social commerce, brand messaging is dyadic, i.e. between a seller and buyers, but often among buyers who are members of a social platform such as Facebook, Instagram, TikTok, and so on. Members subconsciously engage with and amplify marketing content through comments, discussions, sharing, liking and online reviews.

In the present study, distrust of social commerce was measured through four statements, which were aggregated as indicated earlier. Table 5.14 presents the results. The results indicated that most (40.6%) of the respondents agree, 31.9% strongly agree and 16.2% were neutral. Those disagreeing and strongly disagreeing constituted 11.3%. Thus, the results showed a moderate distrust in social commerce, like online payment systems.

Table 5.14: Frequencies of Responses to DOSC Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	18	4.3	4.3
	Disagree	29	7.0	
	Neutral	67	16.2	
	Agree	168	40.6	
	Strongly agree	132	31.9	
	Total	**414**	**100.0**	

5.4.9 Perceived Lack of Social Presence (LSP) Scale

Social presence has gained significant attention in research related to online consumer behaviour, particularly in the context of social commerce. Grounded in the Social Presence Theory (Short, Williams and Christie 1976), the concept of social presence refers to the "the extent to which the social commerce environment enables a customer to establish a personal, warm, intimate and sociable interaction with others" (Zhang, Lu, Gupta and Zhao 2014). In this study, social presence items were used to measure feelings of isolation or disconnection, the lack of social interactions, difficulties in seeking advice, and the absence of community attributes in online shopping platforms. The results are presented in Table 5.15.

Table 5.15: Frequencies of Responses to LSP Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	18	4.3	4.3
	Disagree	35	8.5	12.8
	Neutral	93	22.5	35.2
	Agree	166	40.1	75.4
	Strongly agree	102	24.6	100.0
	Total	**414**	**100.0**	

As indicated in Table 5.15, 40% of the respondents agreed with the statement, and 24.6% strongly agreed. A notable 22.5% remained neutral, while 8.5% disagreed and 4.3% strongly disagreed. Considering the mean score of the scale (M = 3.63), we can conclude that, on average, most respondents feel they are likely to experience isolation or disconnection, face difficulties in obtaining advice, and lack the social interaction or community aspects they are accustomed to in traditional in-store shopping.

5.4.10 No Intention to Shop Online (NISO) Scale

As indicated in earlier chapters, previous studies investigating digital consumer behaviour have focused on the intention than lack of or no intention to shop online. The present study sought to fill in that gap and measured the likelihood of non-online shoppers starting to engage in online shopping. The results are in Table 5.16.

Table 5.16: Frequencies of Responses to NISO Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	0	0	0
	Disagree	12	2.9	2.9
	Neutral	34	8.2	11.1
	Agree	165	39.9	51.0
	Strongly agree	203	49.0	100.0
	Total	**414**	**100.0**	

As shown in Table 5.16, most of the respondents answered to the affirmative of the scale items, which articulated a no intention to shop online and a preference of traditional in-store shopping over online shopping. Almost half (49%) of the respondents strongly agreed, 49.9% agreed, 8.2% were neutral and only 2.9% disagreed. These results indicate that most non-online shoppers have no intention of buying online in the near future.

5.4.11 Digital Illiteracy (Dill) Scale

Previous studies on online shopping have explored the impact of digital literacy on intentions to purchase online (Cahyono and Rizqi 2024; Nazzal, Thoyib, Zain and Hussein 2021. To my knowledge, very few studies (e.g., Cham *et al.* 2022) have explored digital illiteracy with respect to the reluctancy to shop online. In pursuit of bridging this gap, the present study measured whether the respondents were digitally illiterate using four items in the instrument. The descriptive results are presented in Table 5.17.

Table 5.17: Frequencies of Responses to Dill Scale

		Frequency	Valid Percent	Cumulative Percent
Valid	Strongly disagree	11	2.7	2.7
	Disagree	11	2.7	5.4
	Neutral	59	14.3	19.7
	Agree	165	39.9	59.6
	Strongly agree	168	40.6	100.0
	Total	**414**	**100.0**	

As shown in the table, the ‘Strongly agree’ and ‘Agree’ categories are the most frequent responses, at 40.6% and 39.9%, respectively. These results indicated that most of the non-online shoppers were digitally illiterate. Such results are not surprising, as they are in line with previous scholarly work and policy papers lamenting on the digital divide in South Africa, for example, Modjadji (2025) and Vujovic, Jonathan and Hacks (2024).

5.4.12 Poor Promotional Effort (PPE) Scale

Respondents were also asked to evaluate marketing effort of online businesses, especially those in the FMCG sector using statements that portrayed poor promotional effort. Results in Table

5.18 below indicated that most respondents (63.3%) strongly agreed that that online business' promotional effort was poor – not targeted or relevant to them.

Table 5.18: Frequencies of Responses to PPE Scale

		Frequency	**Valid Percent**	**Cumulative Percent**
Valid	Strongly disagree	3	0.7	0.7
	Disagree	12	2.9	3.6
	Neutral	24	5.8	9.4
	Agree	113	27.3	36.7
	Strongly agree	262	63.3	100.0
	Total	**414**	**100.0**	

The frequency analyses presented in this section serve a descriptive and diagnostic purpose rather than a measurement validation function. Specifically, they provide an initial overview of respondents' perceptions and response patterns across the constructs, thereby offering contextual insight into the extent and direction of non-adoption attitudes among the sample. This step is important in highlighting the prevalence and intensity of key barriers prior to conducting inferential analyses. While construct reliability and validity are formally assessed in subsequent sections using appropriate statistical techniques, the frequency distributions complement these analyses by illustrating how respondents engage with the measurement items at an aggregate level. Furthermore, the descriptive results assist in interpreting the hypothesis testing outcomes by providing a clearer understanding of the underlying behavioural tendencies reflected in the data.

The following section presents the analytical process adopted to test the hypotheses and the results thereof.

5.5 HYPOTHESES TESTING

This section elaborates on the empirical testing of the hypothesised relationships delineated in the integrated model (Section 2.4, Chapter 3). Given that the primary objective of the present study is not to predict dependent variables but rather to confirm and elucidate the covariation among measurement and structural model indicators (Jöreskog 1973), covariance-based Structural Equation Modelling (CB-SEM) was the chosen analytical approach. The subsequent discussion is structured into three principal parts: an assessment of unidimensionality and reliability, the execution of CFA, and the examination of the structural model.

Unidimensionality refers to "the existence of one latent trait underlying the set of items" (Hattie 1985: 152), or more simply, it assesses whether a single-factor model adequately fits a set of items designed to measure a concept(s) under investigation (Ravelle and Condon 2025). CFA is employed to specify the number of factors (latent variables) and to examine the association between these latent variables and their observed indicators, thereby validating the measurement instrument (Brown 2015; Dastgeer, Rehman and Rahman 2012). This process is also known as the assessment of the outer model (Goretzko, Siemund and Sterner 2024). In contrast, the structural (inner) model specifies the hypothesised relationships between the factors, including direct and indirect effects, and quantifies the magnitude of these relationships (Brown 2015).

Assessing Unidimensionality and Reliability

To assess unidimensionality of the measurement scales, principal component factor analysis (PCA) was employed as suggested by Germain, Droge and Daugherty (1994). The twelve latent variables in the present study were subjected to PCA independently. Unidimensionality was ascertained where only one component with an Eigenvalue larger than one was extracted for a set of items hypothesised as measuring a latent variable. Table 5.19 presents the results.

Table 5.19: Eigen Values of Measures

Construct	Component	Total	Initial Eigenvalues		KMO/ Bartlett Test
			% of Variance	Cumulative %	
Negative Performance Expectancy	1	**2.800**	56.008	56.008	0.813^{***}
	2	0.685	13.694	69.701	
	3	0.606	12.112	81.813	
	4	0.533	10.652	92.466	
	5	0.377	7.534	100.000	

Negative Effort Expectancy	1	**2.853**	57.069	57.069	0.790***
	2	0.776	15.511	72.580	
	3	0.584	11.681	84.261	
	4	0.419	8.379	92.640	
	5	0.368	7.360	100.000	
Negative Social Influence	1	**2.852**	71.296	71.296	0.813***
	2	0.510	12.753	84.049	
	3	0.322	8.057	92.106	
	4	0.316	7.894	100.000	
Negative Facilitating Conditions	1	**3.072**	61.444	61.444	0.768***
	2	0.974	19.479	80.923	
	3	0.436	8.726	89.649	
	4	0.264	5.278	94.926	
	5	0.254	5.074	100.000	
Technophobia	1	**2.447**	61.178	61.178	0.735***
	2	0.687	17.164	78.342	
	3	0.521	13.014	91.356	
	4	0.346	8.644	100.000	
Perceived Lack of Reciprocity	1	**2.648**	52.958	52.958	0.697***
	2	**1.221**	24.424	77.382	

	3	0.478	9.554	86.936	
	4	0.398	7.959	94.895	
	5	0.255	5.105	100.000	
Distrust in Online Payment Systems	1	**2.415**	60.377	60.377	0.722^{***}
	2	0.854	21.342	81.718	
	3	0.445	11.117	92.836	
	4	0.287	7.164	100.000	
Distrust in Online Social Channels	1	**2.661**	66.513	66.513	0.796^{***}
	2	0.585	14.628	81.142	
	3	0.451	11.274	92.415	
	4	0.303	7.585	100.000	
Perceived Lack of Social Presence	1	**2.426**	60.650	60.650	0.761^{***}
	2	0.718	17.945	78.595	
	3	0.442	11.042	89.637	
	4	0.415	10.363	100.000	
Digital Illiteracy	1	**2.755**	68.885	68.885	0.766^{***}
	2	0.603	15.079	83.964	
	3	0.379	9.476	93.440	
	4	0.262	6.560	100.000	
Poor Promotional Effort	1	**1.700**	56.667	56.667	0.638^{***}
	2	0.703	23.442	80.109	
	3	0.597	19.891	100.000	

Extraction Method: Principal Component Analysis, ***Sig. value <.001.

As indicated in Table 5.19, all the set of indicators, except for items for perceived lack of reciprocity, coalesced under one latent (extracted) construct as hypothesised. Dimensionality is illustrated where only component has an Eigenvalue larger than 1 (in bold), indicating a one-factor structure (Ravelle and Condon, 2025). For perceived lack of reciprocity, two components with Eigenvalues larger than 1 are extracted. These results suggest that the observed items used to measure perceived lack of reciprocity did not measure only this latent construct but measured two distinct constructs. There are two ways of handling such an outcome; either, treat perceived lack of reciprocity as a second-order construct (Becker *et al.* 2022) or refine the outcome to get simple structures as suggested by Dastgeer, Rehman and Rahman (2012).

In the present study, the latter was adopted through assessing the reliability of the scale with all the items and the "Cronbach's alpha if item deleted", see Table 5.20 below.

Table 5.20: Item-Total Statistics for Perceived Lack of Reciprocity

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
LRCP1	13.45	12.011	0.574	0.717
LRCP2	13.54	11.798	0.594	0.710
LRCP3	13.77	11.415	0.612	0.702
LRCP4	14.08	11.580	0.534	0.730
LRCP5	14.28	12.620	0.404	0.775

The Cronbach's alpha for the original scale with five items was .770, and as shown in Table 5.20, deleting item LRCP5 would improve the scale reliability. After deleting this item, the PCA was rerun now with four items and unidimensionality for perceived lack of reciprocity was determined. Refer to Table 5.21.

Table 5.21: Enhanced Unidimensionality for LRCP

	Initial Eigenvalues			KMO/Bartlett
Component	Total	% of Variance	Cumulative %	Test
1	**2.453**	61.320	61.320	0.717^{***}
2	0.812	20.309	81.629	
3	0.478	11.942	93.571	
4	0.257	6.429	100.000	

With unidimensionality ascertained, the scales were used in the confirmatory factor analysis to validate them. The results of the CFA are discussed in subsection 5.5.2.

5.5.1 Outer Measurement Model

The purpose of this subsection is to present the findings from the CFA, a crucial step in validating the measurement properties of the twelve scales employed in this research. Confirmatory Factor Analysis serves as a sophisticated statistical technique to assess the goodness-of-fit between a hypothesised measurement model and the observed data (Goretzko, Siemund and Sterner 2024; Kline 2023). Unlike exploratory approaches, the CFA allows for the explicit testing of predefined factor structures, thereby providing strong evidence for the construct validity of the latent variables (Hair, Page and Brunsveld *et al.* 2020 Kline 2023). By rigorously evaluating various model fit indices, this analysis aims to demonstrate that the chosen indicators are indeed reliable and valid measures of their intended constructs, thereby establishing a solid empirical foundation for subsequent analyses of the structural model (Hu and Bentler 1999).

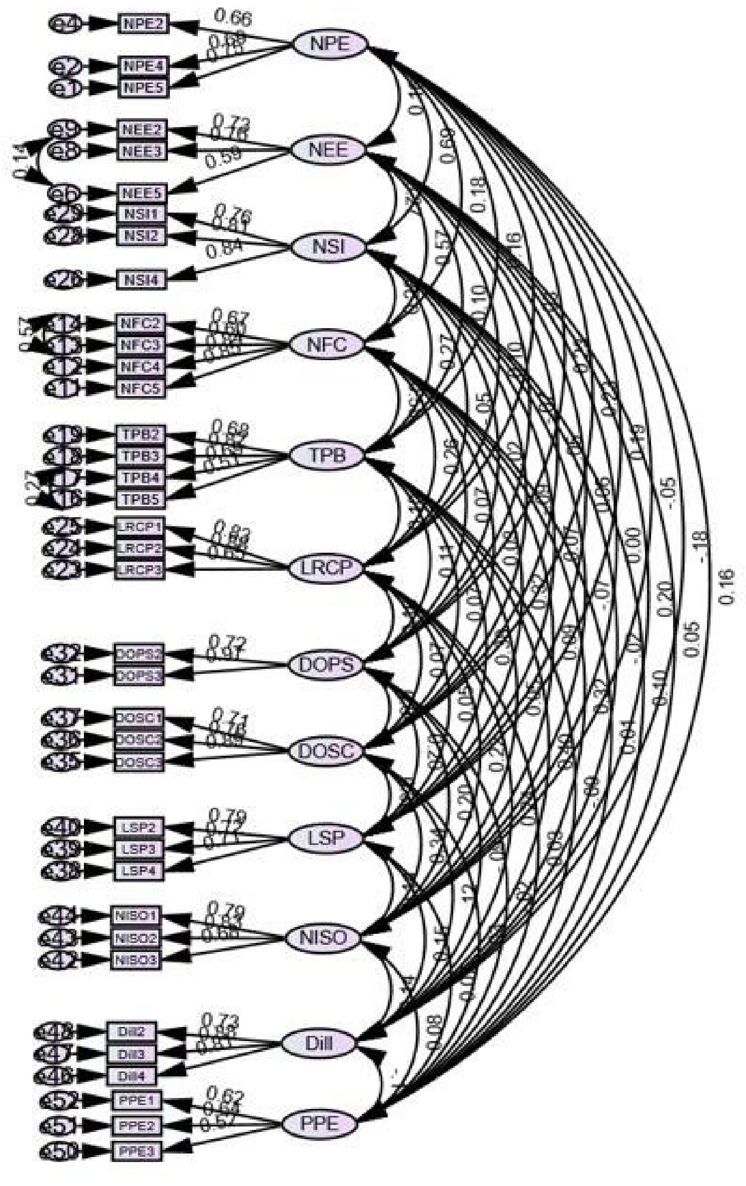
The CFA was conducted using IBM AMOS, Version 29. This software facilitates a covariance-based approach, primarily employing normal-theory-based estimators such as Maximum Likelihood (ML) (Mia, Majri and Rahman 2019; Xinya and Yanyun 2016). However, a critical consideration for this study was the observed violation of multivariate normality linearity assumption in the data (see subsection 5.2.3 and 5.2.4). Under such conditions, standard ML estimation can yield inaccurate chi-square statistics and fit indices, biased parameter estimates and standard errors, and potentially inadmissible solutions (Bollen 1989; Chou, Bentler and Satorra 1991; Xinya and Yanyun 2016).

Given that AMOS does not natively offer alternative robust estimators like Robust Maximum Likelihood (MLR) or Diagonally Weighted Least Squares (DWLS); estimators known for their superior performance with non-normal and non-linear data, even in smaller samples (Du and Bentler 2022; Li 2016), the Maximum Likelihood estimator was used in conjunction with the Bollen-Stine bootstrapping method (Bollen and Stine 1992). This approach was specifically chosen to mitigate the adverse effects of the non-normal data on the CFA results. Consequently, in addition to the conventional model fit indices and their established thresholds (detailed in Table 5.22), the Bollen-Stine bootstrap p-value served as a crucial "robust" indicator for evaluating the overall model fit. A non-significant Bollen-Stine bootstrap p-value (i.e., $p > 0.05$) was therefore required to conclude that the hypothesised model adequately fitted the empirical data (Bollen and Stine 1992; Nevitt and Hancock 2001; Walker and Smith 2017).

Table 5.22: Model Fit Indices Thresholds

Fit Index	**Threshold**	**Source(s)**
χ^2/df	< 3, or < 5	Jöreskog and Sörbom (1981), Anderson and Gerbing (1984)
CFI	> .90, or > .95	Bentler (1990), Hu and Bentler (1999).
TLI	> .90, or > .95	Tucker and Lewis (1973) , Hu and Bentler (1999).
NFI	> .90, or > .95, Up to .80 acceptable.	Bentler and Bonett (1980); Hu and Bentler (1999); Hooper *et a*l. (2008).
IFI	> .90	Bollen (1989); Marsh and Hau (1996).
GFI	> .90, or > .95	Jöreskog and Sörbom (1984); Shevlin and Miles (1998).
RMSEA	<.05 for a close fit,.05 to.08 for fair fit,.08 to.10 for poor fit, and >.10 for unacceptable fit.	Steiger and Lind (1980); Browne and Cudeck (1993); Marsh and Hau (1996); Hu and Bentler (1999).
SRMR	< .05, or < .08	Jöreskog and Sörbom (1984); Byrne (1998); Hu and Bentler (1999).

Figure 5.11 illustrates the proposed measurement model, comprising twelve distinct latent variables. As previously established, the dataset exhibited multivariate non-normality. To rigorously assess the overall model fit under these conditions, a Bollen-Stine bootstrap procedure was employed, consisting of 2000 iterations (Nevitt and Hancock 2001). This resampling technique yielded a Bollen-Stine p-value of 0.063. Crucially, as this p-value was greater than the conventional significance level of 0.05 ($p > 0.05$), the null hypothesis of poor model fit was rejected. Therefore, the proposed measurement model was deemed statistically consistent with the observed data, providing strong evidence for its structural validity.



Model Fit Indices

PCMIN/DF	1.585
CFI	.95
TLI	.94
IFI	.95
NFI	.87
GFI	.90
RMSEA(PCLOSE)	.038(ns)
SRMR	.043

Figure 5.11: Measurement Model for the Non-Online Shopping

In addition to the Bollen-Stine adjusted p-value, all the conventional fit indices depicted in **Figure** 5.11 meet the thresholds highlighted in Table 5.22, thus supporting the proposed model as approximately fitting the data. Table 5.23 below presents the retained indicators and their factor loadings, and the reliability and validity of the latent constructs before assessing the structural model.

Table 5.23: Factor loading, Reliability and Validity

Indicator	Factor Loadings	CR	AVE	MSV	MaxR(H)	Dill	NPE	NEE	NFC	TPB	LRCP	NSI	DOPS	DOSC	LSP	ISO	ME
Dill2	0.731																
Dill3	0.877	0.829	0.62	0.199	0.861	**0.788**											
Dill4	0.81																
NPE2	0.657																
NPE4	0.69	0.776	0.538	0.507	0.789	-0.06	**0.733**										
NPE5	0.754																
NEE5	0.594																
NEE3	0.762	0.774	0.535	0.227	0.785	0.22	0.295	**0.731**									
NEE2	0.728																
NFC5	0.847																
NFC4	0.842	0.857	0.603	0.424	0.888	0.364	0.164	0.476	**0.777**								
NFC3	0.603																
NFC2	0.668																
TPB5	0.512																
TPB4	0.692	0.807	0.516	0.424	0.832	0.446	0.142	0.121	0.651	**0.718**							
TPB3	0.822																
TPB2	0.682																
LRCP3	0.65																
LRCP2	0.885	0.836	0.634	0.095	0.876	0.26	-0.019	0.06	0.309	0.185	**0.796**						
LRCP1	0.831																
NSI4	0.842																
NSI2	0.808	0.863	0.677	0.507	0.866	0.028	0.712	0.374	0.277	0.242	-0.027	**0.823**					
NSI1	0.762																
DOPS3	0.967	0.847	0.738	0.308	0.932	-0.069	0.206	-0.049	0.069	0.09	0.134	0.012	**0.859**				
DOPS2	0.723																
DOSC3	0.888																
DOSC2	0.763	0.836	0.631	0.308	0.854	-0.089	0.178	-0.065	0.045	0.087	0.112	-0.075	0.555	**0.794**			
DOSC1	0.707																
LSP4	0.707																
LSP3	0.722	0.802	0.574	0.162	0.803	0.197	0.19	0.031	0.362	0.403	0.129	0.089	0.214	0.308	**0.758**		
LSP2	0.786																
NISO3	0.678																
NISO2	0.828	0.81	0.589	0.116	0.822	0.159	-0.009	0.007	0.097	0.073	0.221	-0.034	0.188	0.34	0.17	**0.767**	
NISO1	0.786																
PPE3	0.518																
PPE2	0.644	0.678	0.413	0.104	0.682	-0.049	0.322	0.2	0.025	-0.069	-0.007	0.223	-0.002	-0.023	0.054	0.038	**0.643**
PPE1	0.617																

As presented in Table 5.23, the standardised factor loadings (λ) for the measurement model ranged from 0.518 to 0.967, and all were statistically significant ($p < 0.001$). These loadings consistently exceeded the a priori threshold of ≥ 0.5 for item salience, as recommended in the literature (Kline 2023). This indicated that each observed item strongly contributed to its respective latent construct. However, the Poor Promotional Effort (PPE) construct presented issues regarding its reliability and validity. Specifically, its Composite Reliability (CR) was below the recommended threshold of 0.70, and its Average Variance Extracted (AVE) was less than the acceptable threshold of 0.50 (Fornell and Larcker 1981; Hair *et al.* 2019). Despite removing item PPE3, which was close to Kline's suggested borderline for problematic loadings, the PPE construct's reliability and validity did not show sufficient improvement. Consequently, based on these persistent psychometric deficiencies, the PPE construct was removed from all subsequent analyses, including the moderation analysis.

5.5.2 Structural (Inner) Model

With the factorial validity of the measurement model established in the preceding subsection, the next crucial step was to assess the overall fit of the hypothesised structural model. This comprehensive evaluation ensured that the entire theoretical framework, encompassing both measurement and structural components, adequately represented the observed data. The structural model was run to test hypotheses H1 through H10. Given the data characteristics discussed earlier, we again employed Maximum Likelihood (ML) estimation in conjunction with a Bollen-Stine bootstrap procedure, executed with 2000 iterations. This robust approach yielded a Bollen-Stine p-value of 0.054. As this value was greater than the 0.05 significance threshold ($p > 0.05$), the model's fit was deemed acceptable, indicating consistency with the empirical data. The comprehensive results of this structural model analysis are presented in **Figure** 5.11 and Table 5.24.

In addition to the Bollen-Stine bootstrap, the proposed measurement model's fit was evaluated using several conventional model fit indices: The Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Goodness of Fit Index (GFI), Normed Fit Index (NFI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR). All these indices were assessed against their respective thresholds as recommended in the psychometric literature (Hu and Bentler 1999; Kline 2023). Crucially, every index met its designated threshold, thereby providing strong support for the close fit of the hypothesised model to the observed data.

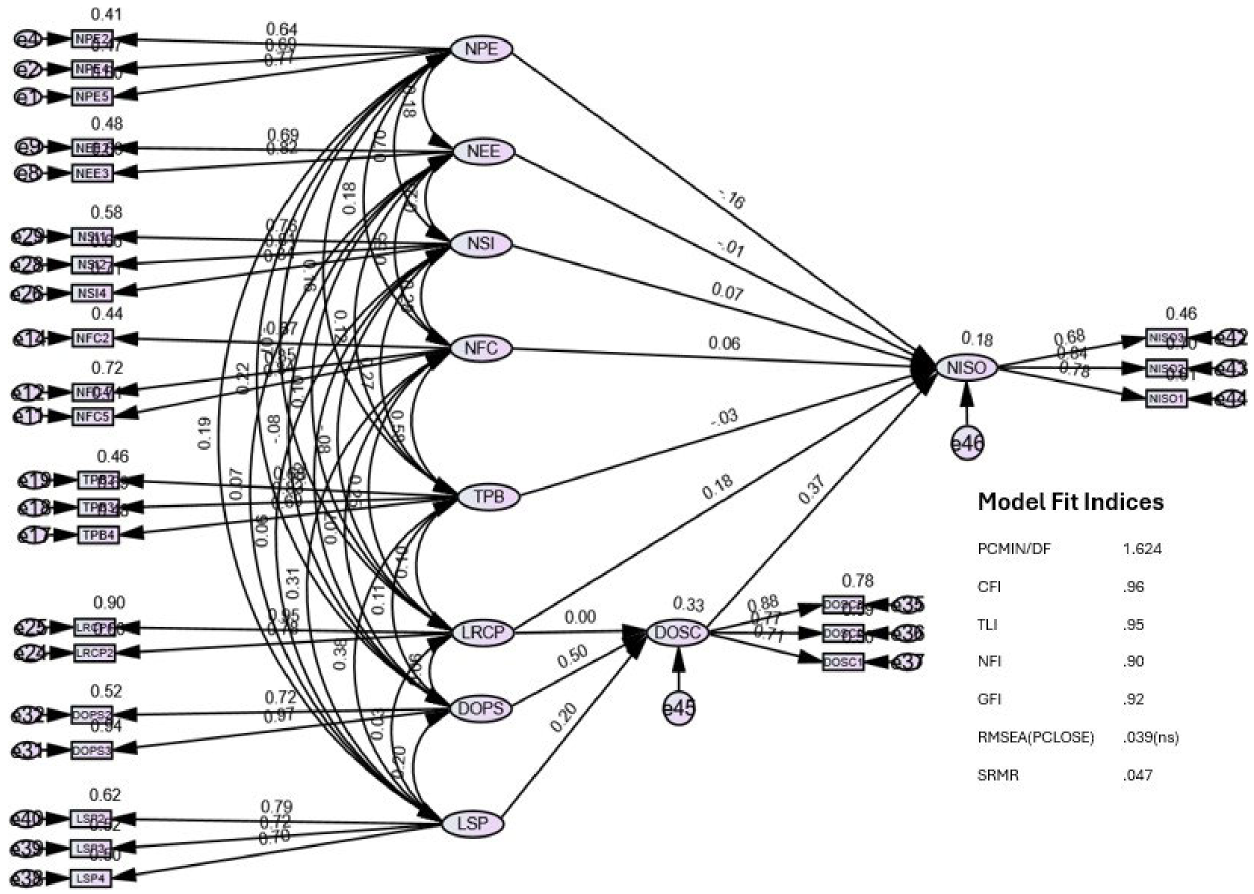


Figure 5.12: Structural Model (Testing H1 – H10)

Furthermore, an examination of the factor loadings (λ) revealed robust item salience. All individual item loadings ranged from 0.64 to 0.97, comfortably exceeding the commonly accepted threshold of 0.50 for practical significance (Hair *et al.* 2018; Kline 2023; Mia, Majri and Rahman 2019). This indicated strong to very strong relationships between observed variables (indicators) and their underlying latent factors (Hair *et al.* 2018). With the measurement model's validity firmly established, we then proceeded to analyse the hypothesised relationships between the latent variables within the structural model. The results of this analysis are presented in Table 5.24.

Table 5.24: The Structural Model and Hypotheses Decisions

Hypothesis	Structural Paths			Std. Estimate	S.E.	C.R.	Lower	Upper	P-value	Decision
H1	NPE	→	NISO	-0.164	0.075	-1.662	-0.36	0.032	0.091	Not supported
H2	NEE	→	NISO	-0.009	0.068	-0.102	-0.184	0.133	0.828	Not supported
H3	NSI	→	NISO	0.071	0.07	0.725	-0.107	0.284	0.375	Not supported
H4	NFC	→	NISO	0.057	0.086	0.535	-0.171	0.285	0.585	Not supported
H5	TPB	→	NISO	-0.028	0.083	-0.331	-0.226	0.147	0.719	Not supported
H6	LRCP	→	NISO	0.183	0.043	3.16	0.035	0.326	0.014	Supported
H7	LRCP	→	DOSC	0.001	0.058	0.016	-0.106	0.104	0.976	Not supported
H8	DOPS	→	DOSC	0.499	0.058	8.068	0.377	0.605	0.001	Supported
H9	LSP	→	DOSC	0.199	0.066	3.658	0.089	0.303	0.001	Supported
H10	DOSC	→	NISO	0.368	0.039	5.834	0.239	0.495	0.001	Supported

To determine whether to accept or reject the study's hypotheses, we examined the critical ratios (t-values) of the estimated paths. For a relationship to be statistically significant, these *t*-values needed to be greater than 1.96 or less than -1.96 (Hair, Page and Brunsveld 2020; Rao, Jain and Millin 2016). As shown in the accompanying table, six of the hypothesised structural relationships (H1 to H5 and H7) were not supported by the data and were consequently rejected. Specifically, our results indicate that negative performance expectancy ($\beta = -0.164$, $t = -1.662$, $p = 0.091$), negative effort expectancy ($\beta = -0.009$, $t = -0.102$, $p = 0.828$), negative social influence ($\beta = 0.071$, $t = 0.725$, $p = 0.375$), and negative facilitating conditions ($\beta = 0.057$, $t = 0.535$, $p = 0.585$) do not significantly predict reluctance (no intention) to shop online.

Similarly, technophobia ($\beta = -0.028$, $t = -0.331$, $p = 0.719$) does not significantly predict reluctance (no intention) to shop online, nor does perceived lack of reciprocity ($\beta = 0.001$, $t = 0.016$, $p = 0.976$) significantly predict distrust in social channels. Conversely, the analysis supported the remaining four hypothesised relationships (H6, H8, H9, and H10), leading to their acceptance. As expected, the critical ratios of these structural paths were all greater than ±1.96 with corresponding significant p-values, aligning with established statistical guidelines. Specifically, the results clearly indicate that perceived lack of reciprocity ($\beta = 0.183$, $t = 3.16$, $p = 0.014$) and distrust in online social channels ($\beta = 0.368$, $t = 5.834$, $p = 0.001$) are significant positive predictors of reluctance to shop online.

Furthermore, distrust in online payment systems ($\beta = 0.499$, $t = 8.068$, $p = 0.001$) and perceived lack of social presence ($\beta = 0.199$, $t = 3.658$, $p = 0.001$) emerged as significant positive predictors of distrust in online social channels. Based on these results, the study can conclude that, on average, a standardised unit increase in perceived lack of reciprocity and distrust in online social channels is associated with a 0.18 and 0.37 standard deviation increase in reluctance to shop online, respectively. Additionally, a standardised unit increase in distrust in online payment systems and perceived lack of social presence is linked to a 0.50 and 0.20 standard deviation rise in distrust in online social channels, respectively. These findings are discussed in greater detail in the subsequent chapter, where they are critically examined against extant literature to address the core research questions.

5.5.3 Effect Sizes (Inner Model)

While the standardised path coefficients (β) were crucial for hypothesis testing and explaining the direct relationships between exogenous and endogenous variables, we also sought to understand the practical significance of these effects through effect sizes. Effect sizes represent the explanatory power of the independent variables in accounting for the variance in the dependent variable (Hair, Page and Brunsveld 2020), offering valuable insight beyond mere statistical significance. Statistical significance tests help us guard against misinterpreting random fluctuations as genuine effects. However, it is the effect sizes that provide a critical lens for assessing the real-world importance and practical implications of the observed relationships (Flora, Crone and Bell 2025; Verdam, Oort and Sprangers 2017). Table 5.25 below presents the determination of effect sizes.

Table 5.25: Effect Sizes of Exogenous on Endogenous Variables

Exogenous Variable	Exogenous Variable	R^2 Incl.	R^2 Excl.	R^2 Incl. – R^2 Excl.	Effect size (f^2)	Label
	NISO	0.18				
LRCP			0.16	0.02	0.024	Small
DOSC			0.06	0.12	0.146	Small
	DOSC	0.33				
DOPS			0.11	0.22	0.328	Medium
LSP			0.31	0.02	0.030	Small

As shown in the table above, effect sizes for independent variables whose effects were statistically significant were determined using the following formula suggested in Hair, Page and Brunsveld (2020). Effect sizes are reported using Cohen's (1988) thresholds ranging from ≥ 0.02 as a small effect, ≥ 0.15 as medium, and ≥ 0.35 as large effect.

$$f^2 = \frac{R^2\,Included - R^2\,Excluded}{1 - R^2}$$

The research model (see **Figure 3.2 in Chapter 3)** incorporated two endogenous variables: No Intention to Shop Online (NISO) and Distrust in Online Social Channels (DOSC). Consequently, two squared multiple correlation (R^2) values were calculated to quantify the proportion of variance explained in each endogenous variable by its respective predictors. For NISO, the R^2 value was 0.18, indicating that 18% of its variance was explained by its two statistically significant predictors: perceived Lack of Reciprocity (LRCP) and Distrust in Online Social Channels (DOSC). To further assess the practical significance of these individual predictors, the effect size (f^2) was computed. The f^2 for LRCP on NISO was 0.024, denoting a small effect. Conversely, the f^2 for DOSC on NISO was 0.146, which suggests a moderate effect (Cohen 1988).

Regarding DOSC, the R^2 value was 0.33, signifying that 33% of its variance was explained by Distrust in Online Payment Systems (DOPS) and perceived Lack of Social Presence (LSP). Examining the individual effect sizes, the f^2 for DOPS on DOSC was 0.328, indicating a medium effect. Lastly, the f^2 for LSP on DOSC was 0.03, classifying it as a small effect (Cohen 1988).

5.5.4 Moderation Effect

The research model had two moderators (Poor Promotion Effort and Digital illiteracy). The former, as explained earlier in Subsection 5.5.2, were removed from the analysis, leaving the latter for moderation effect testing. In this analysis, the moderation effect of Digital illiteracy on the relationship between (1) Negative Performance Expectancy and the reluctance (no intention) to shop online (H12a), (2) Negative Effort Expectancy and the reluctance (no intention) to shop online (H12b), and (3) Technophobia and the reluctance (no intention) to shop online (H12c) was tested. The moderation analysis was conducted using the Hayes Process macro v4.3.1 for SPSS (Hayes 2022).

While Table 5.24 shows that the hypothesised direct paths (H1, H2 and H5) were not significant predictors of reluctance (no intention) to shop online, it is crucial to note that this does not forbid testing of the moderation effect on these paths (Hair *et al.* 2021; Hayes 2022; Part and Yi 2022). The moderation analysis was conducted using Process Macro Model 1, with 5000 bootstrapping samples and all variables were centred. The overall models testing the three moderation hypotheses were not significant: H12a model F (3, 410) = 1.598, p = 0.189, R^2 = 0.012; H12b model F (3, 410) = 1.699, p = 0.167, R^2 = 0.012; and H12c model F (3, 410) = 1.798, p = 0.189, R^2 = 0.013. Hence, only the interaction effects values are presented in the Table.

Table 5.26: Moderation Effects

Hypothesis	Interaction	Coeff.	se	*t*	*p*	LLCI	ULCI
H12a	Int_1: NPE x Dill	0.004	0.051	0.071	0.943	-0.096	0.103
H12b	Int_2: NEE x Dill	0.012	0.048	0.256	0.798	-0.083	0.107
H12c	Int_5: TPB x Dill	0.045	0.058	0.767	0.444	-0.070	0.159

The interaction values between Digital illiteracy and the three predictors (NPE, NEE and TPB) were all not significant; H12a: b = 0.004, SE = 0.051, t = 0.071, p < 0.943, H12b: b = 0.012, SE = 0.048, t = 0.256, p < 0.798, and H12c: b = 0.045, SE = 0.058, t = 0.767, p < 0.444. These results indicate that the relationships between the three predictors (NPE, NEE and TPB) and the outcome variable (No intention to shop online) were not moderated by digital illiteracy. As such hypotheses H1, H2 and H5 were not supported.

5.6 SUMMARY OF THE CHAPTER

T This chapter presented and interpreted the data collected for the study, beginning with data cleaning and preparation to ensure suitability for statistical analysis. The sample of 414 respondents was well-balanced and demographically representative, with key variables such as age, gender, ethnicity, occupation, income, and education examined in relation to digital access and internet use. Descriptive statistics for the twelve latent constructs revealed consistent agreement with statements reflecting negative expectations and perceptions about online shopping. The measurement model was rigorously validated using CFA, confirming unidimensionality, reliability, and validity for all but one construct. Poor Promotional Effort which was removed due to inadequate reliability and validity measures. The remaining constructs demonstrated strong factor loadings, high composite reliability, and acceptable average variance extracted, providing a solid foundation for the structural model. Overall, the chapter ensured data integrity and measurement soundness, setting the stage for hypothesis testing in the next chapter, which will explore the causal relationships underlying consumers' reluctance to engage in online shopping.

CHAPTER SIX

DISCUSSIONS AND KEY FINDINGS

6.1 INTRODUCTION

This chapter presents the discussion and conclusions of the study. It begins with a summary of the key findings, providing context to the results in relation to the study's objectives. It then proceeds to analyse both the supported and rejected hypotheses in comparison with existing literature, highlighting areas of alignment, discrepancies, and emerging insights that contribute to a deeper understanding of the research problem.

6.2 SUMMARY OF KEY FINDINGS

The empirical analysis yielded several critical insights into the factors influencing consumers' non-adoption of FMCG online shopping in post-pandemic South Africa. Of the twelve hypotheses tested, four received significant support while seven were rejected, with one construct (Poor Promotional Effort) removed due to insufficient stability. Specifically, it failed to retain at least two valid measurement items, as recommended by Hair, Page and Brunsveld (2020) and Kline (2023), rendering it conceptually and statistically weak. The low factor loadings and inadequate composite reliability suggested that the construct did not consistently capture the intended dimension of promotional inadequacy within the South African online FMCG context. This instability may also reflect contextual realities where promotional exposure and marketing communication are not perceived as major determinants of non-adoption compared to more salient trust-related and experiential factors. Thus, its removal was both methodologically necessary and theoretically justified to ensure the robustness, validity, and parsimony of the final measurement model. The overall findings presented a clear picture of online shopping non-adoption drivers that both challenge and extend existing theoretical frameworks.

The study confirmed that trust-related factors played the most substantial role in shaping non-adoption behaviour. Perceived lack of reciprocity emerged as a significant predictor ($\beta = 0.183$, $p = 0.014$), supporting SET's emphasis on balanced value exchanges in digital commerce (Degutis *et al.* 2023; Gouldner 1960; Shanahan, Tran and Taylor 2019). Similarly, distrust in online payment systems demonstrated a strong positive relationship with distrust in social commerce channels ($\beta = 0.499$, $p < 0.001$), aligning with previous research on payment security concerns in emerging markets (Lee *et al.* 2018). The importance of interpersonal elements was further underscored by the finding that lack of social presence significantly contributed to distrust in social channels ($\beta = 0.199$, $p < 0.001$), reinforcing Zhang *et al.'s* (2014) work on the role of human interaction in e-commerce. Most crucially, distrust in social channels directly increased non-adoption intentions ($\beta = 0.368$, $p < 0.001$), highlighting platform distrust as a primary barrier to adoption (Wang *et al.* 2022).

The findings suggested that non-adoption behaviour among South African consumers is largely driven by low levels of trust in digital platforms and online transactions, rather than a lack of access or technological skill. In practical terms, this means that many consumers preferred traditional, face-to-face retail experiences where they can see, touch, and pay for products directly. Consumers may feel that online platforms offer limited mutual value, perceiving that retailers benefit more from digital transactions than they do as consumers, especially when issues like delayed deliveries, poor customer support, and lack of redress mechanisms arise. This erodes the sense of fairness and discourages repeat or first-time online purchases.

Persistent concerns about fraud, data breaches, and failed transactions reflected a widespread lack of confidence in online payment infrastructure. Many South Africans still prefer cash-on-delivery or in-store card payments, as these are seen as more secure and transparent. This distrust is magnified by previous experiences of online scams and low consumer protection enforcement. The absence of human interaction or social assurance cues in online shopping environments reduces consumer confidence. In a society where trust is often built through interpersonal relationships, the impersonal nature of digital commerce limits emotional comfort and perceived reliability. Consumers are therefore hesitant to transact on platforms that feel "faceless" or disconnected.

Overall, distrust in social and digital platforms translates into non adoption of online grocery and social commerce services. This means that despite the availability of e-commerce infrastructure and increasing smartphone penetration, a large proportion of consumers remain digitally excluded in behavioural terms, choosing traditional retail channels over digital ones. Contrary to expectations derived from UTAUT (Venkatesh *et al.* 2003), none of the inverted traditional technology adoption factors (negative performance expectancy, effort expectancy, social influence, and facilitating conditions) and technophobia displayed significant effects on non-adoption (all $p > 0.05$). This result aligned with Dobson and Jackson's (2017) view that non-adoption can be due to active resistance or disinterest, instead of lagging adoption, disenfranchisement or displacement, and suggests that in post-pandemic South Africa, trust deficits may overshadow conventional usability concerns. Similarly, technophobia failed to emerge as a significant predictor ($\beta = -0.028$, $p = 0.719$), implying that in this context, specific trust issues may be more salient than general technology anxiety (Khasawneh 2018). The anticipated moderating effects of digital illiteracy on key relationships were also not supported (all $p > 0.44$), challenging common assumptions about digital skills as a primary adoption barrier (Cham, Cheah, Cheng and Lim 2022).

Effect size analysis reinforced these patterns, with distrust in social channels demonstrating a medium effect on non-adoption ($f^2 = 0.146$) and payment system distrust showing a particularly strong impact on social channel distrust ($f^2 = 0.328$). By contrast, the collectively minimal explanatory power of rejected UTAUT constructs (<5% of variance explained) suggests their limited relevance for understanding non-adoption in this context. The unexpected reliability issues with the Poor Promotional Effort construct (CR = 0.678, AVE = 0.413), which necessitated its removal from analysis, may indicate either measurement challenges or the construct's contextual irrelevance to South African non-adopters.

These findings collectively paint a picture where trust deficits and perceived inequalities in value exchange dominate non-adoption decisions, while traditional adoption factors and digital literacy concerns recede in importance. The results suggest that in post-pandemic South Africa, the barriers to e-commerce adoption may be more fundamentally rooted in social and transactional trust issues than in technology acceptance factors or skill limitations.

6.3 DISCUSSION OF FINDINGS IN RELATION TO LITERATURE

This sub-section discusses the study’s findings in relation to existing literature, focusing on both the rejected and supported hypotheses. The discussion aims to interpret the statistical results within established theoretical and empirical frameworks, highlighting areas where the findings align with or diverge from previous research.

6.3.1 Rejected Hypotheses: Unexpected Non-Significant Relationships

This study's application of an inverted UTAUT framework as illustrated in Section 3.4 in Chapter 3, hypothesised that negative constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, together with technophobia, would predict

reluctance to adopt online shopping in South Africa. However, all five variables proved statistically non-significant, challenging conventional technology adoption paradigms while revealing critical contextual nuances.

The statistical non-significance of negative performance expectancy (β = -0.164, p = 0.091) and negative effort expectancy (β = -0.009, p = 0.828) is contrary to the foundational propositions of the UTAUT (Venkatesh *et al.* 2003) but aligned with the inverted UTAUT's premise that non-adopters operate under fundamentally different cognitive frameworks than adopters. While UTAUT traditionally assumes users evaluate technologies based on perceived utility and ease, South African non-adopters in this study demonstrated what might be termed pre-experiential disengagement, active resistance or disinterest (Dobson and Jackson 2017; Mainardes, de Souza and Correia 2020); a state where individuals lack even the basic exposure required to form judgments about efficacy or complexity of online shopping system. As Daroch, Nagrath and Gupta (2021) observed in analogous settings, individuals who have never engaged with online shopping platforms lacked the experiential framework to evaluate their efficacy or navigability, rendering performance and effort expectations theoretically inert. This suggested that non-adoption may stem not from active dissatisfaction but from disengagement, wherein perceived barriers eclipse any potential benefits before first-hand trial occurs.

Similarly, negative social influence's statistical non-significance (β = 0.071, p = 0.375) reflected a key divergence from the conventional UTAUT, which assumed that social referents actively shape behavioural outcomes (Venkatesh, Thong and Zu 2012). The inverted framework proposed that peer disapproval and behaviour, injunctive and descriptive beliefs (Ajzen 2020; Fishbein and Ajzen 2010), would deter adoption, yet findings suggested that non-adopters exist in social ecosystems where online shopping is neither practiced nor discussed sufficiently to generate normative pressure. While South Africa has a relatively high rate of internet penetration and is witnessing high e-commerce growth (Mastercard 2024), not so many South Africans seem to have been influenced by others' online shopping habits. This accentuates that in South Africa's emerging e-commerce landscape (Mofokeng 2021), non-adopters may exist outside the social networks where online shopping is a salient topic, resulting in weak injunctive or descriptive norms. This aligns with Hungilo and Setyohadi's (2020) research in Tanzania, where social influence exerted negligible effects in low-adoption contexts due to the absence of robust peer benchmarks.

The statistically non-significant relationship between NFC and online shopping reluctance (β = 0.057, p = 0.585) constituted an unexpected finding that diverged from Venkatesh, Thong and Zu (2012) theoretical framework positing a direct association between facilitating conditions and adoption behaviour. While theoretical reasoning would suggest that negative facilitating conditions should positively predict online shopping reluctance, this null finding may reflect inherent limitations in the facilitating conditions construct's explanatory power under conditions of environmental uncertainty. Venkatesh *et al*. (2003) acknowledged that facilitating conditions demonstrated reduced predictive validity when individuals possessed incomplete information or faced behavioural uncertainty, circumstances under which external factors may inadequately capture or predict behaviour (Ajzen 1991; Sheeran, Trafimow and Armitage 2003).

Furthermore, Ajzen and Madden (1986) stipulated that facilitating conditions only effectively predict behaviour when individuals' perceptions accurately reflect their actual behavioural control. Within South Africa's nascent e-commerce ecosystem (Mofokeng 2021), substantial market uncertainty may preclude non-adopters from forming accurate perceptions of their actual control over online shopping behaviour, thereby attenuating the relationship between perceived facilitating conditions and behavioural intentions. This contextual limitation may explain the observed non-significant effect, suggesting that environmental maturity moderates the [negative] facilitating conditions-behaviour relationship.

Finally, technophobia, though widely implicated in technology resistance literature (Nimrod 2018; Osiceanu 2015), did not significantly correlate with non-adoption ($\beta = -0.028$, $p = 0.719$). This divergence may reflect contextual prioritisation of risks. For instance, in South Africa, where payment fraud and data breaches dominate public discourse (Ramalepe 2023), concrete distrust in transactional security may overshadow generalised anxiety about technology. Higueras-Castillo, Liébana-Cabanillas and Villarejo-Ramos (2023) similarly noted that technophobia's predictive power diminishes when users face more immediate, tangible threats, a dynamic particularly salient in emerging markets.

Collectively, these rejected hypotheses illuminate a critical theoretical nuance: non-adoption in South Africa appears driven less by evaluative barriers (e.g., "online shopping is hard/useless") than by structural and experiential voids (e.g., no referent networks, infrastructural exclusion). This necessitates a recalibration of UTAUT for non-adoption contexts, emphasising pre-adoption experiential deficits and systemic inequalities over individual perceptions.

6.3.2 Supported Hypotheses: Trust and Social Exchange as Core Barriers

The empirical results demonstrated that the reluctance to adopt online shopping in South Africa is not primarily a function of usability assessments but is fundamentally rooted in a breakdown of trust and the perceived violation of core principles of social exchange. The supported hypotheses revealed a multi-layered architecture of distrust, spanning transactional, social, and reciprocal dimensions.

6.3.2.1 The Significance of a Perceived Lack of Reciprocity

The finding that a perceived lack of reciprocity significantly predicted no intention to shop online (β = 0.183, p = 0.014) provides robust empirical support for the application of the inverted SET in understanding online shopping non-adoption. This relationship underscores that non-adopters are engaged in a rational, albeit negative, cost-benefit analysis. Crucially, the cost is not merely financial but encompasses the perceived value of personal data.

This result confirms that non-adopters perceive a fundamental inequity in the proposed digital exchange. They are acutely aware that they are asked to surrender valuable assets, personal data, financial information, and privacy, but remain unconvinced that e-commerce platforms offer adequate value in return (Shanahan, Tran and Taylor 2019; Pallant *et al.* 2022). This is not a simple mistrust of security; it is a deeper scepticism about the fairness of the exchange itself. While e-commerce businesses promise personalised marketing communications or services in exchange for personal information (Giese and Stabauer 2022; Urbonavicius *et al.* 2021; Zeng *et al.* 2020), such a value proposition is deemed to be insufficient compensation for the perceived risk and loss of control. This creates a privacy calculus (Culnan and Armstrong 1999) or personalisation-privacy paradox (Zhu, Ou, van den Heuvel and Liu 2017), where the perceived risks and costs overwhelmingly outweigh the anticipated benefits.

This finding aligns with Degutis *et al*. (2023), who argued that the success of data-driven commerce hinged on consumers feeling that benefits were commensurate with their disclosure. In the South African context, where economic inequality is pronounced, this sensitivity to exploitative or unequal exchanges is likely to be heightened. Consumers may be inherently wary of powerful corporate entities, perceiving data collection as an extractive process that benefits the platform far more than the individual. The finding is also consistent with previous studies' (for example, Maseeh *et al.* 2021; Saeed 2023; Wolverton and Cenfetelli 2019) findings of a negative relationship between privacy concerns and e-commerce adoption.

6.3.2.2 Distrust in Online Payment Systems - The Tangible Fear

The data revealed a clear causal pathway through which specific fears culminated in a generalised distrust of the social commerce environment. The strong, statistically significant effect of distrust in online payment systems on distrust in social channels (β = 0.499, p = 0.001) highlights the paramount importance of transactional security. This finding is powerfully consistent with the literature, identifying payment security as a critical barrier in emerging markets (Lee *et al.* 2018; Moody, Galletta and Lowry 2014).

This empirical finding necessitates a fundamental reconceptualisation of payment security within online commerce platforms, positioning it not as a back end (technical) function, but as the most critical front-facing element of their trust-building strategy. When consumers doubt the security of the payment gateway, that doubt instantly and completely contaminates their perception of the entire brand and channel. This observation aligns with established literature examining the antecedents of e-commerce distrust, particularly regarding online payment systems. McKnight and Choudhury (2006) delineated the risk of fraudulent website operations that extract payment without service delivery, the impersonal nature of e-commerce transactions that preclude physical product evaluation and heightened perceived risk, and the requirement for disclosure of personal information that engenders privacy concerns within the personalisation-privacy paradox (Zhu *et al.* 2017).

Critically, these findings substantiated the 'trust transfer' phenomenon (Stewart 2003), wherein consumer confidence in the primary platform becomes contingent upon trust perceptions of critical third-party intermediaries, specifically payment processing systems. The present findings confirmed that trust in a critical third-party intermediary (the payment system) is transferred to trust in the social commerce platform. While existing scholarship has predominantly examined trust transfer through positive trust attribution, with distrust conceptualised merely as the antithesis of trust (Lee *et al.* 2018; McKnight and Choudhury 2006), the present findings contribute to this theoretical domain by demonstrating the potent effects of negative transfer. The negative trust transfer phenomenon resonated with contemporary research by Cui *et al*. (2018), Duong, Lin, Wu and Wang (2025), Lee *et al.* (2018), and Zhang and Wang (2021), who similarly documented the interdependent nature of trust relationships within digital commerce ecosystems.

The South African context provides particular salience to these findings, given the country's extensively documented challenges with cybercrime and financial fraud (Ramalepe 2023; South African Banking Risk Information Centre; SABRIC 2023). Within this environment, consumer apprehension regarding online payment security is not paranoia but a rational response and a contextually appropriate risk assessment informed by objective threat conditions. The high-stakes nature of financial transactions makes payment security a hygiene factor; its absence is a definitive deal-breaker, regardless of other positive attributes a platform may possess (Kim, Ferrin and Rao 2008).

6.3.2.3 Lack of Social Presence - The Intangible Void

This finding further elucidated that distrust formation extended beyond transactional vulnerabilities to encompass fundamental social-psychological deficits within digital commerce environments. The significant positive relationship between perceived lack of social presence and distrust in social channels (β = 0.199, p = .001) demonstrated that trust construction possesses critical social-emotional dimensions, which when absent, breeds distrust of a social commerce platform. This finding supported the tenets of SPT (Short, Williams and Christie 1976) and its application to e-commerce (Lu, Fan and Zhou 2016; Zhang *et al.* 2014).

Although empirical investigations that specifically examined the relationship between perceived social presence deficits and distrust within social commerce platforms remained absent from the extant literature, present findings demonstrated theoretical consistency with adoption-focused research when social presence was conceptualised as a continuum. Notably, Rashid *et al.* (2022) identified social presence as a significant moderator in the relationship between social commerce constructs and trust in social commerce sellers. Similarly, Lu, Fan and Zhou (2016) and Jiang, Rashid and Wang (2019) demonstrated that social presence influences social commerce purchase intention through trust-building mechanisms with sellers, while Hassan, Rashid and Lee (2015) further documented that social presence enhances purchase intention through improved customer experience quality.

While these adoption-centric investigations validated the foundational principles of the SPT, the present study's contribution lies in demonstrating the theoretical framework's explanatory power at the opposite end of the social presence continuum. Specifically, these findings confirmed that as social presence approaches its lower threshold, systematic trust deficits accumulate within social commerce environments. Non-adopters are not just afraid of being defrauded; they feel isolated and unsupported in the digital marketplace. While social commerce increases the degree of social presences in e-commerce (Lu, Fan and Zhou 2016), the lingering perceived absence of warm, interpersonal interaction, such as the ability to seek advice or reassurance from a salesperson, gauge a product's quality firsthand, or observe the reactions of other shoppers, creates a void that fosters apprehension and distrust (Gefen and Straub 2004). For product categories like FMCG, where tactile evaluation (e.g., produce freshness) and low-involvement impulse buys are common, this absence is particularly acute.

6.3.2.4 The Proximal Driver: Distrust in Social Channels

Ultimately, the most powerful direct predictor of non-adoption intention is the generalised distrust in online social channels ($\beta = 0.368, p = 0.001$). This finding, positions platform distrust not merely as an outcome of other fears, but as the primary proximal psychological barrier to adoption. It acts as the final gatekeeper, synthesising multiple specific concerns about social commerce, including distrust in online payments, and perceived lack of social presence into an overall negative attitude towards the platform's integrity and benevolence (Wang *et al.* 2022; Zhao, Huang and Su 2019). This result confirmed that in a social commerce context, the channel itself becomes the object of distrust, paralysing behavioural intention regardless of any potential perceived usefulness or ease of use a specific product might offer.

These results are consistent with previous research examining platform perceptions and behavioural intentions, though they extend the theoretical understanding in important ways. Yahia, Al-Neama and Kerbache (2018) demonstrated how social media platform perceptions influence behavioural intention within a pro-adoption framework, while Asma and Adreen (2022) established a significant positive relationship between Instagram store trust and purchase intention, further confirming the impact of social commerce platforms on consumer behaviour. However, the present study provides a complementary perspective by examining the non-adoption context, revealing that consumer perceptions, specifically distrust in social commerce platforms, serve as barriers that impede online shopping adoption. This finding offers a theoretical counterpoint that enriches the understanding of how platform perceptions operate across the adoption-resistance spectrum.

In synthesis, these supported hypotheses paint a coherent picture: the path to non-adoption is paved by a cascade of distrust. Specific, rational fears about unfair value exchange, insecure transactions, and an impersonal environment converge to create a generalised and powerful distrust of the social commerce platform, which directly and decisively results in the intention to reject online shopping altogether. This model revealed that the core of the problem is not technological aversion but a profound crisis of trust in the digital market's fundamental fairness and safety.

6.3.3 Non-Significant Moderation by Digital Illiteracy

The tested moderation hypotheses (H12a, H12b, H12c) proposed that digital illiteracy would amplify the positive relationships between NPE, NEE, TPB, and the intention not to shop online. Contrary to expectations, the analysis revealed no statistically significant moderating effects across all tested interactions (all $p > 0.05$). This null finding is a critical result in itself, challenging conventional wisdom and offering a more sophisticated understanding of the digital divide in the South African e-commerce context.

6.3.3.1 A Challenge to Assumptions about the Digital Divide

The statistically non-significance of digital illiteracy as a moderator contradicted a substantial body of literature that often positions a simple skills deficit as a primary barrier to technology adoption (Cahyono and Rizqi 2024; Cham *et al.* 2022; Nazzal *et al.* 2022; van Deursen and van Dijk 2019). The present findings suggested that within the non-adopter segment, the relationship negative technology perceptions and avoidance behaviours remain consistent regardless of digital skill levels, a finding that necessitated theoretical reconsideration of how digital literacy operates in technology resistance contexts. Two theoretical interpretations emerged from this finding, each offering distinct insights into the mechanisms underlying e-commerce non-adoption in the South African context.

The first interpretation positioned digital illiteracy as a threshold barrier rather than a differential moderating variable. Within the non-adopter cohort, digital literacy levels may be sufficiently homogeneous and universally low to preclude meaningful statistical moderation. This phenomenon aligned with the concept of the conceptualisation of the second-level digital divide, which emphasises skills and usage gaps beyond mere access considerations (Hargittai, 2002; van Deursen and van Dijk 2019).

In the South African digital landscape, where internet penetration has exponentially increased while meaningful digital engagement remains constrained (Modjadji 2025; Vujovic, Jonathan and Hacks 2024), this interpretation suggested that widespread skills deficits function as a precondition for non-adoption rather than a variable that differentially influences other barriers.

Under this framework, digital illiteracy operates as a constant that uniformly prevents entry into the adoption consideration set, thereby rendering its moderating potential statistically undetectable within the non-adopter population.

The second, and theoretically more compelling, interpretation posited that motivational barriers have achieved such prominence that they supersede skills-based considerations entirely. This perspective suggested that individuals may possess sufficient functional competence to navigate e-commerce platforms but consciously abstain due to fundamental concerns about trust, value equity, and systemic reliability. This finding resonated with Selwyn's (2006) concept of ‘relevance deprivation,’ wherein non-use represents a deliberate choice based on perceived lack of relevance or benefit rather than technological incapacity.

Within the high-risk, low-trust context characteristic of the South African digital economy (Pieterse 2021; Sutherland 2017) overwhelming motivational barriers, particularly those related to institutional or platform distrust and perceived value inequity, appear to dominate the decision calculus. This dominance effectively nullified the moderating influence of digital skills [illiteracy], as the fundamental question shifted from "can I use this technology?" to "should I trust this system?" The latter consideration transcended technical competence and operates at the level of institutional confidence and social capital.

6.3.3.2 Contextualising this Finding within the Broader Model

This result synergises with other key findings in the study. The fact that the direct UTAUT-based constructs (NPE, NEE) were themselves statistically non-significant predictors means there was essentially no main effect for digital illiteracy to moderate. If perceptions of low usefulness and high difficulty are not themselves primary drivers, it is logically consistent that a skills deficit would not amplify these weak relationships.

Furthermore, this finding reinforced the central thesis that socio-psychological factors (trust, equity) are more salient than techno-functional factors (skills, usability) in explaining non-adoption in this specific context. It suggested that interventions aimed solely at boosting digital literacy, for example, teaching people how to use a shopping cart or search for products, are likely to be ineffective if they do not simultaneously, and primarily, address the foundational crisis of trust, the perceived lack of reciprocal value and social presence. Potential adopters need to be convinced why they should engage in e-commerce before they need to be taught how to shop online.

Therefore, the statistically non-significant moderating role of digital illiteracy should not be dismissed as an unimportant result. Instead, it provides crucial evidence for a paradigm shift in understanding the digital divide in e-commerce. It moves the focus away from a deficit model of lacking skills and towards a model of rational rejection based on a calculated assessment of risk and reward. For South African online shopping non-adopters in this study, the decision to not shop online appears to be a reasoned stance based on trust and equity considerations, a stance that is held consistently regardless of their self-assessed level of digital skill.

6.4 SUMMARY OF THE CHAPTER

This chapter discussed the study's findings in relation to existing literature, highlighting that non-adoption of FMCG online shopping in South Africa is primarily driven by trust-related factors rather than technological barriers. Perceived lack of reciprocity, distrust in online payment systems, and low social presence emerged as the main inhibitors of adoption. These results challenge traditional technology adoption models by revealing that socio-psychological factors, rather than ease of use or performance expectations, play a more significant role in shaping consumer behaviour. Overall, the chapter emphasises that building trust and strengthening relational connections are essential for promoting online shopping adoption in low-trust environments.

CHAPTER SEVEN

CONCLUSIONS, CONTRIBUTIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

This chapter presents conclusions, summarises the key findings, theoretical contributions, practical recommendations, and future research directions of the study. It begins by presenting conclusions drawn from each research objective, outlining how the findings enhance the understanding of factors influencing consumers' reluctance to adopt online shopping for FMCG in South Africa. The chapter then discusses the study's theoretical contributions, particularly how it extends existing frameworks UTAUT, SET, TTT, and SPT to the context of e-commerce non-adoption. Practical recommendations are also provided to guide retailers, policymakers, and FMCG online platforms in addressing barriers such as distrust, limited reciprocity, and lack of social presence. The chapter concludes by identifying limitations and proposing directions for future research to further explore behavioural, psychological, and contextual factors affecting online shopping adoption.

7.2 CONCLUSIONS

In line with achieving the research objectives of the study, the following conclusions are drawn:

7.2.1 Research objective one

The first objective was to examine the extent to which negative performance expectancy, negative effort expectancy, negative social influence, and negative facilitating conditions predict consumers' reluctance to shop for FMCG online. To achieve this objective, the following hypotheses were tested:

- H1: Negative performance expectancy significantly predict a lack of intention to shop online.
- H2: Negative effort expectancy significantly predict a lack of intention to shop online.
- H3: Negative social influence significantly predicts a lack of intention to shop online.
- H4: Negative facilitating conditions significantly predict a lack of intention to shop online.

The results revealed that all four hypotheses were not supported. This implies that negative perceptions related to performance expectancy, effort expectancy, social influence, and facilitating conditions do not significantly influence consumers' reluctance to adopt FMCG online shopping in the post-COVID-19. Therefore, consumers' reluctance to buy FMCG online may not be due to technology-related issues, but rather to practical and experience-based factors such as a lack of trust in online retailers, concerns about delivery reliability, strong habits of shopping in physical stores, and the perception that online shopping offers little added value. In practical terms, this means that retailers should focus on improving service reliability, building stronger customer trust, and creating more rewarding online shopping experiences. Future efforts should also aim to understand customers' day-to-day shopping preferences and expectations, as these factors appear to play a greater role in influencing their shopping choices than technological challenges.

7.2.2 Research objective two

The second objective was to determine the direct influence of technophobia, perceived lack of reciprocity, and distrust in online shopping channels on consumers' reluctance to shop for FMCG online. To achieve this objective, the following hypotheses were tested:

- H5: Technophobia significantly predict a lack of intention to shop online.
- H6: Perceived lack of reciprocity significantly predict a lack of intention to shop online.

The results revealed that H5 was not supported, while H6 was supported. The findings suggest that technophobia does not significantly influence consumers' reluctance to shop for FMCG online, indicating that most consumers are comfortable using digital platforms. However, the perceived lack of reciprocity was found to have a significant effect, implying that consumers are discouraged when they feel that online retailers do not offer fair value, mutual benefit, or appreciation for their loyalty. Therefore, to encourage online shopping adoption, retailers should focus on building reciprocal relationships through strategies such as loyalty rewards, personalised offers, and transparent engagement that foster a sense of fairness and mutual gain.

7.2.3 Research objective three

The third objective was to investigate the relationship between (i) perceived lack of reciprocity, (ii) distrust in online payment systems, and (iii) lack of social presence, and how these factors contribute to the development of distrust in online shopping channels which then leads to reluctance to shop online. To achieve this objective, the following hypotheses were tested:

- H7: Perceived lack of reciprocity significantly influence distrust in online shopping channels.
- H8: Distrust of online payment systems significantly influence distrust in online shopping channels.
- H9: Lack of social presence significantly influence distrust in online shopping channels.
- H10: Distrust of online shopping channels significantly predict a lack of intention to shop online.

The results revealed that H7 was not supported, while H8, H9, and H10 were supported. The findings indicate that perceived lack of reciprocity does not significantly influence distrust in online shopping, suggesting that consumers' perceptions of fairness or mutual benefit are not a major determinant of distrust. However, distrust in online payment systems and lack of social presence both significantly contribute to higher levels of distrust in online shopping channels. This highlights that consumers remain cautious about the security and interpersonal aspects of online transactions. Furthermore, distrust in online shopping channels was found to significantly predict a lack of intention to shop online, reinforcing the crucial role of trust in shaping consumer behaviour. Therefore, online retailers should prioritise secure payment systems, enhance social presence through interactive communication, and implement trust-building mechanisms to reduce consumer apprehension and promote online shopping adoption.

7.2.4 Research objective four and five

The fourth and fifth objectives were to assess the moderating effects of poor promotional effort on the relationships between consumers' negative expectations, technophobia, distrust in online payment systems, and their reluctance to shop for FMCG online. To achieve these objectives, the following hypotheses were tested:

- H11a: Poor promotional effort positively moderates the effect of negative performance expectancy on the lack of intention to shop online.
- H11b: Poor promotional effort positively moderates the effect of technophobia on the lack of intention to shop online.
- H11c: Poor promotional effort positively moderates the effect of distrust in online payment systems on distrust of online shopping channels.
- H11d: Poor promotional effort positively moderates the effect of distrust in online shopping channels on the lack of intention to shop online.

The statistical analysis showed that poor promotional effort construct could not be reliably measured, as the items designed to assess it did not yield consistent or accurate results. Even after removing the weakest item (PPE3), the overall reliability and validity of the construct remained below acceptable research standards. Consequently, the poor promotional effort variable was removed from further analysis, and the study was unable to test how poor promotional effort might influence the relationship between consumers' negative perceptions, technophobia, distrust, and their reluctance to engage in online shopping. This outcome highlights the need for better measurement tools and clearer conceptualisation of promotional effort in future studies, as ineffective marketing communication and lack of promotional visibility may still play a critical role in discouraging online shopping adoption in practice.

7.2.5 Research objective six

The sixth objective was to explore the extent to which digital illiteracy moderates the relationship between (i) negative performance expectancy, (ii) negative effort expectancy, and (iii) technophobia on consumers' reluctance to shop for FMCG online. To achieve this objective, the following hypotheses were tested:

- H12a: Lack of digital literacy positively moderate the effect of negative performance expectancy on the lack of intention to shop online.
- H12b: Lack of digital literacy positively moderate the effect of negative effort expectancy on the lack of intention to shop online.
- H12c: Lack of digital literacy positively moderate the effect of technophobia on the lack of intention to shop online.

The results revealed that all three hypotheses were not supported. The findings indicate that digital illiteracy did not significantly moderate the relationship between negative performance expectancy, negative effort expectancy, and technophobia on consumers' reluctance to shop online. This suggests that even though some consumers may possess limited digital skills, this factor alone does not strengthen the negative perceptions or fears that discourage them from engaging in online shopping. Therefore, improving consumers' digital skills alone may not be sufficient to drive online shopping adoption; retailers must also focus on building trust, ensuring reliable service delivery, and creating value-driven online experiences to encourage greater participation in online FMCG shopping.

7.2.6 Research objective seven

The seventh and last objective was to propose a framework to assist retailers in enhancing the adoption of FMCG online shopping. This objective was successfully achieved and is discussed in Section 7.3 under theoretical contributions, where the proposed framework outlines strategies for improving consumer trust, engagement, and overall adoption of online shopping platforms.

7.3 THEORETICAL CONTRIBUTIONS

This study makes several significant contributions to the theoretical understanding of technology non-adoption, particularly within the context of e-commerce for FMCG in emerging markets. By integrating and inverting constructs from the UTAUT, SET, TTT, and SPT, this research offers a more refined and contextually grounded framework for explaining why consumers resist online shopping, even in a post-pandemic era where digital channels have become increasingly prevalent.

The findings challenge the universal applicability of traditional technology adoption models and highlight the primacy of trust-related factors in shaping non-adoption behaviour. The contributions are fourfold, (i) encompassing a critique of UTAUT's limitations, (ii) an extension of Social Exchange, Social Presence and Trust Transfer theories, (iii) a contextualisation of technophobia, and (iv) a reconceptualisation of the digital divide.

7.3.1 Recalibrating UTAUT for non-adoption contexts

One of the most significant theoretical contributions of this study is its critical interrogation of the UTAUT framework (Venkatesh *et al*. 2003; Venkatesh, Thong and Xu 2012) in a non-adoption context. The original UTAUT model and its subsequent extensions have been overwhelmingly applied to understand the drivers of technology adoption and use. By inverting the core UTAUT constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, this study hypothesised that their negative counterparts would predict non-adoption.

However, the empirical results demonstrated that none of these inverted constructs had a statistically significant effect on consumers' intentions to not shop online for FMCG. This striking null finding suggests that the cognitive and social processes that drive non-adoption are not merely the inverse of those that lead to adoption. Non-adopters, particularly in emerging markets, may not be engaging in a rational evaluation of a technology's utility or ease of use, as UTAUT presupposes. Instead, their resistance appears to be rooted in more fundamental issues of trust and perceived value, which precede any consideration of the technology's performance or usability. This phenomenon is highlighted in extant research that argued against referring to distrust as a mere opposite of trust, instead insisting that it is distinct and can co-exist with trust (Dimoka 2010; Moody, Galletta and Lowry 2014).

Thus, the most substantial contribution of this research lies in its empirical challenge to the presumed universality of the UTAUT in explaining digital behaviour. The consistent non-significance of all inverted UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) demonstrates that the cognitive calculus of the non-adopter is fundamentally different from that of the adopter. The study moves beyond merely applying UTAUT to a new population and instead reveals its contextual boundary conditions.

It empirically establishes that in environments characterised by high perceived risk and low institutional trust – hallmarks of many emerging markets (Arcuri, Brogi and Gandolfi 2017; Pieterse 2021; Sutherland 2017) – the explanatory power of UTAUT is significantly diminished. In such environments, traditional usability and utility concerns are eclipsed by more foundational issues of security, fairness, and social embeddedness. This necessitates a paradigm shift in non-adoption research, from a focus on laggards who are slow to perceive usefulness, to one of rational rejecters who actively opt out due to a calculated assessment of risk versus reward (Joseph 2005; Sharma and Gandhi 2024).

Consequently, this research contributes a Trust-Mediated Model of Non-Adoption, proposing that UTAUT variables may only become salient after primary trust barriers have been overcome. The study's results align with the arguments of researchers who have called for a more critical approach to technology adoption models (Bringula 2016; Joseph 2005; Sharma and Gandhi 2024), recognising that they may not adequately capture the complex socio-economic and psychological factors that underpin resistance to technology. This research, therefore, contributes to a growing body of literature that seeks to move beyond the traditional, often deterministic, assumptions of technology acceptance models and to develop more contextually sensitive theoretical frameworks.

7.3.2 Refining social exchange theory: personalisation-privacy paradox in E-commerce

This study also makes a contribution to SET by demonstrating its applicability to the context of e-commerce non-adoption. The finding that a perceived lack of reciprocity is a statistically significant predictor of non-adoption intentions provides strong empirical support for the core tenets of SET, which posit that individuals are motivated to engage in exchanges that they perceive as fair and equitable. In the context of online shopping, this study has revealed that non-adopters are engaged in a sophisticated cost-benefit analysis, where the ‘costs’ include not only financial outlay but also the surrender of personal data and the perceived loss of privacy. The ‘benefits,’ in turn, are not seen as sufficient enough to warrant these costs.

This extends SET by highlighting the unique nature of the ‘exchange’ in the digital realm. Unlike traditional face-to-face transactions, online exchanges are often characterised by information asymmetry, with consumers having limited visibility into how their data is being used, and access to comprehensive product information compared to sellers (Pandey, Mittal and Chawla, 2024). This study showed that in such an environment, the perception of reciprocity becomes a critical determinant of trust and, consequently, of adoption behaviour. By empirically validating the role of reciprocity in a non-adoption context, this research provides a valuable extension to SET and offers a powerful lens through which to understand consumer resistance to data-driven marketing and e-commerce.

The contribution is twofold. (i) it operationalised and validated the privacy calculus (Culnan and Armstrong 1999) as a core mechanism of non-adoption. It demonstrated that consumers conduct a rational, albeit negative, assessment where the costs of data surrender and privacy risk are deemed to outweigh the benefits of personalisation and convenience (Aivazpour and Rao 2020). (ii) it identified the specific nature of the inequity. The findings suggested that the failure of reciprocity is not just about the amount of value returned but also about the type of value and the trust in the entity providing it. In an unequal society as in South Africa (Makgetla 2020), the exchange is perceived as inherently exploitative, extending SET by highlighting how macro-societal inequities can micro-manifest in individual consumer assessments. This theoretical extension bridges a critical gap between micro-level consumer behaviour and macro-level social structures.

7.3.3 Integrating trust and social presence concepts

A further theoretical contribution of this research resides in its comprehensive articulation of trust's multidimensional architecture within e-commerce ecosystems. Through integrating TTT and SPT, this research has demonstrated how discrete trust-related concerns aggregate to generate pervasive distrust toward social commerce platforms, subsequently precipitating non-adoption behaviours. The finding that distrust in online payment systems has a strong positive effect on distrust in social channels, provides compelling evidence for the trust transfer phenomenon. It shows that trust is not a monolithic construct but is, in fact, a chain of dependencies, where weak links, such as a perceived lack of payment security and privacy concern, can undermine trust in the entire ecosystem.

Furthermore, the study's finding that a lack of social presence contributes to distrust in social channels reinforces the importance of the human element in digital transactions. This aligns with SPT, which argued that a sense of personal connection and human contact is crucial for building trust in mediated communication (Short, Williams, and Christie, 1976; Lu, Fan and Zhou 2016; Zhang *et al*. 2014). In the context of e-commerce, this suggests that non-adopters are not simply evaluating the technical features of a platform but are also assessing its capacity to provide a sense of social connection and reassurance. This is a particularly important insight in the context of FMCG, where consumers may be accustomed to the social interactions that are a feature of traditional brick-and-mortar shopping.

By integrating these different theoretical perspectives, this study offers a more holistic and nuanced understanding of the architecture of trust in e-commerce. It moves beyond a simplistic focus on platform-specific trust to a more comprehensive model that incorporates the role of third-party intermediaries (such as payment gateways) and the importance of social and interpersonal factors.

7.3.4 Contextualising Technophobia

This study makes a valuable contribution to the literature on technophobia by demonstrating that its influence on technology adoption is highly context dependent. The finding that technophobia was not a significant predictor of non-adoption in this study is counter-intuitive, given the extensive body of research that has linked technology anxiety to resistance to new technologies (Cabrera-Sánchez, Ramos-de-Luna, Carvajal-Trujillo and Villarejo-Ramos 2020; Koul and Eydgahi, 2020; Subero-Navarro, Pelegrín-Borondo, Reinares-Lara and Olarte-Pascual 2022). However, this result can be explained by the specific context of this research. In a country such as South Africa, where concerns about cybercrime and financial fraud are widespread (Marakalala and Madzivhandila 2025; Ramalepe 2023), it is plausible that specific, tangible fears about the security of online transactions may overshadow more generalised anxieties about technology itself. In other words, non-adopters in this context may not be ‘technophobic’ in a general sense, but rather ‘transaction-phobic’, where their fears are not directed at the technology per se, but at the perceived risks associated with using that technology for financial transactions.

This finding has important implications for how to conceptualise and measure technophobia in non-adoption contexts. It suggests that future research should move beyond generalised measures of technology anxiety and instead focus on more specific, contextually relevant fears and concerns. In doing so, researchers can develop a more accurate understanding of the psychological barriers to technology adoption in different cultural and socio-economic contexts.

7.3.5 Reconceptualising the digital divide: from skills deficit to rational rejection

The statistically non-significant moderating role of digital illiteracy calls for a critical re-evaluation of the nature of the digital divide in e-commerce. This study contributes to the literature by challenging the dominant 'deficit model', which posits that non-use is primarily due to a lack of digital skills or access (Verhees and Verbong 2015).

Instead, the findings support a model of 'rational rejection', where non-adoption is a conscious choice based on a compelling rationale of distrust and perceived inequity. This aligns with and empirically supports Selwyn's (2006) concept of relevance deprivation. The contribution here is the demonstration that in high-risk contexts, motivational barriers (e.g., Why should I?) so overwhelmingly dominate the decision-making process that they nullify the influence of skills-based barriers (e.g., Can I?). This shifts the theoretical focus for researchers and policymakers away from simply building digital literacy and towards the more complex task of building digital trust and demonstrating tangible value, offering a more effective framework for addressing digital exclusion.

This study does not merely add another variable to existing models; but rather provides compelling empirical evidence that necessitates the rethinking of which models are most relevant for understanding the pervasive phenomenon of digital non-adoption in emerging markets. The study's theoretical contributions are fourfold. (i) It recalibrates UTAUT for non-adoption contexts, (ii) extends SET to the digital realm, (iii) integrates multiple trust-related theories to provide a more holistic understanding of the architecture of trust in e-commerce, and (iv) contextualises the role of technophobia. Taken together, these contributions offer a more refined, contextually grounded, and theoretically robust framework for understanding the complex phenomenon of e-commerce non-adoption in emerging markets.

7.4 RECOMMENDATIONS

The findings of this study move beyond theoretical debate to offer clear, evidence-based guidance for stakeholders seeking to bridge the digital commerce divide in South Africa and similar emerging markets. The ineffectiveness of traditional technology acceptance factors and the overwhelming primacy of trust-related barriers necessitate a fundamental shift in strategy. Recommendations are targeted at two key groups: FMCG retailers and e-commerce platforms, and policymakers.

7.4.1 For FMCG retailers and E-commerce platforms

i. Building trust as the foundation of adoption

The clear message from non-adopters is that trust is the currency of adoption. Before showcasing product variety, price, or convenience, e-commerce platforms must first prove their trustworthiness to consumers. In an environment where online transactions are still perceived as risky, trust functions as the fundamental prerequisite for engagement and continued use. Consumers are unlikely to explore the benefits of online shopping if their initial concerns about security, authenticity, or fairness remain unaddressed.

Therefore, strategies must be reoriented from promoting product-centric attributes such as assortment, price competitiveness, or convenience to building foundational consumer trust. This shift calls for a humanised and transparent digital experience that reassures customers at every touchpoint. Retailers should view trust-building not as a one-time marketing effort, but as a continuous relational process that integrates transparency, reliability, and mutual benefit into the business model.

ii. Enhancing reciprocity and fair value exchange

To address the perceived lack of reciprocity that fuels non-adoption, companies must demonstrate a fair value exchange for consumer data (Degutis *et al*. 2023; Shanahan, Tran and Taylor 2019; Pallant *et al*. 2022). This entails moving beyond opaque data extraction toward transparent engagement and reframing data collection as a means of delivering immediate, personalised value for instance, through exclusive discounts or loyalty programmes. Such practices align with the principles of SET (Gouldner 1960; Shanahan, Tran and Taylor 2019) by ensuring that both consumers and retailers benefit equitably from digital interactions.

iii. Transforming security into a trust-building value proposition

Given the strong influence of distrust in online payment systems, security must evolve from a back-end technical process into a front-facing value proposition that builds consumer confidence. E-commerce platforms should make security a visible and integral part of their brand identity by collaborating with reputable payment providers such as Mastercard, PayPal, or Visa, and clearly displaying these partnerships to leverage trust transfer. Visible security credentials such as SSL certificates, Payment Card Industry Data Security Standard (PCI-DSS) compliance badges, and trusted payment seals should be prominently showcased across websites and apps to reassure customers that their data is protected. Additionally, financial protection guarantees, including refund policies and fraud protection assurances, should be clearly communicated to address fears of financial loss and demonstrate accountability.

Beyond conventional measures, the adoption of blockchain technologies offers a transformative approach to safeguarding transactions and personal data. Blockchain-enabled smart contracts create transparent, tamper-proof systems that significantly reduce vulnerability to fraud and cybercrime. Collectively, these interventions elevate payment security from a technical safeguard to a strategic trust-building mechanism and a central element of marketing communication. By positioning security as part of the customer experience, online retailers can convert skepticism into trust and strengthen consumer willingness to adopt and repeatedly engage in online shopping.

iv. Engineering social presence and human interaction

To overcome the distrust that often stems from a lack of social presence, retailers and e-commerce platforms need to humanise the online shopping experience by embedding interaction, empathy, and community into their digital environments. One effective approach is to integrate real-time live chat support so that customers can receive immediate assistance similar to speaking with a salesperson in-store. Retailers can also leverage user-generated content, such as product reviews, ratings, and testimonials, to provide credible social proof that reassures hesitant shoppers. These authentic voices build confidence and help bridge the trust gap that often exists in impersonal digital transactions.

Additionally, businesses should promote two-way engagement through social media channels, comment sections, and post-purchase follow-ups to create a sense of dialogue and care. Platforms can go a step further by enabling shopper-to-shopper interaction, such as community forums, Q&A sections, or group discussions, which replicate the communal and advisory atmosphere found in physical stores. By weaving these social and interactive elements into the online experience, retailers can make digital shopping feel more personal, trustworthy, and emotionally engaging, transforming it from a purely transactional process into a socially connected retail journey.

7.3.2 Implementation Strategies for FMCG Retailers and Digital Platform Providers

Building on the empirical findings of this study, which demonstrate that non-adoption of online FMCG shopping is largely driven by distrust, perceived risk, effort expectancy, digital illiteracy, and perceived lack of reciprocity, it is imperative that FMCG retailers and digital platform providers move beyond generic recommendations and adopt targeted operational strategies. These strategies must directly address the specific cognitive, behavioural, and structural barriers identified, thereby facilitating the transition from non-adoption to active participation.

i. Risk Reduction and Trust Assurance Mechanisms

Given the strong prevalence of distrust in online payment systems and platforms, retailers must prioritise mechanisms that reduce perceived risk and build initial consumer confidence. Practical interventions include the introduction of cash-on-delivery options, first-time user guarantees, and money-back assurances, which lower the perceived financial and performance risks associated with trial. In addition, platforms should prominently display secure payment badges, encryption certifications, and trusted third-party partnerships to signal credibility. These measures are essential in converting abstract notions of security into visible and tangible assurances, thereby addressing the trust deficit that discourages initial adoption.

ii. Platform Usability and Accessibility Enhancement

The findings indicating high levels of negative effort expectancy and digital illiteracy suggest that many non-adopters perceive online shopping platforms as complex and difficult to use. To mitigate this, retailers must invest in user-centric design principles, ensuring that platforms are intuitive, simple to navigate, and optimised for mobile devices. Features such as guest checkout, step-by-step onboarding tutorials, and multilingual interfaces can significantly reduce cognitive effort and improve accessibility. Additionally, simplifying the purchasing process by minimising the number of steps required to complete a transaction can enhance ease of use, particularly for first-time users and digitally inexperienced consumers.

iii. Enhancing Reciprocity through Value-Based Personalisation

The perception of a lack of reciprocity highlights the need for retailers to demonstrate a fair and transparent value exchange. Consumers must perceive that the data they provide results in meaningful benefits. To achieve this, retailers should implement data-driven personalisation strategies, including tailored promotions, personalised product recommendations, and loyalty reward programmes. Importantly, these benefits should be communicated clearly and delivered consistently to reinforce trust and fairness. By doing so, retailers align their practices with the principles of reciprocal exchange, thereby transforming consumer perceptions from exploitation to mutual benefit.

iv. Improving Delivery Reliability and Transparency

Concerns regarding delivery reliability remain a significant deterrent to online FMCG shopping. Retailers must therefore invest in efficient and transparent logistics systems that enhance both actual and perceived reliability. This includes providing real-time order tracking, flexible delivery scheduling, and accurate delivery time windows. Furthermore, implementing clear and user-friendly return and refund policies can reduce uncertainty and build consumer confidence in the service. Ensuring product quality upon delivery, particularly for perishable goods, is also critical in reinforcing trust and encouraging repeat engagement.

v. Embedding Visible Trust Signals across Digital Touchpoints

Trust must be consistently communicated throughout the consumer journey. Retailers should embed visible trust signals across all digital interfaces, including verified customer reviews, ratings, testimonials, and transparent policy disclosures. These elements serve as social proof and reduce uncertainty by providing reassurance from other users' experiences. Additionally, clear communication regarding privacy policies, data usage, and transaction security can further strengthen consumer confidence. The consistent presence of such signals transforms trust from a conceptual expectation into a continuous and observable experience.

vi. Enhancing Social Presence and Customer Engagement

The lack of social presence identified in the study suggests that online shopping is often perceived as impersonal and isolating. To address this, retailers must incorporate interactive and engagement-driven features that replicate elements of the in-store experience. This can be achieved through live chat support, WhatsApp-based customer service, and AI-assisted interaction tools that provide immediate assistance. Moreover, encouraging user-generated content, such as reviews, ratings, and product discussions, can foster a sense of community and social interaction. These strategies not only enhance engagement but also reduce psychological distance between the consumer and the platform.

The roadmap for converting non-adopters is clear: build trust first, demand adoption later. Overcoming the trust deficit that characterises the South African e-commerce landscape requires a concerted, multi-stakeholder approach. Retailers must pivot to prioritise security, transparency, and human connection as their primary market offerings, while policymakers must work to create a safer and more educative regulatory environment. By implementing these evidence-based recommendations, stakeholders can begin to dismantle the real barriers to adoption and unlock the significant economic potential of the non-adopter market.

7.3.3 For policymakers and regulatory bodies

For policymakers and regulatory bodies, the findings underscore that fostering e-commerce growth requires creating an environment of institutional trust that protects consumers and empowers them to participate confidently. The high perceived risk of fraud demands a robust public-sector response, including strengthening the Consumer Protection Act (CPA) and Protection of Personal Information Act (POPIA) to explicitly and effectively govern online interactions, transactions and disputes, and enhancing the capacity and public visibility of cybercrime units to both prosecute offenders and reassure the public (SABRIC 2023).

Beyond implementation, there is a critical need to reframe national digital literacy initiatives to address the specific barriers identified in this study. Rather than focusing solely on basic internet skills, programmes should advance towards ‘e-commerce literacy, educating citizens on how to evaluate platform credibility, understand secure payment protocols, and exercise their rights as online consumers. Such targeted education, ideally delivered in partnership with trusted e-commerce brands and community organisations, can help transform the prevailing narrative of risk into one of empowered participation, directly addressing the rational rejection model evidenced by the data (Selwyn 2006; van Deursen and van Dijk 2019).

7.4 LIMITATIONS AND FUTURE RESEARCH

While this study provides significant insights into the drivers of FMCG e-commerce non-adoption in South Africa, its findings must be considered within the context of its limitations, which also present valuable avenues for future scholarly inquiry.

A primary limitation is the study's cross-sectional design, which provides a snapshot of non-adoption intentions at a single point in time. This design captures perceptions and attitudes but cannot definitively establish causality or observe how these relationships might evolve as the e-commerce landscape matures or after individuals gain direct experience (Malhotra, Nunan and Birks 2017). Future studies should adopt longitudinal designs to examine how non-adopters' perceptions and trust evolve as they gain experience with online grocery platforms. For example, research could explore whether positive transactional experiences reduce initial distrust or whether negative experiences reinforce non-adoption. Such longitudinal work could provide stronger causal insights and inform dynamic intervention strategies.

Furthermore, the data relied on self-reported measures from a sample identified as non-adopters. This approach risks potential biases, including social desirability bias, where participants might overstate their concerns to align with perceived social norms, or recall bias, where their stated reasons for non-adoption may be post-hoc rationalisations rather than genuine drivers (Podsakoff *et al.* 2003). Future research could triangulate data collection by combining self-reports with observational or behavioral data, such as platform usage logs or purchase histories, to more accurately capture adoption barriers. Experimental designs could also simulate online shopping scenarios to observe behavioral responses in controlled settings.

The exclusion of the Poor Promotional Effort (PPE) construct due to insufficient reliability (CR = 0.678, AVE = 0.413) represents another limitation. Its removal suggests either a measurement issue or that the construct itself may not be a salient barrier for this specific population (Hair *et al*. 2018; Hair, Page and Brunsveld 2020). However, it leaves a gap in understanding the potential role of marketing and awareness campaigns in non-adoption. Future research should refine the PPE construct using qualitatively informed indicators, such as consumer perceptions of ad relevance, messaging clarity, and channel effectiveness (Clow & Baak, 2021). Comparative studies could also evaluate the impact of promotional strategies across different socio-economic and cultural groups within South Africa to identify context-specific best practices.

The findings highlight the importance of trust, reciprocity, and perceived exploitation in non-adoption decisions. Future studies could incorporate additional constructs to extend the Trust-Mediated Model of Non-Adoption, such as:

- Digital literacy and technological self-efficacy: Understanding whether skills or confidence in using digital platforms moderate adoption intentions.
- Cultural and social norms: Investigating how familial, community, or peer expectations influence trust formation and non-adoption.
- Perceived risk dimensions: Exploring financial, privacy, and security concerns more deeply to capture nuanced deterrents to adoption.
- Environmental and ethical concerns: Assessing whether sustainability preferences or social responsibility perceptions affect e-commerce engagement.

The quantitative design of this study provides generalizable patterns but limits understanding of deeper motivations. Future research should use qualitative methods, such as in-depth interviews, focus groups, or ethnographic observations, to explore:

- The cultural and sub-cultural basis of reciprocity expectations.
- How non-adopters interpret fairness, exploitation, and trust in e-commerce interactions.
- The rituals, processes, and experiences that might foster trust in high-risk environments (Creswell & Poth, 2024).

Integrating qualitative insights with quantitative modeling would yield a richer, culturally grounded understanding of non-adoption and allow the development of more effective, targeted interventions.

Future studies could examine differences in non-adoption across specific online grocery platforms, mobile apps, and social commerce channels. Comparative research could identify whether barriers are universal or platform-specific, providing actionable guidance for retailers in customizing trust-building and promotional strategies.

7.5 CONCLUSION

This study investigated the factors influencing the non-adoption of online shopping for FMCG among South African consumers, using a post-positivist, quantitative research approach. The research was grounded in an integrated theoretical framework that combined an inverted UTAUT with inverted SET, TTT, and SPT. By adopting this multi-theoretical lens, the study shifted focus from traditional adoption drivers to the psychological, relational, and social barriers that deter consumers from engaging with online FMCG platforms. The investigation revealed that trust-related factors such as perceived lack of reciprocity, distrust in online payment systems, and lack of social presence were the primary drivers of non-adoption, rather than utilitarian or technological concerns.

The thesis was structured into seven chapters to systematically address the research problem. Chapter One provided an overview of the study, including the background, problem statement, research questions, objectives, scope, and a preliminary summary of findings. Chapter Two reviewed the literature on online shopping, highlighting both global and local perspectives and foregrounding the underexplored phenomenon of non-adoption. Chapter Three developed the integrated theoretical framework and hypotheses, articulating how negative UTAUT constructs, technophobia, trust, social exchange, and social presence interact to influence FMCG online shopping reluctance. Chapter Four detailed the research methodology, including the rationale for the post-positivist paradigm, quantitative survey design, sampling strategy, data collection via online questionnaires, and analysis using SEM. Chapter Five presented and interpreted the empirical results, confirming that distrust and social exchange concerns significantly predicted non-adoption, while traditional technological barriers had limited impact. Chapter Six discussed these findings in the context of existing literature, highlighting theoretical and practical implications and offering recommendations for enhancing trust and engagement in online FMCG retail.

Finally, Chapter Seven summarised the contributions of the study, acknowledged limitations, and proposed actionable strategies for FMCG online retailers, policymakers, and highlighted the need for future research. The study contributes both theoretically and practically by providing a comprehensive explanation of non-adoption in the South African FMCG e-commerce context. It demonstrates that overcoming reluctance requires more than improving convenience or usability; retailers must prioritise trust-building, transparent value exchange, secure payment systems, and humanised digital experiences. By addressing these barriers, e-commerce platforms can foster consumer confidence, reduce resistance, and promote inclusive participation in South Africa’s growing digital retail economy. Ultimately, the study concludes that trust is the currency of online FMCG adoption. Efforts to promote inclusivity in South Africa’s digital commerce landscape must therefore begin with rebuilding and reinforcing consumer trust rather than assuming that technological access alone will translate to adoption. The findings not only bridge a critical theoretical gap but also provide a pragmatic framework for transforming non-adopters into active online consumers. This framework, if applied strategically, can support retailers in designing trust-oriented digital ecosystems that align with local consumer psychology, thereby accelerating the equitable digital transformation of South Africa’s retail economy.

REFERENCES

Aaronson, S.A. and Struet, T. 2020. Data Is Divisive: A History of Public Communications on E-commerce, 1998–2020. *The Centre for International Governance Innovation (CIGI) Papers No. 247*.

Abad, V.M., Jiménez, P.M. and González, Q.C. 2022. E-Commerce, social media and Social Inclusion: A Typology of Users Over 60 Years of Age in Spain. *Communication & Society,* 35(3): 141-154f

Abrahão, R. de S., Moriguchi, S. N. and Andrade, D. F. 2016. Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT), *RAI Revista de Administração e Inovação,* 13(3): 221–230.

Abu-AlSondos, I., Alkhwaldi, A., Salhab, H., Shehadeh, M. and Ali, B. 2023. Customer attitudes towards online shopping: A systematic review of the influencing factors. *International Journal of Data and Network Science*, 7(1): 513–524.

Abutabenjeh, S. and Jaradat, R. 2018. Clarification of research design, research methods, and research methodology: A guide for public administration researchers and practitioners. *Teaching Public Administration,* 36(3): 237-258.

Aguinis, H., Gottfredson, R.K. and Joo, H. 2013. Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, 16(2): 270-301.

Ahad, N.A., Yin, T.S., Othman, A.R. and Yaacob, C.R. 2011. Sensitivity of normality tests to non-normal data. *Sains Malaysiana*, 40(6): 637-641.

Ahmad, R., Nawaz, M.R., Ishaq, M.I., Khan, M.M. and Ashraf, H.A. 2023. Social exchange theory: Systematic review and future directions. *Frontiers in Psychology*, 13: 1015921.

Ahmed, S.K. 2024. How to choose a sampling technique and determine sample size for research: A simplified guide for researchers? O*ral Oncology Reports,* 12, 100662.

Aivazpour, Z. and Rao, V.S. 2020. Information disclosure and privacy paradox: the role of impulsivity. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 51(1): 14-36.

Ajzen, I. 2020. The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, 2(4): 314-324.

Ajzen, I. 1991. The theory of planned behavior. *Organization and Human Decision Process,* 50, 179–211.

Ajzen, I. 1985. From intentions to actions: A theory of planned behavior. In J. Kuhl & J.

Ajzen, I. and Fishbein, M. 1980. *Understanding attitudes predicting social behavior*. Englewood Cliffs, NJ: Prentice Hall.

Alamgir Hossain, M. and Quaddus, M. 2012. Antecedents Of Continuance Intention Of RFID Technology In Western Australian Farms.

Alao, O.D., Joshua, J.V., Adebayo, A.O., Agbaje, M.O., Onanuga, G.A. and Abereowo, O. 2016. Adaptive multiple user-device interface generation for websites. *International Journal of Computer Science and Mobile Computing*, 5(9): 199-206.

Albugami, M.A. and Zaheer, A. 2023. Measuring e-commerce service quality for the adoption of online shopping during COVID-19: Applying unified theory and use of technology model (UTAUT) Model Approach. *International Journal of Technology*, *14*(4): 705-712.

Allanson, P.E. and Notar, C.E. 2020. Statistics as measurement: 4 scales/levels of measurement. *Education Quarterly Reviews*, 3(3): 375-385.

Allison, P.D. 2012. *Logistic regression using SAS: Theory and application*. 2nd ed. Cary, NC: SAS Institute.

Ameen, N., Tarhini, A., Shah, M.H., Madichie, N., Paul, J. and Choudrie, J. 2021. Keeping customers' data secure: A cross-cultural study of cybersecurity compliance among the Gen-Mobile workforce. *Computers in Human Behavior*, *114*:106531.

Asma, S. and Afreen, A. 2022. The antecedents of Instagram store purchase intention: Exploring the role of trust in social commerce. *Vision*, 0(0). Available: https://doi.org/10.1177/09722629221133887. (Accessed 03 January 2024).

Anderson, J.C. and Gerbing, D.W. 1984. The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. *Psychometrika*, 49(2): 155-173.

Ang, C. 2021. *Timeline: Key Events in the History of Online Shopping*. Available: https://www.visualcapitalist.com/sp/history-of-online-shopping/ (Accessed 01 June 2024).

Angamuthu. R. 2020. A Study on Online Shopping in India – An Overview. *International Journal of Research and Analytical Reviews (IJRAR),* 7(1): 676-682.

Antwi, S.K. and Hamza, K. 2015. Qualitative and quantitative research paradigms in business research: A philosophical reflection. *European Journal of Business and Management*, 7(3): 217-225.

Arcuri, M.C., Brogi, M. and Gandolfi, G. 2017. Cyber risk: A big challenge in developed and emerging markets. In: *Identity Theft: Breakthroughs in Research and Practice.* 292-307. IGI Global Scientific Publishing.

Asiedu, R. O. and Dube, F. N. 2020. Antecedents of Chinese Consumer' Online Shopping Behaviour. *Asian Journal of Business Research,* 10(2): 91–110.

Astivia, O.L.O. and Zumbo, B.D. 2019. Heteroskedasticity in multiple regression analysis: What it is, how to detect it and how to solve it with applications in R and SPSS. *Practical Assessment, Research & Evaluation*, 24(1): 1.

Attuquayefio, S. and Addo, H. 2014. Using the UTAUT model to analyze students' ICT adoption. *International Journal of Education and Development using ICT,* 10(3): 75–86.

Ajzen, I. 1991. The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2): 179-211.

Babbie, E.R. 2020. *The practice of social research*. New York: Cengage Au.

Baethge, C., Klier, J., Klier, M. and Lindner, G. 2017. Customers' influence makes or breaks your brand's success story–quantifying positive and negative social influence in online customer networks. In *International Conference on Information Systems (ICIS)* 1-20. Association for Information Systems (AIS).

Bagozzi, R.P. and Yi, Y. 2012. Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science,* 40: 8-34.

Ball, H.L. 2019. Conducting online surveys. *Journal of Human Lactation*, 35(3): 413-417.

Banaji, J. 2020. *A brief history of commercial capitalism*. Haymarket books.

Bandara, R., Fernando, M. and Akter, S. 2020. Addressing privacy predicaments in the digital marketplace: A power-relations perspective. *International Journal of Consumer Studies,* 44(5): 423–434.

Bandura, A. 1999. A social cognitive theory of personality. In: Pervin, L. and John, O. eds.. *Handbook of personality. Theory and Research,* 2nd ed. New York, Guildford Publications 154–196.

Barth, S. and De Jong, M. D. 2017. The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review. *Telematics and Informatics,* 34(7): 1038–1058.

Batada, I. 2021. Modeling online shopping behaviour during COVID-19 using the TOE framework. *ABAC Journal*, *41*(3): 46.

Batterton, K.A. and Hale, K.N. 2017. The Likert scale what it is and how to use it. *Phalanx,* 50(2), 32-39.

Beaunoyer, E., Dupéré, S. and Guitton, M. J. 2020. COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies. *Computers in human behavior,* 111: 106424.

Becker, J.M., Cheah, J.H., Gholamzade, R., Ringle, C.M. and Sarstedt, M. 2022. PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, 35(1): 321-346.

Behera, R.K., Bala, P.K. and Rana, N.P. 2023. Assessing factors influencing consumers' non-adoption intention: exploring the dark sides of mobile payment. *Information Technology & People*, *36*(7): 2941-2976.

Belch, G.E. and Belch, M.A. 2016. *Advertising & promotion*. The McGraw-Hill/Irwin Series i Marketing.

Bellamy, C., 2012. Types of research design. In: *Principles of methodology: Research design in docial dcience.* London: SAGE Publications Ltd. 69-83.

Belinda, B. and Peat, J. 2014. *Medical statistics: a guide to SPSS, data analysis, and critical appraisal.* 2nd ed. Chichester: Wiley.

Benson, L.G. and Ndoro, T.T. 2022. An investigation into online shopping cart abandonment in South Africa. International Review of Management and Marketing, 12(3): 26.

Bentler, P.M. and Bonett, D.G., 1980. Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88(3): 588-606. Available: https://doi.org/10.1037/0033-2909.88.3.588 (Accessed 22 February 2025).

Bentler, P.M. 1990. Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2): 238-246.

Bernard, H.R. 2011. *Research methods in anthropology: Qualitative and quantitative approaches.* 5th ed. New York: Altamira Press.

Bianchi, C. and Andrews, L. 2012. Risk, trust, and consumer online purchasing behaviour: a Chilean perspective. *International Marketing Review,* 29(3): 253–275.

Biocca, F., Harms, C. and Burgoon, J.K. 2003. Toward a more robust theory and measure of social presence: Review and suggested criteria. *Presence: Teleoperators & Virtual Environments,* 12(5): 456-480.

Black, G.S. 2005. Predictors of consumer trust: likelihood to pay online. *Marketing Intelligence & Planning*, 23(7): 648-658.

Blau, P. 1964. (republished in 2017). *Exchange and power in social life*. New York: Routledge.

Boateng, S.L. and Boateng, R. 2014. Philosophical Debates in Marketing and the Application of Critical Realism to Online Relationship Marketing. In Boateng, S.L. (eds.) *Chapter 2 (in print) Essays from my PhD*, Pearl Richards Foundation. Available: http://dx.doi.org/10.2139/ssrn.2393044. (Accessed 03 March 2024).

Bollen, K.A. and Stine, R.A. 1992. Bootstrapping goodness-of-fit measures in structural equation models. *Sociological Methods & Research*, 21(2): 205-229.

Bollen, K.A. 1989. A new incremental fit index for general structural equation models. *Sociological Methods & Research*, 17(3): 303-316.

Bourdeau, M. 2022. Auguste Comte. In: Zalta, E.N. & Nodelman, U. eds. *Standford Encyclopedia of Philosophy* (Spring ed.) Available: https://plato.stanford.edu/archives/spr2023/entries/comte/. (Accessed 28 November 2024).

Bourg, L., Chatzidimitris, T., Chatzigiannakis, I., Gavalas, D., Giannakopoulou, K., Kasapakis, V., Konstantopoulos, C., Kypriadis, D., Pantziou, G. and Zaroliagis, C. 2023. Enhancing shopping experiences in smart retailing. *Journal of Ambient Intelligence and Humanized Computing*, *14*(12): 15705-15723.

Bonfanti, A., Vigolo, V., Vannucci, V. and Brunetti, F. 2023. Creating memorable shopping experiences to meet phygital customers' needs: evidence from sporting goods stores. *International Journal of Retail & Distribution Management*, *51*(13): 81-100.

Braun, S. and Osman, D. 2024. Online grocery shopping adoption versus non-adoption among the over-50s in Germany. *Electronic commerce research*, *24*(2): 825-862.

Brown, T.A. 2015. *Confirmatory factor analysis for applied research*. 2nd ed. New

York: The Guilford Press.

Browne, M.W. and Cudeck, R. 1993. Alternative ways of assessing model fit. In K.A. Bollen and J.S. Long (Eds.), *Testing structural equation models*. 136-162. Thousand Oaks, CA: Sage.

Bryman, A. 2016. *Social research methods*. 5th ed. London: Oxford University Press.

Bulacan, J.E., Milan, B.C. and Fernandez, R. 2022. Impact of price, time, trust, and convenience to Shopee consumers' online shopping behavior. *International Journal of Social and Management Studies*, 3(4): 34-47.

Bulsara, H.P. and Vaghela, P.S. 2020. Blockchain technology for e-commerce industry. *International Journal of Advanced Science and Technology*, 29(5): 3793-3798.

Burns, A.C., Bush, R.F. and Sinha, N. 2014. *Marketing research.* 7th ed. Harlow: Pearson.

Burns, A.C., Bush, R.F. and Veeck, A. 2014. *Marketing research.* 8th ed. Harlow: Pearson.

Burrell, G. and Morgan, G. 1979. *Sociological Paradigms and Organisational Analysis*. London: Heinemann Educational Books.

BusinessTech. 2022. *The explosive growth of e-commerce in South Africa*. Available: https://businesstech.co.za/news/business/568272/the-explosive-growth-of-e-commerce-in-south-africa/ (Accessed 16 June 2024).

Byrne, B.M. 1998. *Structural equation modeling with LISREL, PRELIS, and SIMPLIS: Basic concepts, applications, and programming*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Cabrera-Sánchez, J.P., Ramos-de-Luna, I., Carvajal-Trujillo, E. and Villarejo-Ramos, Á.F. 2020. Online recommendation systems: Factors influencing use in e-commerce. *Sustainability*, 12(21): 8888.

Cahyono, T.D. and Rizqi, R.M. 2024. The impact of digital marketing, financial literacy, and digital literacy on purchasing intent for online products. *Indonesian Business Review*, 7(2): 83-93.

Callegaro, M., Manfreda, K.L. and Vehovar, V. 2015. *Web survey methodology*. London: Sage Publications.

Carifio, J. and Perla, R. 2008. Resolving the 50-year debate around using and misusing Likert scales. *Medical Education,* 42(12): 1150-1152.

Celik, H. 2016. Customer online shopping anxiety within the Unified Theory of Acceptance and Use Technology (UTAUT) framework. *Asia Pacific Journal of Marketing and Logistics,* 28(2). Available: https://doi.org/10.1108/APJML-05-2015-0077 (Accessed 15 March 2022).

Cevik, F. and Koc, T. 2022. Building Trust in E-Commerce: A Practical Trust Guide for Evaluation. *Alphanumeric Journal,* 10(2): 167-184

Chaffey, D. and Ellis-Chadwick, F. 2019. Digital Marketing: Strategy and Implementation. Pearson Education.

Cham, T.H., Cheah, J.H., Cheng, B.L. and Lim, X.J. 2022. I Am too old for this! Barriers contributing to the non-adoption of mobile payment. *International Journal of Bank Marketing*, 40(5): 1017-1050.

Chang, H. H., Fu, C. S. and Jain, H. T. 2016. Modifying UTAUT and innovation diffusion theory to reveal online shopping behavior: Familiarity and perceived risk as mediators. *Information Development,* 32(5), 1757–1773. Available: https://doi.org/10.1177/0266666915623317 (Accessed 24 February 2023).

Chang, Y.S. and Fang, S.R. 2013. Antecedents and distinctions between online trust and distrust: Predicting high-and low-risk internet behaviors. Journal of Electronic Commerce Research, 14(2): 149.

Chen, Q. and Zhang, N. 2015. Does e-commerce provide a sustained competitive advantage? An investigation of survival and sustainability in growth-oriented enterprises. Sustainability, 7(2): 1411-1428.

Chen, L.R., Chen, F.S. and Chen, D.F. 2023. Effect of social presence toward livestream e-commerce on consumers' purchase intention. *Sustainability*, 15(4): 3571.

Chen, X., Huang, Q., Davison, R. M. and Hua, Z. 2015. What drives trust transfer? The moderating roles of seller-specific and general institutional mechanisms. *International Journal of Electronic Commerce,* 20(2): 261–289.

Chen, Y., Wu, J. and Chang, H. 2013, Examining the mediating effect of positive moods on trust repair in e-commerce, *Internet Research,* 23(3): 355-371. Available: https://doi.org/10.1108/10662241311331772 (Accessed 22 February 2023).

Chibvura, F.R., Doba, Y.G. and Mupamhanga, M.M. 2023. E-retailing as innovative entrepreneurship and enhancing employment creation: A case study of PLANET54. COM. In *Mbali Conference 2023 Proceedings*. 108.

Chou, C.P., Bentler, P.M. and Satorra, A. 1991. Scaled test statistics and robust standard errors for non-normal data in covariance structure analysis: a Monte Carlo study. *British Journal of Mathematical and Statistical Psychology*, 44(2): 347-357.

Clemes, M.D., Gan, C. and Zhang, J. 2014. An empirical analysis of online shopping adoption in Beijing, China. *Journal of Retailing and Consumer Services*, 21(3): 364-375.

Cloete, G. 2021. *The influence of personality traits on consumers' willingness to buy groceries online in South Africa*. Doctoral dissertation, Cape Peninsula University of Technology. Available: https://etd.cput.ac.za/handle/20.500.11838/3585 (Accessed 07 December 2024).

Cloete, E., Courtney, S. and Fintz, J. 2002. Small Businesses' Acceptance and Adoption of e-Commerce in the Western-Cape Province of South-Africa. The Electronic Journal of Information Systems in Developing Countries, 10(1): 1-13.

Cochran, W.G. 1977. *Sampling techniques,* 3rd ed. New York: John Wiley & Sons.

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*, 2nd ed. Hillsdale, NJ: Lawrence Earlbaum Associates.

Collis, J. and Hussey, R. 2021. *Business research: A practical guide for students*. Bloomsbury Publishing.

Cope, J. 2003. Entrepreneurial learning and critical reflection discontinuous events as triggers for 'higher-level' learning. *Management Learning,* 34(4): 429–450.

Copeland, L.R., Bhaduri, G. and Huang, O. 2023. Understanding Chinese Gen Z and their online shopping intentions through TAM. *Asia Pacific Journal of Marketing and Logistics*, 35(10): 2361–2376. Available: https://doi.org/10.1108/APJML-03-2022-0241. (Accessed 30 May 2022).

Cowling, N. 2024. *E-commerce in South Africa - statistics & facts.* Statista. Available: https://www.statista.com/topics/11038/e-commerce-in-south-africa/#topFacts. (Accessed 17 June 2024).

Creswell, J.W. and Poth, C.N. 2024. *Qualitative inquiry and research design: Choosing among five approaches,* 5th ed. London: Sage Publications.

Creswell, J.W. and Creswell, J.D. 2018. *Research design: Qualitative, quantitative, and mixed methods approaches*, 5th ed. London: Sage Publications.

Cuesta-Valino, P., Gutierrez-Rodriguez, P. and Garcia-Henche, B. 2022. Word of mouth and digitalization in small retailers: Tradition, authenticity, and change. *Technological Forecasting and Social Change*, *175*: 121382.

Cui, Y., Mou, J., Liu, Y. and Kurcz, K. 2018. Understanding cross-border m-commerce acceptance: An integration of commitment-trust theory and trust transfer theory. *Thirty Ninth International Conference on Information Systems*, San Francisco, California, 13-16 December. ISBN: 978-1-5108-8104-4

Culnan, M.J. and Armstrong, P.K. 1999. Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization science*, 10(1): 104-115.

Cummings, P. 2013. Missing data and multiple imputation. *JAMA Paediatrics*, 167(7): 656–661.

Dai, D.N., Stephens, P. and Si, Z. 2024. E-grocery as a new site of financialization? Financial drivers of the rise and fall of China's E-grocery sector. Food Security, 16(2): 471-485.

Đalić, I. and Terzić, S. 2021. Violation of the assumption of homoscedasticity and detection of heteroscedasticity. *Decision Making: Applications in Management and Engineering*, 4(1): 1-18.

Dang, H. L., Bao, N. V. and Cho, Y. C. 2023. Consumer Behavior Towards E-Commerce in the Post-COVID-19 Pandemic: Implications for Relationship Marketing and Environment. *Asian Journal of Business Environment,* 13(1): 9–19.

Dang, V. T. and Pham, T. L. 2018. An empirical investigation of consumer perceptions of online shopping in an emerging economy: Adoption theory perspective. *Asia Pacific Journal of Marketing and Logistics,* 30(4): 952–971.

Daoud, J.I. 2017. December. Multicollinearity and regression analysis. In: *Journal of Physics: Conference series*, 949(1): 012009. IOP Publishing.

Darke, P.R., Brady, M.K., Benedicktus, R.L. and Wilson, A.E. 2016. Feeling close from afar: The role of psychological distance in offsetting distrust in unfamiliar online retailers. *Journal of Retailing,* 92(3): 287-299.

Daroch, B., Nagrath, G. and Gupta, A. (2021). A study on factors limiting online shopping behaviour of consumers. *Rajagiri Management Journal*, 15(1): 39-52.

Das, K.R. and Imon, A.H.M.R. 2016. A brief review of tests for normality. *American Journal of Theoretical and Applied Statistics*, 5(1): 5-12.

Dastgeer, G., Rehman, A.U. and Rahman, W. 2012. Examining data and measurement model specification in SEM: An illustration from management development. *Journal of Business & Economics*, 4(1): 62-88.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly,* 13(3): 319–339.

Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. 1992. Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology,* 22: 1111–1132.

Deepika, S. 2016. A Study on Online Shopping Behaviour Among Working Women. *International Journal of Research in Finance and Marketing*, 6(1): 66-74.

Degutis, M., Urbonavičius, S., Hollebeek, L. D. and Anselmsson, J. 2023. Consumers' willingness to disclose their personal data in e-commerce: A reciprocity-based social exchange perspective. *Journal of Retailing and Consumer Services*, 74: 103385.

del Río, M.E. and Arroyo, D.R. 2024. Cultural Influences on Dynamic Pricing and Consumer Price Sensitivity in FMCG Industry. *Law and Economy*, *3*(8): 68-77.

Deng, W., Su, T., Zhang, Y. and Tan, C. 2021. Factors Affecting Consumers' Online Choice Intention: A Study Based on Bayesian Network. *Frontiers in Psychology, 12*: 731850.

Desmichel, P. and Kocher, B. 2020. Luxury single-versus multi-brand stores: The effect of consumers' hedonic goals on brand comparisons. *Journal of Retailing*, *96*(2): 203-219.

Dibal, N.P., Okafor, R. and Dallah, H. 2017. Challenges and implications of missing data on the validity of inferences and options for choosing the right strategy in handling them. *International Journal of Statistical Distributions and Applications*, 3(4): 87-94.

Dimoka, A. 2010. What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. *Mis Quarterly*, 373-396.

Djurica, D. and Figl, K. 2017. The effect of digital nudging techniques on customers' product choice and attitudes towards e-commerce sites. In: *Twenty-third Americas Conference on Information Systems*, Boston, Massachusetts, USA, 10-12 August 2017. Curan Associates, Inc.1-5.

Dludla, N. 2020. *South African e-commerce is a COVID-fired market of risk and reward.* Reuters. Available: https://www.reuters.com/article/idUSL8N2EF5RI/. (Accessed 14 April 2024).

Do Espírito Santo, P.M. and Trigo, A. 2020. Influence of website design on e-trust and positive word of mouth intentions in E-commerce fashion websites. In: *Information Systems: 17th European, Mediterranean, and Middle Eastern Conference, EMCIS 2020*, *Dubai, United Arab Emirates*, November 25–26, 2020, Proceedings. 316-330. Springer International Publishing.

Dobson, P. and Jackson, P. (2017). Using critical realism and reflexivity to explain broadband non-adoption in rural Australia. *Australasian Journal of Information Systems*, 21: 1-13.

Du Plessis, C. 2010. Mobile marketing communications to the youth: An analysis of the MXit platform. In: Marca,D.A., Shishkov, B. and van Sinderen, M. eds. *2010 International Conference on e-Business (ICE-B), IEEE*. Athens, Greece, 26 – 28 July. SciTePress, 1-9

Du, H. and Bentler, P.M., 2022. 40-Year old unbiased distribution free estimator reliably improves SEM statistics for nonnormal data. *Structural Equation Modeling: A Multidisciplinary Journal*, 29(6): 872-887.

Duong, N.T., Lin, H.H., Wu, T.L. and Wang, Y.S. 2025. Understanding consumer trust dynamics and purchase intentions in a multichannel live streaming e-commerce context: a trust transfer perspective. *International Journal of Human–Computer Interaction*, 41(14): 9123-9136.

Eger, L., Komárková, L., Egerová, D. and Mičík, M. 2021. The effect of COVID-19 on consumer shopping behaviour: Generational cohort perspective. *Journal of Retailing and Consumer Services,* 61: 102542.

Ekşioğlu, M., Varol, S. and Duman, Y. 2015. An investigation of user-experience design of e-commerce websites. In *Proc. The World Congress on Electrical Engineering and Computer Systems and Science.* 13-15 July, Barcelona, Spain. *(EECSS2015)*: 316-324.

Emerson, R. M. 1962. Power-dependence relations. *American Sociological Review,* 27(1): 31–41.

Erdmann, A., Yazdani, M., Mas Iglesias, J.M. and Marin Palacios, C. 2024. Pricing powered by artificial intelligence: An assessment model for the sustainable implementation of AI supported price functions. *Informatica*, 1-28.

Erjavec, J. and Manfreda, A. 2022. Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior. *Journal of Retailing and Consumer Services*, 65: 102867.

Erjavec, J. and Manfreda, A. 2021. Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior. *Journal of Retailing and Consumer Services, 65*: 102867–102867.

Ernst, A.F. and Albers, C.J. 2017. Regression assumptions in clinical psychology research practice-a systematic review of common misconceptions. *PeerJ,* 5: 3323

Fan, J., Zhou, W., Yang, X., Li, B. and Xiang, Y. 2019. Impact of social support and presence on swift guanxi and trust in social commerce. *Industrial Management & Data Systems,* 119(9), 2033-2054. Available: https://doi.org/10.1108/IMDS-05-2019-0293. (Accessed 13 June 2022).

Faqih, K.M. 2016. An empirical analysis of factors predicting the behavioral intention to adopt Internet shopping technology among non-shoppers in a developing country context: Does gender matter? *Journal of Retailing and Consumer Services,* 30: 140-164.

Farshid, M., Paschen, J., Eriksson, T. and Kietzmann, J. 2018. Go boldly! Explore augmented reality (AR), virtual reality (VR), and mixed reality (MR) for business. *Business horizons,* 61(5): 657-663.

Felix, R., Rauschnabel, P.A. and Hinsch, C. 2017. Elements of strategic social media marketing: A holistic framework. *Journal of Business Research,* 70: 118-126.

Fernando, J. G. and Jain, S. K. 2022. Digital illiteracy of teachers and its impact on online learning. *Technoarete Transactions on Applications of Information and Communication Technology (ICT) in Education*, 1(3): 1–6.

Field, A. 2024. *Discovering Statistics Using IBM SPSS Statistics*. 6th ed. London: SAGE Publications.

Fishbein, M. and Ajzen, I. 1975. *Belief, attitude, intention behavior. An introduction to theory and research*. Reading, MA: Addison-Wesley Publishing.

Fishbein, M. and Ajzen, I. 2010. *Predicting and changing behavior: The reasoned action approach*. New York: Psychology Press.

Flannelly, L.T., Flannelly, K.J. and Jankowski, K.R. 2014. Fundamentals of measurement in health care research. *Journal of Health Care Chaplaincy,* 20(2): 75-82.

Flora, D.B., Crone, G. and Bell, S.M. 2025. Effect Size Interpretation in Structural Equation Models. *Structural Equation Modeling: A Multidisciplinary Journal*, 1-8.

Fornell, C. and Larcker, D.F. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1): 39-50.

Fortes, N. and Rita, P. 2016. Privacy concerns and online purchasing behaviour: Towards an integrated model. *European Research on Management and Business Economics,* 22(3): 167–176.

Fouka, G. and Mantzorou, M. 2011. What are the major ethical issues in conducting research? Is there a conflict between the research ethics and the nature of nursing? *Health Science Journal,* 5(1): 3-14.

Frazier, G.L. and Rody, R.C. 1991. The use of influence strategies in interfirm relationships in industrial product channels. *Journal of Marketing,* 55(1): 52-69.

Fuyane, N. 2021. Research methodology choice dilemma: A conceptual note to emerging researchers. *International Journal of Business & Management studies,* 2(2): 29-43.

Gaoaketse, L., Ligaraba, N. and Chuchu, T. 2023. Factors influencing purchase intention of motor vehicles during the COVID-19 pandemic: An empirical study in South Africa. *International Journal of Research in Business and Social Science*, 12(3): 41–54. Available: https://doi.org/10.20525/ijrbs.v12i3.2429. (Accessed 11 October 2024).

Gauri, D.K., Jindal, R.P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J.R., Fogarty, J., Carr, S. and Howerton, E. 2021. Evolution of retail formats: Past, present, and future. *Journal of Retailing*, *97*(1): 42-61.

Gaskin, J. 2022. *Data Prep, Gaskination's StatWiki*, Available; https://statwiki.gaskination.com/index.php?title=Data_Prep. (Accessed 28 February 2025).

Gefen, D., Karahanna, E. and Straub, D.W. 2003. Trust and TAM in online shopping: An integrated model. *MIS quarterly*, 51-90.

Gefen, D. and Straub, D.W. 2004. Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services. *Omega,* 32(6): 407-424.

Giese, J. and Stabauer, M. 2022. Factors that influence cookie acceptance: Characteristics of cookie notices that users perceive to affect their decisions. In: *International Conference on Human-Computer Interaction*. Held Virtually, 26 June-1st July, 272-285. Cham: Springer International Publishing.

Goga, S., Paelo, A. and Nyamwena, J. 2019. *Online retailing in South Africa: an overview*. CCRED Working Paper No. 2. Available: SSRN: https://ssrn.com/abstract=3386008 (Accessed 16 June 2024).

Goretzko, D., Siemund, K. and Sterner, P. 2024. Evaluating model fit of measurement models in confirmatory factor analysis. *Educational and Psychological Measurement*, 84(1): 123-144.

Grimshaw, J., Campbell, M., Eccles, M. and Steen, N. 2000. Experimental and quasi-experimental designs for evaluating guideline implementation strategies. *Family practice, 17*(suppl_1): S11-S16.

Grossoehme, D.H. 2014. Overview of qualitative research. *Journal of Health Care Chaplaincy,* 20(3): 109-122.

Guba, E.G. and Lincoln, Y.S. 1994. Competing paradigms in qualitative research. In: Denzin, N.K. and Lincoln, Y.S. eds. *Handbook of qualitative research*. Thousand Oaks, CA: Sage Publications, 105–117.

Guba, E. G. (ed.) 1990. *The paradigm dialog*. Newbury Park, CA: Sage Publications.

Gunawan, R., Anthony, G. and Anggreainy, M.S. 2021. The effect of design user interface (UI) e-commerce on user experience (UX). In *2021 6th International Conference on New Media Studies*. Tangerang, Indonesia, 12-13 October. *(CONMEDIA)*: 95-98. IEEE.

Gunawardena, C.N. 1995. Social presence theory and implications for interaction and collaborative learning in computer conferences. *International Journal of Educational Telecommunications,* 1(2): 147-166.

Gunter, B., Nicholas, D., Huntington, P. and Williams, P. 2002. Online versus offline research: implications for evaluating digital media. *Aslib Proceedings,* 54(4): 229-239.

Guo, H., Liu, Y., Shi, X. and Chen, K. Z. 2020. The role of e-commerce in the urban food system under COVID-19: lessons from China. *China Agricultural Economic Review,* 13(2): 436–455.

Gupta, C.P., Kumar, V.V.R. and Khurana, A. 2024. Artificial Intelligence Application in E-Commerce: Transforming Customer Service, Personalization and Marketing. In: *2024 11th International Conference on Computing for Sustainable Global Development* (INDIACom), 10-16.

Hagtvedt, H. and Chandukala, S.R. 2023. Immersive retailing: The in-store experience. *Journal of Retailing*, *99*(4): 505-517.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. 2018. *Multivariate Data Analysis*. 8th ed. London: Cengage Learning.

Hair Jr, J., Page, M. and Brunsveld, N. 2020. *Essentials of business research methods*. 4th ed. New York: Routledge.

Hansen, D.S. 2021. *The Effects of Consumer Perceptions on Retailers' Brick-and-Mortar and E-Commerce Sales Segments*. Capella University.

Harpe, S.E. 2015. How to analyze Likert and other rating scale data. *Currents In Pharmacy Teaching and Learning*, 7(6): 836-850.

Hargittai, E. 2001. Second-level digital divide: Mapping differences in people's online skills. *First Monday* 7(4): 1-19.

Hassan, S., Rashid, R. and Li, F. 2015. Utilising Modified UTAUT to Understand Students' Online Shopping Behaviour: A Case of E-Retail Co-Operative Website in Malaysia. *Journal of Electronic Commerce In Organizationa,* 13: 74–90.

Hattie, J. 1985. Methodology review: assessing unidimensionality of tests and ltems. *Applied Psychological Measurement*, 9(2): 139-164.

Hayes, A.F. 2022. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach,* 3rd ed. New York: The Guilford Press.

Heale, R. and Twycross, A. 2015. Validity and reliability in quantitative studies. *Evidence-based nursing,* 18(3): 66-67.

Healey, N.M., Baron, S. and Ilieva, J. 2002. Online surveys in marketing research: pros and cons. *International Journal of Market Research*, 44(3): 361-382.

Hernández García, Á., Iglesias Pradas, S., Chaparro Peláez, J.J. and Pascual Miguel, F.J. 2011. Exploring the attitudes and intentions of non-shoppers in the acceptance of e-commerce. *Journal of Universal Computer Science*, 17(9): 1314-1328.

Hernández-García, Á., Iglesias-Pradas, S. and Urueña-López, A. 2013. A characterization of non-buyers in B2C E-commerce and the drivers to turn them into E-shoppers. In: *Information Systems, E-learning, and Knowledge Management Research*. Springer, Berlin, Heidelberg, 89–97.

Hew, J.J., Lee, V.H., Ooi, K.B. and Lin, B. 2016. Mobile social commerce: The booster for brand loyalty? *Computers in Human Behavior,* 59: 142-154.

Heyns, G. J. and Kilbourn, P. J. 2022. Online shopping behaviour and service quality perceptions of young people in South Africa: A COVID-19 perspective. *Journal of Transport and Supply Chain Management* 16(0): a777. Available: https://doi.org/10.4102/jtscm.v16i0.777 (Accessed 19 August 2024).

Higueras-Castillo, E., Liébana-Cabanillas, F. J. and Villarejo-Ramos, Á. F. 2023. Intention to use e-commerce vs physical shopping. Difference between consumers in the post-COVID era. *Journal of Business Research*, 157: 113622.

Homans, G. C. 1958. Social behavior as exchange. *American Journal of Sociology,* 63(6): 597–606.

Houston, L., Yu, P., Martin, A. and Probst, Y. 2020. Heterogeneity in clinical research data quality monitoring: a national survey. *Journal of Biomedical Informatics*, 108: 103491.

Hsu, M.H., Chang, C.M. and Chuang, L.W. 2015. Understanding the determinants of online repeat purchase intention and moderating role of habit: The case of online group-buying in Taiwan. *International Journal of Information Management*, 35(1): 45-56.

Hu, L.T. and Bentler, P.M. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1): 1-55.

Huang, Z. and Benyoucef, M. 2013. From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications,* 12(4): 246-259.

Humbani, M. and Wiese, M. 2019. An integrated framework for the adoption and continuance intention to use mobile payment apps. *Marketing,* 37(2): 646-664.

Humphreys, L. 2013. Mobile social media: Future challenges and opportunities. *Mobile Media & Communication,* 1(1), 20-25. Available: https://doi.org/10.1177/2050157912459499 . Accessed 01 January 2025).

Hungilo, G. G. and Setyohadi, D. B. 2020. Factors influencing acceptance of online shopping in Tanzania using UTAUT2. *Journal of Internet Banking and Commerce,* 25(1): 1–23.

Iglesias-Pradas, S., Pascual-Miguel, F., Hernández-García, Á. and Chaparro-Peláez, J. 2013. Barriers and drivers for non-shoppers in B2C e-commerce: A latent class exploratory analysis. *Computers in Human Behavior,* 29(2): 314–322.

Imran, M., Asif, M. and Sajjad, W. 2022. Impact of employment status on online shopping preferences: A case study of women in Rawalpindi. *Journal of Business Insight and Innovation*, 1(1): 19-28.

In'nami, Y. and Koizumi, R. 2013. Review of sample size for structural equation models in second language testing and learning research: A Monte Carlo approach. *International Journal of Testing,* 13(4): 329-353.

Innes, M., Roberts, C., Preece, A. and Rogers, D. 2016. Of Instruments and Data: Social Media Uses, Abuses and Analysis. In: N.G. Fielding, R.M. Lee and G. Blank (eds.). *The SAGE Handbook of Online Research Methods*. 2nd ed. Los Angeles: SAGE Publications.

International Trade Administration. 2024 *Annual Performance Plan 2024*. Pretoria: ITAC. Available: https://www.thedtic.gov.za/wp-content/uploads/ITAC-on-its-APP-2023-24-final.pdf. (Accessed 24 May 2025).

Iofrida, N., De Luca, A.I., Strano, A. and Gulisano, G. 2018. Can social research paradigms justify the diversity of approaches to social life cycle assessment? *The International Journal of Life Cycle Assessment,* 23: 464-480.

Isharyani, M.E., Sopha, B.M., Wibisono, M.A. and Tjahjono, B. 2024. Retail technology adaptation in traditional retailers: A technology-to-performance chain perspective. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1): 100204.

Jacoby, J. and Kaplan, L. B. 1972. The components of perceived risk. Paper read at the *Annual Conference of the Association for Consumer Research*. Chicago, Illinois. 382–393.

Jamieson, S. 2004. Likert scales: How to (ab)use them. *Medical Education,* 38: 1212–1218.

Jiang, C., Rashid, R.M. and Wang, J. 2019. Investigating the role of social presence dimensions and information support on consumers' trust and shopping intentions. *Journal of Retailing and Consumer Services,* 51: 263-270.

Johnson, E.K. and Hong, S.C. 2023. Instagramming social presence: A test of social presence theory and heuristic cues on Instagram sponsored posts. *International Journal of Business Communication,* 60(2): 543-559.

Johnson, O. and Ramirez, S. A. 2020. The influence of showrooming on Millennial generational cohorts online shopping behaviour. *International Journal of Retail & Distribution Management,* 49(1): 81–103.

Jöreskog, K.G. 1973. Analysis of covariance structures. In: *Multivariate analysis–III*, 263-285. Academic Press.

Jöreskog, K.G., and Sörbom, D. 1984. *USREL VI users guide* (3rd ed.). Moorsvilfe, IN: Scientific Software

Joseph, R.C. 2005. To adopt or not to adopt-that is the question. In: *Proceedings of the Eleventh Americas Conference on Information Systems*, Omaha, NE, USA 11th – 14th August 2005.

Joubert, Y.T.H. and Erdis, C. 2019. Influence of retailers' website system quality factors on online shopping in South Africa. African Journal of Science, Technology, Innovation and Development, 11(2): 211-221.

Joullié, J.E. 2016. The philosophical foundations of management thought. *Academy of Management Learning & Education,* 15(1): 157-179.

Kakkar, S. and Monga, V. 2017. A Study on Artificial Intelligence in Ecommerce. *International Journal of Advances in Engineering & Scientific Research*, 4(4): 62-68.

Kang, H. 2013. The prevention and handling of the missing data. *Korean Journal of Anesthesiology*, 64(5): 402-406.

Kankam, P.K. 2019. The use of paradigms in information research. *Library & Information Science Research,* 41(2): 85-92.

Kaplan, A. D., Kessler, T. T. and Hancock, P. A. 2020. How Trust is Defined and its Use in Human-Human and Human-Machine Interaction. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* 64(1): 1150–1154. Available: https://doi.org/10.1177/1071181320641275. (Accessed 10 July 2023).

Karunasingha, A. and Abeysekera, N. 2022. The mediating effect of trust on consumer behavior in social media marketing environments. *South Asian Journal of Marketing,* 3(2): 135–149.

Katrodia, A. 2023. Consumer buying behaviour post and pre COVID analysis-specific reference to South Africa. *International Journal of Business and Economic Development (IJBED)*, *11*(1).

Katta, R.M. and Patro, C.S. 2016. Online Shopping Behavior: A Study of Factors Influencing Consumer Satisfaction on Online viz-a-viz Conventional Store Shopping. *International Journal of Sociotechnology and Knowledge Development*, 8(4): 21-36.

Kemp, S. 2024. *Digital 2024: South Africa. DataReportal*. Available: https://datareportal.com/reports/digital-2024-south-africa (Accessed 17 June 2024).

Khan, K. and Nikov, A. 2011. A mixed-reality-oriented eCommerce customer interface. In *Proceedings of the European Computing Conference*. 152-157.

Khan, I., Hollebeek, L.D., Fatma, M., Islam, J.U. and Riivits-Arkonsuo, I. 2020. Customer experience and commitment in retailing: does customer age matter? *Journal of Retailing and Consumer Services*, *57*: 102219.

Khan, N., Hassan, A.U., Fahad, S. and Naushad, M. 2020. Factors affecting tourism industry and its impacts on global economy of the world. *Available at SSRN 3559353*.

Kibuacha, F. 2021. *E-Commerce in South Africa: The Growth, and the Future*. Available: https://www.geopoll.com/blog/e-commerce-south-africa/ (Accessed 16 June 2024).

Kim, J.H., Kim, M., Park, M. and Yoo, J. 2023. Immersive interactive technologies and virtual shopping experiences: Differences in consumer perceptions between augmented reality (AR) and virtual reality (VR). *Telematics and Informatics*, 77: 101936.

Kim, J.Y. 1998. Universal service and Internet commercialization: Chasing two rabbits at the same time. *Telecommunications Policy,* 22(4-5): 281-288.

Kim, D.J., Ferrin, D.L. and Rao, H.R. 2008. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2): 544-564.

Kim, Y., Rangel, J. and Colabianchi, N. 2024. Food environments and cardiovascular disease: evidence from the health and retirement study. *American Journal of Preventive Medicine*, *67*(2): 201-209.

King, D.B., O'Rourke, N. and DeLongis, A. 2014. Social media recruitment and online data collection: A beginner's guide and best practices for accessing low-prevalence and hard-to-reach populations. *Canadian Psychology/Psychologie canadienne,* 55(4): 240.

Kline, R.B. 2016. *Principles and Practice of Structural Equation Modeling*. 4th ed. London: Guilford Press.

Koch, J. 2025. *Top 5 Payment Processing Security Risks You Need to Know as a Business. DivergeIT®,* Available: https://www.divergeit.com/blog/payment-processing-security. (Accessed 06 July 2025).

Koch, J., Frommeyer, B. and Schewe, G. 2020. Online shopping motives during the COVID-19 pandemic – lessons from the crisis. *Sustainability,* 12(24): 10247.

Konakh, M.S. and Borinshteyn, Y.R. 2019. The essence and genesis of scientific knowledge: philosophical problems. *Perspectives. Socio-Political Journal, 4:* 11-19.

Koul, S. and Eydgahi, A. 2020. The impact of social influence, technophobia, and perceived safety on autonomous vehicle technology adoption. *Periodica Polytechnica Transportation Engineering*, 48(2):133-142.

Kuhn, T.S. 1962. *The structure of scientific revolutions*. Chicago: University of Chicago press

Kuhn, T.S. 1997. *The structure of scientific revolutions* (962): 3rd ed. Chicago: University of Chicago press.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R. and Kannan, P.K. 2016. From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing,* 80(1): 7-25.

Kuzon, W. M., Urbanchek, M. G. and McCabe, S. 1996. The seven deadly sins of statistical analysis. *Annals of Plastic Surgery,* 37: 265–272.

Kyriazos, T.A. 2018. Applied Psychometrics: Sample size and sample power considerations in factor analysis (EFA, CFA) and SEM in general. *Psychology,* 9: 2207 - 2230.

Laliberte, M., 2023. *A Brief History of Online Shopping*. Available: https://www.odmworld.com/blog/brief-history-of-online-shopping/(Accessed 01 June 2024).

Lari, A.H., Vaishnava, K. and Manu, K.S. 2022. Artificial intelligence in E-commerce: applications, implications and challenges. *Asian Journal of Management,* 13(3): 235-244.

Law, M., Kwok, R. and Ng, M. C. W. 2016. An extended online purchase intention model for middle-aged online users. *Electronic Commerce Research and Applications,* 20: 132–146.

Lawrence, J.E. and Tar, U.A. 2010. Barriers to e-commerce in developing countries. *Information, society and justice journal*, *3*(1): 23-35.

Lee, C. H. and Cranage, D. A. 2011. Personalisation–privacy paradox: The effects of personalisation and privacy assurance on customer responses to travel Web sites. *Tourism Management,* 32(5): 987–994.

Lee, S. M. and Lee, D. 2020. "Untact": a new customer service strategy in the digital age. *Service Business,* 14(1): 1–22.

Lee, S.J., Ahn, C., Song, K.M. and Ahn, H. 2018. Trust and distrust in e-commerce. *Sustainability*, 10(4): 1015.

Leedy, P. and Ormrod, J. E. 2014. *Practical Research Planning and Design,* 10th ed. Edinburgh: Pearson Educational Inc.

Leong, L.Y., Hew, T.S., Ooi, K.B. and Wei, J. 2020, Predicting mobile wallet resistance: a two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management,* 51: 102047.

Leong, T. K. and Meng, T. P. 2022. Antecedents of trust and its impact on online social shopping purchase intention based on social exchange theory. *International Journal of Business and Technology Management, 4*(3): 20–38.

Letourneau, N. and Allen, M. 2006. Post-positivistic critical multiplism: A beginning dialogue. In: Cody, W.K. eds.*Philosophical and theoretical perspectives for advanced nursing practice*. 4th ed. London: Jones and Bartlett, Publishers.

Leys, C., Delacre, M., Mora, Y.L., Lakens, D. and Ley, C. 2019. How to classify, detect, and manage univariate and multivariate outliers, with emphasis on pre-registration. *International Review of Social Psychology*, 32(1): 1-10.

Leys, C., Klein, O., Dominicy, Y. and Ley, C. 2018. Detecting multivariate outliers: Use a robust variant of the Mahalanobis distance. *Journal of experimental social psychology, 74*: 150-156.

Li, C., Hou, Y. and Yu, Z. 2019. Research on data cleaning technology based on instance level. *Journal of Physics: Conference Series*, 1213(2): 022021. IOP Publishing.

Li, C.H. 2016. Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, 48: 936-949.

Lian, J.W. and Yen, D.C. 2014. Online shopping drivers and barriers for older adults: age and gender differences. *Computers in Human Behavior, 37*: 133–143.

Liana, E. and Noermijati, N. 2024. Determination of Management Science: Ontology, Epistemology and Axiology Perspectives. *International Journal of Advanced Multidisciplinary,* 3(3): 12-23.

Liao, C. H., Hsieh, J. K. and Kumar, S. 2023. Does the verified badge of social media matter? The perspective of trust transfer theory. *Journal of Research in Interactive Marketing*, (ahead-of-print).

Lincoln, Y.S., Lynham, S.A. and Guba, E.G. 2011. Paradigmatic controversies, contradictions, and emerging confluences, revisited. *The Sage Handbook of Qualitative Research,* 4(2): 97-128.

Lipka, A., Wiards, F.J., Markgraf, R., Zukowski, V.F. and Sonde, T.O. 2024. Experiences from transactions: the future of traditional retail stores (Doctoral dissertation, Dublin Business School).

Little, R.J. and Rubin, D.B. 2019. *Statistical analysis with missing data*. Chichester: John Wiley & Sons.

Liu, Y. and De, A. 2015. Multiple imputation by fully conditional specification for dealing with missing data in a large epidemiologic study. *International Journal of Statistics in Medical Research*, 4(3): 287.

Loeb, S., Dynarski, S., McFarland, D., Morris, P., Reardon, S. and Reber, S. 2017. *Descriptive analysis in education: A guide for researchers*. (NCEE 2017–4023). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance.

Lu, B., Fan, W. and Zhou, M. 2016. Social presence, trust, and social commerce purchase intention: An empirical research. *Computers in Human Behavior,* 56: 225-237.

Lüders, M. 2008. Conceptualizing personal media. *New Media & Society,* 10(5): 683-702. Available: https://doi.org/10.1177/1461444808094352 (Accessed 23 November 2022).

Luo, X. 2002. Trust production and privacy concerns on the Internet: A framework based on relationship marketing and social exchange theory. *Industrial marketing management,* 31(2): 111-118.

Made, R. N. and Nyoman, N. I. 2023. Digital literacy, privacy violation experience and the impact on online purchase intention. *Russian Journal of Agricultural and Socio-Economic Sciences,* 135(3): 35–41.

Makgetla, N. 2020. Inequality in South Africa: an overview. *Pretoria, South Africa: Trade and Industrial Policy Strategies, Working Paper*.

Mahroof, K. 2019. A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal of Information Management,* 45: 176-190.

Mainardes, E.W., de Souza, I.M. and Correia, R.D. 2020. Antecedents and consequents of consumers not adopting e-commerce. *Journal of Retailing and Consumer Services,* 55: 102138.

Makhitha, K.M., Van Scheers, L. and Mogashoa, C. 2019. Which consumer attributes influence South African consumers to shop online. *Journal of Business and Retail Management Research,* 13(4): 213-325.

Makhitha, M. and Dlodlo, N. 2014. Examining salient dimensions of online shopping and the moderating influence of gender: The case of students at a South African University. *Mediterranean Journal of Social Sciences,* 5(23): 1838-1848.

Maluleke, W., Motseki, M. M., Mokwena, R. J. and Dlamini, S. 2021. The modus operandi of perpetrators for credit card fraud in the Vaal Region, South Africa. *Cogent Social Sciences,* 7(1): 1930337.

Mani, Z. and Chouk, I. 2017. Drivers of consumers' resistance to smart products. *Journal of Marketing Management*, 33(1-2): 76-97.

Mann, C. L. 2000. Electronic Commerce in Developing Countries. *Washington DC: Institute for International Economics. Working Paper, 3*.

Marakalala, M.C. and Madzivhandila, A.C. 2025. An Overview of Forensic Investigators in the Investigation of Mobile Fraud: The Study Case of the South African Banking Industry. *OIDA International Journal of Sustainable Development*, 18(09): 99-110.

Margolis, M., 1999. Statistics for nominal and ordinal data. *Public administration and public policy*, 71: 207-226.

Marjanen, H., Kohijoki, A. M., Saastamoinen, K. and Engblom, J. 2019. Old dogs learning new tricks? The effect of age and generation on shopping behaviour. *The International Review of Retail, Distribution and Consumer Research,* 29(5): 549–567.

Marsden, J.R. and Pingry, D.E. 2018. Numerical data quality in IS research and the implications for replication. *Decision Support Systems*, 115: A1-A7.

Marsh, H.W. and Hau, K.T. 1996. Assessing goodness of fit: Is parsimony always desirable?. The journal of experimental education, 64(4): 364-390.

Martínez-Córcoles, M., Teichmann, M. and Murdvee, M. 2017. Assessing technophobia and technophilia: Development and validation of a questionnaire. *Technology in Society,* 51: 183-188.

Maseeh, H.I., Jebarajakirthy, C., Pentecost, R., Arli, D., Weaven, S. and Ashaduzzaman, M. 2021. Privacy concerns in e-commerce: A multilevel meta-analysis. *Psychology & Marketing*, 38(10): 1779-1798.

Mastercard. 2024. *SA online retail passes 6% of total retail*. Available: https://www.mastercard.com/news/eemea/en/newsroom/press-releases/en/2024/may/sa-online-retail-passes-6-of-total-retail/. (Accessed 25 October 2024).

Mayer, B., Muche, R. and Hohl, K. 2012. Software for the handling and imputation of missing data-An overview. *Journal of Clinical Trials, 2:* 103. doi:10.4172/jctr.1000103

Mawejje, J. 2024. Government expenditure, informality, and economic growth: Evidence from Eastern and Southern African countries. African Development Review, 36(1): 125-138.

McCrindle, M. and Fell. A. 2020. Understanding Generation Alpha. McCrindle Research. Available: https://generationalpha.com/wpcontent/uploads/2020/02/Understanding-Generation-Alpha-McCrindle.pdf. (Accessed 23 March 2023).

McKinsey & Company. 2020. *Survey: South African consumer sentiment during the coronavirus crisis.* Available: https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/survey-south-african-consumer-sentiment-during-the-coronavirus-crisis. (Accessed 12 April 2024.

McKnight, D.H. and Choudhury, V. 2006, August. Distrust and trust in B2C e-commerce: do they differ? In: Fox M.S. and Spencer B. ed. *Proceedings of the 8th international conference on electronic commerce: The new e-commerce: innovations for conquering current barriers, obstacles and limitations to conducting successful business on the internet*. Fredericton, New Brunswick, Canada, 13th-16th August. New York, NY, United States: Association for Computing Machinery, 482-491.

Mehrabian, A. and Russell, J. A. 1974. *An approach to environmental psychology*. Cambridge: The MIT Press.

Mehrabian, A. 1968. Some referents and measures of nonverbal behavior. *Behavior Research Methods & Instrumentation,* 1(6): 203-207.

Mehta, S., Saxena, T. and Purohit, N. 2020. The new consumer behaviour paradigm amid COVID-19: permanent or transient? *Journal of Health Management,* 22(2): 291–301.

Menard, S. 2011. *An introduction to logistic regression diagnostics*. 1st ed. Thousand Oaks: SAGE Publications Inc.

Mia, M.M., Majri, Y. and Rahman, I.K.A. 2019. Covariance based-structural equation modeling (CB-SEM) using AMOS in management research. *Journal of Business and Management*, 21(1): 56-61.

Mishra, P., Pandey, C.M., Singh, U. and Gupta, A. 2018. Scales of measurement and presentation of statistical data. *Annals of Cardiac Anaesthesia, 21*: 419-422.

Mishra, P., Pandey, C.M., Singh, U., Gupta, A., Sahu, C. and Keshri, A. 2019. Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, 22(1): 67-72.

Misra, P.K. and Verma, A. 2023. Consumer Satisfaction in shopping mall: A Sociological study in context of shopping mall attributes. *South Asian Journal of Social Sciences and Humanities*, *4*(5): 1-20.

Modak, A. and Mupepi, M.G. 2017. Dancing with WhatsApp: Small businesses pirouetting with social media. In *Conference Proceedings by Track (Vol. 51),* 2017 Midwest DSI Annual Conference, Grand Rapids, Michigan, 51-66.

Modjadji, M.M. 2025. *Bridging divides: tackling technological change, inequality, and digital illiteracy in a fragmented South Africa*. In: STG Policy Papers, Policy Brief Issue 2025/02. Florence School of Transnational Governance, EUI.

Moeti, M.N., Mokwena, S.N. and Malebana, D.D. 2021. The acceptance and use of online shopping in Limpopo province. *South African Journal of Information Management,* 23(1): 1-9.

Mofokeng, T. E. 2021. The impact of online shopping attributes on customer satisfaction and loyalty: Moderating effects of e-commerce experience. *Cogent Business & Management,* 8(1), 1968206.

Mohrman, S.A. and Lawler III, E.E. 2012. Generating knowledge that drives change. *Academy of Management Perspectives*, 26: 41-51.

Möller, K. and Halinen, A. 2022. Clearing the paradigmatic fog—how to move forward in business marketing research. *Industrial Marketing Management,* 102: 280-300.

Molm, L. D. 2003. Theoretical comparisons of forms of exchange. *Sociological theory,* 21(1): 1-17.

Molm, L. D., Takahashi, N. and Peterson, G. 2000. Risk and trust in social exchange: An experimental test of a classical proposition. *American Journal of Sociology,* 105(5): 1396–1427.

Moody, G.D., Galletta, D.F. and Lowry, P.B. 2014. When trust and distrust collide online: The engenderment and role of consumer ambivalence in online consumer behavior. *Electronic Commerce Research and Applications*, 13(4): 266-282.

Moon, J., Choe, Y. and Song, H. 2021. Determinants of consumers' online/offline shopping behaviours during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health,* 18(4): 1593.

Motseki, M. and Tseko, M. J. 2022. Exploring the challenges of forensic technology in responding to credit card fraud in Sedibeng Region, South Africa. *International Journal of Research in Business and Social Science (2147-4478),* 11(4): 205–212.

Mou, J., Shin, D. H. and Cohen, J. F. 2017. Trust and risk in consumer acceptance of e-services. *Electronic Commerce Research*, 17: 255–288.

Mtotywa, M.M. and Kekana, C. 2023. Post COVID-19 online shopping in South Africa: A mediation analysis of customer satisfaction on e-service quality and purchase intention. *African Journal of Science, Technology, Innovation and Development*, *15*(5): 533-546.

Munsch, A. 2021. Millennial and Generation Z digital marketing communication and advertising effectiveness: A qualitative exploration. J*ournal of Global Scholars of Marketing Science,* 31(1): 10–29.

Musasa, T. and Tlapana, T. 2023. Assessing the significance of retail service quality on shopping frequency: an adaptation of retail service quality (RSQS) model. *European Journal of Management Studies*, *28*(2): 135-147.

Musikavanhu, T. B. and Musakuro, R. N. 2023. Consumer adoption of online grocery shopping in South Africa. *South African Journal of Information Management*, 25(1): 1–14.

Nazzal, A., Thoyib, A., Zain, D. and Hussein, A.S. 2021. The influence of digital literacy and demographic characteristics on online shopping intention: An empirical study in Palestine. *The Journal of Asian Finance, Economics and Business*, 8(8): 205-215.

Nazzal, A., Thoyib, A., Zain, D. and Hussein, A. S. 2022. The Effect of Digital Literacy and Website Quality on Purchase Intention in Internet Shopping through Mediating Variable: The Case of Internet Users in Palestine. *Webology,* 19(1): 2414–2434.

Necula, S.C. and Păvăloaia, V.D. 2023. AI-Driven Recommendations: A Systematic review of the state of the art in E-Commerce. *Applied Sciences,* 13(9): 5531.

Nepomuceno, M.V., Laroche, M. and Richard, M.O. 2014. How to reduce perceived risk when buying online: The interactions between intangibility, product knowledge, brand familiarity, privacy and security concerns. *Journal of Retailing and Consumer Services,* 21(4): 619-629.

Nery-da-Silva, G., de Araujo, M.H. and de Souza Meirelles, F. 2024. Contributions to the segmentation of e-commerce nonusers: clustering the reasons not to shop online, *Revista de Gestão,* 31(2): 201-214.

Neuman, W.L., 2014. *Social research methods: Qualitative and quantitative approaches*. 7th ed. Harlow: Pearson Education.

Nevitt, J. and Hancock, G.R. 2001. Performance of bootstrapping approaches to model test statistics and parameter standard error estimation in structural equation modeling. *Structural Equation Modeling*, 8(3): 353-377.

Nguyen, D.H., De Leeuw, S., Dullaert, W. and Foubert, B.P. 2019. What is the right delivery option for you? Consumer preferences for delivery attributes in online retailing. Journal of Business Logistics, 40(4): 299-321.

Nigatu, W. G. and Atsbeha, B. W. 2021. The Challenges and Opportunities of E-Commerce in Ethiopia: A Review. *Academia Letters, November*. Available: https://doi.org/10.20935/AL3444 (Accessed 02 January 2025).

Nikou, S. and Aavakare, M. 2021. An assessment of the interplay between literacy and digital technology in higher education. *Education and Information Technologies,* 26(4): 3893–3915.

Nimrod, G. 2018. Technophobia among older Internet users. *Educational Gerontology,* 44: 148–162. Available: https://doi.org/10.1080/03601277.2018.1428145 (Accessed 28 March 2022).

Norman, G. 2010. Likert scales, levels of measurement and the "laws" of statistics, *Advances in Health Sciences Education* 15(5): 625–32.

Nunnally, J.C. and Bernstein, I.H. 1967. *Psychometric theory* (226). New York, NY: McGraw-Hill.

Nunnally, J.C. 1967. *Psychometric Theory*. New York: McGraw-Hill.

Nur, T. and Gosal, G. A. 2021. Mobile Payment Usage in Online Shopping among Gen Z in the JABODETABEK Area: META-UTAUT Approach. *2021 International Conference on Information Management and Technology.* Jakarta, Indonesia, 19-20 August., IEEE, 1: 464–469.

O'Brien, R.M. 2007. A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41(5): 673–690.

OECD. 2020a. *COVID-19 and the retail sector: impact and policy responses*, OECD Policy Responses to Coronavirus (COVID-19), OECD Paris, Available: http://www.oecd.org/coronavirus/policy-responses/covid-19-and-the-retail-sector-impact-and-policy-responses-371d7599/. (Accessed 10 April 2024).

OECD. 2020b. *OECD Policy responses to Coronavirus (COVID-19): E-commerce in the time of COVID-19.* Available: https://www.oecd.org/coronavirus/policy-responses/e-commerce-in-the-time-of-covid-19-3a2b78e8/#section-d1e102. (Accessed 10 April 2024).

Oematan, M.E., Rahayu, S. and Trisnawati, J.D. 2024. The effect of perceived usefulness and perceived ease of use on behavioral intention mediated by user satisfaction in e-commerce users. *Jurnal Ekonomi*, *13*(3): 472-479.

Oldest.org. 2023. *17 Oldest Internet Search Engines Ever*. Available: https://eqmindexes.com/wp-content/uploads/2017/01/EQM_OLR-Infographics.pdf. (Accessed 01 June 2024).

Oliveira, T., Alhinho, M., Rita, P. and Dhillon, G. (2017). Modelling and testing consumer trust dimensions in e-commerce. *Computers in Human Behavior,* 71: 153–164.

Olutade, E.O. 2024. An OLR Approach to the Impact of Social Media Platforms as Influencing Factor to Engaging Generation Y in Actual Purchase of Fast-Moving Consumer Goods: A Comparison of Two Sub-saharan African Countries. *Christopher University Journal of Management and Social Sciences*, 4(1): 258-270.

Omonedo, P. and Bocij, P. 2014. E-commerce versus m-commerce: Where is the dividing line. *International Journal of Social, Behavioural, Educational, Business and Industrial Engineering*, 8(11): 3610-3615.

Onwuegbuzie, A.J. and Collins, K.M. 2007. A typology of mixed methods sampling designs in social science research. *Qualitative report,* 12(2): 281-316.

Osei-Frimpong, K. and McLean, G. 2018. Examining online social brand engagement: A social presence theory perspective. *Technological Forecasting and Social Change,* 128: 10-21.

Osiceanu, M.E., 2015. Psychological implications of modern technologies: "technophobia" versus "technophilia". *Procedia-Social and Behavioral Sciences,* 180: 1137-1144.

Ozow. (n.d.). *Fraud within the payment industry in South Africa*. Available: https://ozow.com/white-paper/fraud-within-the-payment-industry-in-south-africa. (Accessed 05 April 2024).

Pace, D.S. 2021. Probability and non-probability sampling-an entry point for undergraduate researchers. I*nternational Journal of Quantitative and Qualitative Research Methods*, 9(2): 1-15.

Pallant, J.I., Pallant, J.L., Sands, S.J., Ferraro, C.R. and Afifi, E. 2022. When and how consumers are willing to exchange data with retailers: An exploratory segmentation. *Journal of retailing and consumer services*, 64: 102774.

Palvia, P. 2009. The role of trust in E-commerce relational exchange: A unified model. *Information & Management*, 46(4): 213-220, , Available: https://doi.org/10.1016/j.im.2009.02.003. (Accessed 12 June 2024).

Pandey, S., Mittal, S. and Chawla, D. 2024. Tackling consumer information asymmetry and perceived uncertainty for luxury re-commerce through seller signals. *Journal of Retailing and Consumer Services*, 79: 103736.

Pantano, E., Pizzi, G., Scarpi, D. and Dennis, C. 2020. Competing during a pandemic? Retailers' ups and downs during the COVID-19 outbreak. *Journal of Business Research*, 116: 209–213.

Parasuraman, A., Zeithaml, V. A. and Malhotra, A. 2005. ES-QUAL a Multiple-Item Scale for Assessing Electronic Service Quality. *Journal of Service Research,* 7(3): 213–233.

Park, S.J. and Yi, Y. 2022. Assessing moderator effects, main effects, and simple effects without collinearity problems in moderated regression models. *Journal of Business Research,* 145: 905-919.

Pentz, C. D., Du Preez, R. and Swiegers, L. 2020. To bu (Y) or not to bu (Y): Perceived risk barriers to online shopping among South African Generation Y consumers. *Cogent Business & Management,* 7(1): 1827813.

Pérez-Hernández, J. and Sánchez-Mangas, R. 2011. To have or not to have Internet at home: Implications for online shopping. *Information Economics and Policy,* 23(3-4): 213-226.

Pieterse, H. 2021. The cyber threat landscape in South Africa: A 10-year review. *The African Journal of Information and Communication*, 28: 1-21.

Pillay, E. and Mayayise, T. 2021. The significance of key constructs on consumer purchase intention in online retail in a Covid-19 climate. *African Conference on Information Systems and Technology,* 10: 1-16.

Ping, N.L., Hussin, A.R.C. and Ali, N.M. 2019. December. Constructs for artificial intelligence customer service in E-commerce. *In 2019 6th International Conference on Research and Innovation in Information Systems (ICRIIS).* Johor Bahru, Malaysia. 2-3rd December1-6.

Pino, G., Amatulli, C., Nataraajan, R., De Angelis, M., Peluso, A.M. and Guido, G. 2020. Product touch in the real and digital world: How do consumers react? *Journal of Business Research*, *112*: 492-501.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5): 879-903.

Prashar, S., Sai Vijay, T. and Parsad, C. 2016. Segmenting online shoppers: a study of consumers' web portal selection motivations for e-shopping. *Asian Academy of Management Journal,* 21(1).

Prensky, M. 2001. Digital natives, digital immigrants part 1. *On the Horizon,* 9(5): 1–6.

Puiu, S., Demyen, S., Tănase, A., Vărzaru, A.A., and Bocean, C.G. 2022. Assessing the adoption of mobile technology for commerce by Generation Z. *Electronics,* 11(6): 866.

Putranto, L.S. 2019, April. The use of an online survey to speed up the data collection process. In: *IOP Conference Series: Materials Science and Engineering,* 508(1): 012013. IOP Publishing.

Putri, N., Prasetya, Y., Handayani, P.W and Fitriani, H. 2024. TikTok Shop: How trust and privacy influence generation Z's purchasing behaviors. *Cogent Social Sciences*, 10(1): 2292759

Ramalepe, P. 2023. *Digital payment fraud on the rise in South Africa, warns Ombudsman for Banking Services.* News24 Available: https://www.news24.com/news24/tech-and-trends/news/digital-payment-fraud-on-the-rise-in-south-africa-warns-ombudsman-for-banking-services-20230807. (Accessed 05 April 2024).

Ramos, F.R., Martinez, L.M., Martinez, L.F., Abreu, R. and Rubio, L. 2025. Mapping e-commerce trends in the USA: a time series and deep learning approach. *Journal of Marketing Analytics*, 1-29.

Rao, P.H., Jain, S.K. and Millin, A. 2016. Would private sector be inclined to take up initiatives to address water crisis in India? *Vikalpa*, 41(2): 103-116.

Rashid, R. M., Pitafi, A. H., Qureshi, M. A. and Sharma, A. 2022. Role of social commerce constructs and social presence as moderator on consumers' buying intentions during COVID-19. *Frontiers in Psychology,* 13*:* 1–11. Available: https://doi.org/10.3389/fpsyg.2022.772028. (Accessed 02 December 2024).

Rasty, F., Mirghafoori, S.H., Saeida Ardekani, S. and Ajdari, P. 2021. Trust barriers to online shopping: Investigating and prioritizing trust barriers in an intuitionistic fuzzy environment. *International Journal of Consumer Studies,* 45(5): 1030-1046.

Raza, S. A. and Khan, K. A. 2021. Corona fear and e-commerce adoption in an emerging economy: paradigm shift of consumer intention. *Foresight,* 24(2): 195-209.

Regmi, P.R., Waithaka, E., Paudyal, A., Simkhada, P. and Van Teijlingen, E. 2016. Guide to the design and application of online questionnaire surveys. *Nepal Journal of Epidemiology,* 6(4): 640.

Renub Research. 2025. *Global Dietary Supplements Market – Health Trends & Forecast 2025–2033*. Available: https://www.renub.com/dietary-supplements-market-p.php. (Accessed: 21 September 2025)

Retnowati, E. and Mardikaningsih, R. 2021. Study on online shopping interest based on consumer trust and shopping experience. *Journal of Marketing and Business Research),* 1(1): 15-24.

Rice, R.E. and Case, D. 1983. Electronic message systems in the university: A description of use and utility. *Journal of Communication,* 33(1): 131–152. Available: https://doi.org/10.1111/j.1460-2466.1983.tb02380.x (Accessed 24 February 2023).

Richetin, J., Conner, M. and Perugini, M. 2011. Not doing is not the opposite of doing: Implications for attitudinal models of behavioral prediction. *Personality and Social Psychology Bulletin,* 37(1): 40-54.

Roberts, N., and Dinger, M. 2016. The impact of virtual customer community interactivity on organizational innovation: an absorptive capacity perspective, *IEEE Transactions on Professional Communication,* 59(2): 110–125.

Rogers, E. M. 1983. *Diffusion of Innovation*. 3rd ed. New York, NY: The Free Press.

Rogers, E. M. 1995. *Diffusion of innovations*. 4th ed. New York: Free Press.

Rogers, R. W. 1975. A protection motivation theory of fear appeals and attitude change. *Journal of Psychology,* 91: 93–114.

Rogerwilco. 2019. *The R34bn opportunity cost of online CX.* Available: https://www.rogerwilco.co.za/blog/2019-south-african-digital-customer-experience-report (Accessed March 12, 2024).

Ronit, P. 2011. Technophilia: A new model for technology adoption. *UK Academy for Information Systems Conference Proceedings 2011.* Paper 41 Available: http://aisel.aisnet.org/ukais2011/41 (Accessed 05 May 2024).

Roopa, S. and Rani, M.S. 2012. Questionnaire designing for a survey. *Journal of Indian Orthodontic Society*, 46(4_suppl1): 273-277.

Roper, J.R.J. 2023. *The Rise of E-Commerce: From Dot to Dominance*. Croydon: Pen and Sword Books Ltd.

Rubin, D.B. 2018. Multiple imputation. In: *Flexible imputation of missing data*, 2nd ed. 29-62. Chapman and Hall/CRC.

Saeed, S. 2023. A customer-centric view of E-commerce security and privacy. *Applied Sciences*, 13(2): 1020.

Saidu, M., Shagari, S., Kabir, M. and Abubakar, A. 2023. Improving University Students' Data Analysis Outputs through Effective Data Collection, Cleaning, Screening and Normalisation. *Applied Quantitative Analysis*, 3(2): 32-45.

Sallis, J.E., Gripsrud, G., Olsson, U.H. and Silkoset, R. 2021. *Research Methods and Data Analysis for Business Decisions: A Primer Using SPSS*. Cham: Springer.

Saunders, M.N.K., Lewis, P. and Thornhill, A. 2019. *Research Methods for Business Students.* 8th ed. Harlow: Pearson

Saprikis, V. and Avlogiaris, G. 2021. Factors that determine the adoption intention of direct mobile purchases through social media apps. *Information*, *12*(11: 449.

Schiefermair, J. and Stabauer, M. 2020. The effects of cookie notices on perceived privacy and trust in E-Commerce. In: *HCI in Business, Government and Organizations: 7th International Conference, HCIBGO 2020, Held as Part of the 22nd HCI International Conference, HCII 2020,* Copenhagen, Denmark, July 19–24, 2020, Proceedings 22, 535-549. Springer International Publishing.

Schumacker, R.E. and Lomax, R.G. 2016. *A beginner's guide to Structural Equation Modeling.* 4th ed. New York: Routledge.

Schwiderski-Grosche, S. and Knospe, H. 2002. Secure mobile commerce. *Electronics and Communication Engineering Journal,* 14(5): 228-238.

Sekaran, U. and Bougie, R. 2016. *Research methods for business: A skill building approach*. Seventh Edition. Chichester: John Wiley & Sons.Sekaran, U. and Bougie, R, 2019. *Research methods for business: A skill building approach*. Eighth Edition. Chichester: John Wiley & Sons.

Selwyn, N. 2006. Digital division or digital decision? A study of non-users and low-users of computers. *Poetics*, 34(4-5): 273-292.

Senaviratna, N.A.M.R. and Cooray, T.M.J.A. 2019. Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, 5(2): 1-9.

Serdar, C.C., Cihan, M., Yücel, D. and Serdar, M.A. 2021. Sample size, power and effect size revisited: simplified and practical approaches in pre-clinical, clinical and laboratory studies. *Biochemia medica, 31*(1): 27-53.

Shanahan, T., Tran, T.P. and Taylor, E.C. 2019. Getting to know you: Social media personalization as a means of enhancing brand loyalty and perceived quality. *Journal of Retailing and Consumer Services*, 47: 57-65.

Sharma, A. and Gandhi, A.V. 2024. Consumer adoption study for innovative technology products and services in an emerging economy. *International Journal of Innovation Science*, 16(3): 482-500.

Sheeran, P., Trafimow, D. and Armitage, C. J. 2003. Predicting behaviour from perceived behavioural control: Tests of the accuracy assumption of the theory of planned behaviour. *British Journal of Social Psychology*, 42(3): 393-410.

Shevlin, M. and Miles, J.N. 1998. Effects of sample size, model specification and factor loadings on the GFI in confirmatory factor analysis. *Personality and Individual differences*, 25(1): 85-90.

Shorten, A. and Moorley, C. 2014. Selecting the sample. *Evidence-based Nursing,* 17(2): 32-33.

Short, J., Williams, E. and Christie, B. 1976. *The social psychology of telecommunications.* London: John Wiley & Sons.

Soundrapandian, E. and Priya, K. 2024. Factors limiting consumer's preference towards the online shopping; a critical analysis. In *3rd International Conference on Reinventing Business Practices, Start-ups and Sustainability (ICRBSS 2023):* 249-258. Atlantis Press.

Shrestha, N. 2020. Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics*, 8(2): 39-42.

Sim, J. J., Loh, S. H., Wong, K. L. and Choong, C. K. 2021. Do we need trust transfer mechanisms? An M-commerce adoption perspective. *Journal of Theoretical and Applied Electronic Commerce Research,* 16(6): 2241-2262.

Smith, C. 2017. *SA e-commerce growing by leaps and bounds*. Available: https://www.fin24.com/Companies/Retail/sa-e-commerce-growing-by-leaps-and-bounds-20170222 (Accessed 16 June 2024).

Smith, J.K. and Heshusius, L. 1986. Closing down the conversation: The end of the quantitative-qualitative debate among educational inquirers. *Educational Researcher,* 15: 4-13.

Snyman, A. and Mulder, D. 2014. The use of Twitter in branding: the case of the University of the Free State. *Communitas,* 19: 156-174.

Song, Y., Son, Y.J. and Oh, D. 2015. Methodological issues in questionnaire design. *Journal of Korean Academy of Nursing*, 45(3): 323-328.

Song, Y., Escobar, O., Arzubiaga, U. and De Massis, A. 2022. The digital transformation of a traditional market into an entrepreneurial ecosystem. *Review of Managerial Science*, *16*(1): 65-88.

Soper, D.S. 2025. *A-priori sample size calculator for Structural Equation Models* [Software]. Available: https://www.danielsoper.com/statcalc (Accessed 27 February 2025).

South African Post Office (SAPO). 2017. *South African Post Office 2016/2017 Annual Report*. Available: https://www.postoffice.co.za/about/annualreport/PartA.pdf. (Accessed 15 June 2024. Springer.

South African Banking Risk Information Centre (SABRIC). (2023), "Annual crime statistics", Available: www.sabric.co.za/media/20oouwbg/sabric-annual-crime-stats-2020.pdf. (Accessed 20 June 2024).

Sposito, V.A., Hand, M.L. and Skarpness, B. 1983. On the efficiency of using the sample kurtosis in selecting optimal lpestimators. *Communications in Statistics-simulation and Computation*, 12(3): 265-272.

Stahl, C. C. and Literat, I. 2023. #GenZ on TikTok: the collective online self-portrait of the social media generation. *Journal of Youth Studies,* 26(7): 925-946.

Statista. 2024. The Metaverse market in South Africa is experiencing significant growth and development. Available: https://www.statista.com/outlook/amo/metaverse/south-africa#market-size (Accessed 28 July 2024).

Statista. 2025. Robo-Advisors - Saudi Arabia. Available: https://www.statista.com/outlook/fmo/wealthmanagement/digital-investment/robo-advisors/saudi-arabia. (Accessed 04 July 2025).

Statistics South Africa. 2020. *Business impact survey of the COVID-19 pandemic in South Africa.* Available: https://www.statssa.gov.za/publications/Report-00-80-01/Report-00-80-01June2020.pdf. (Accessed 11 April 2024).

Statistics South Africa (StatsSA). 2017. *Five facts about the retail industry*. Available: http://www.statssa.gov.za/?p=11101. (Accessed 16 June 2024).

Steiger, J.H. and Lind, J.M. 1980. Statistically-based tests for the number of common factors. Paper presented at the *Annual Meeting of the Psychometric Society*, Iowa City.

Steinicke, F. and Wolf, K. 2020. New digital realities – Blending our reality with virtuality. *i-com,* 19: 61 - 65.

Stewart, K. J. 2003. Trust transfer on the world wide web. *Organization Science, 14*(1): 5–17.

Subero-Navarro, Á., Pelegrín-Borondo, J., Reinares-Lara, E. and Olarte-Pascual, C. 2022. Proposal for modeling social robot acceptance by retail customers: CAN model+ technophobia. *Journal of Retailing and Consumer Services,* 64: 102813.

Suh, B. and Han, I. 2003. The impact of customer trust and perception of security control on the acceptance of electronic commerce. *International Journal of electronic commerce*, *7*(3): 135-161.

Sullivan, G.M. and Artino Jr, A.R. 2013. Analyzing and interpreting data from Likert-type scales. *Journal of graduate medical education,* 5(4): 541-542.

Sutherland, E. 2017. Governance of cybersecurity-the case of South Africa. *The African Journal of Information and Communication*, 20: 83-112.

Swinyard, W.R. and Smith, S.M. 2004. Activities, Interests, And Opinions of Online Shoppers and Non-Shoppers. *International Business & Economics Research Journal,* 3(4): 37–48.

Swinyard, W.R. and Smith, S.M. 2003. Why people (don't) shop online: A lifestyle study of the internet consumer. *Psychology & Marketing*, 20(7): 567-597.

Sztompka, P. 1999. *Trust: A sociological theory*. Cambridge: University Press.

Tabachnick, B.G. and Fidell, L.S. 2014. *Using Multivariate Statistics*. 6th ed. Essex: Pearson Education Limited.

Tabachnick, B.G. and Fidell, L.S. 2018. *Using Multivariate Statistics*. 7th ed. NY: Pearson.

Talukder, M. S., Sorwar, G., Bao, Y., Ahmed, J. U. and Palash, M. A. S. 2020. Predicting antecedents of wearable healthcare technology acceptance by elderly: A combined SEM-Neural Network approach. *Technological Forecasting and Social Change,* 150: 119793.

Talwar, S., Talwar, M., Kaur, P. and Dhir, A. 2020. Consumers' resistance to digital innovations: A systematic review and framework development. *Australasian Marketing Journal*, 28(4): 286-299.

Tankard, K. 1998. History, the Internet and South Africa. *South African Historical Journal,* 38(1): 20-33.

Tanlaka, E.F., Ewashen, C. and King-Shier, K. 2019. Postpositivist critical multiplism: Its value for nursing research. *Nursing Open,* 6(3): 740-744.

Taylor, S. and Todd, P. 1995. Assessing IT usage: The role of prior experience. *MIS Quarterly*, 561–570.

Teixeira, R., Duarte, A.L.D.C.M., Macau, F.R. and de Oliveira, F.M. 2022. Assessing the moderating effect of brick-and-mortar store on omnichannel retailing. *International Journal of Retail & Distribution Management*, *50*(10): 1259-1280.

Thangavel, P. and Chandra, B. 2024. Digital immigrants versus digital natives: Decoding their e-commerce adoption behavior. *SAGE Open*, 14(4): 21582440241282437.

The Economist. 2020. *South Africa's post-pandemic consumer: Building on new foundations*. Available: https://impact.economist.com/perspectives/sites/default/files/eiu-sa-post-pandemic-consumer.pdf. (Accessed 12 April 2024).

Thompson, R. L., Higgins, C. A. and Howell, J. M. 1994. Influence of experience on personal computer utilization: Testing a conceptual model. *Journal of Management Information Systems,* 11(1): 167–187.

Tian, Y. and Stewart, C. 2008. *History of e-commerce*. In: Khosrow-Pour, M. ed. Encyclopedia of E-Commerce, E-Government, and Mobile Commerce. Available: 10.4018/9781599049434.ch001. (Accessed 10 April 2024).

Tinonetsana, F. and Msosa, S.K. 2023. SHIFTS IN CONSUMER BEHAVIOURAL TRENDS DURING AND POST THE COVID-19 PANDEMIC: AN ANALYSIS USING THE THEORY OF REASONED ACTION. *Business Excellence & Management*, *13*(4).

Tlapana, T. 2020. Exploring Retail Customer Service, a Case of Retail Food Chains in Kwazulu-Natal. *Publishing House of Rzeszow University of Technology*, 55.

Tobias-Mamina, R.J., Kempen, E., Chinomona, R. and Sly, M. 2020. The influence of instagram advertising on destination visit intention. *African Journal of Hospitality, Tourism and Leisure,* 9(3): 274-287.

Tornatzky, L.G. and Fleischer, M. 1990. *The processes of technological innovation*. Lexington, MA: Lexington Books.

Tsagris, M. and Pandis, N. 2021. Normality test: Is it really necessary? *American Journal Of Orthodontics and Dentofacial Orthopedics*, 159(4): 548-549.

Tucker, L.R. and Lewis, C. 1973. A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, 38(1): 1-10.

Tuteja, G., Gupta, S. and Garg, V. 2016. Consumer trust in internet shopping: An empirical investigation. *Paradigm,* 20(2): 191-215.

United Nations Economic Commission for Africa and African Development Bank. 2022. West African Studies Africa's Urbanisation Dynamics 2022 The Economic Power of Africa's Cities: The Economic Power of Africa's Cities. OECD Publishing.

Urbonavicius, S., Degutis, M., Zimaitis, I., Kaduskeviciute, V. and Skare, V. 2021. From social networking to willingness to disclose personal data when shopping online: Modelling in the context of social exchange theory. *Journal of Business Research, i* 76-85.

Van Deursen, A.J. and Van Dijk, J.A. 2019. The first-level digital divide shifts from inequalities in physical access to inequalities in material access. *New Media & Society*, 21(2): 354-375.

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.

Venkatesh, V., Thong, J. Y. and Xu, X. 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178.

Verdam, M.G., Oort, F.J. and Sprangers, M.A. 2017. Structural Equation Modelling based effect-size indices were used to evaluate and interpret the impact of response shift effects. *Journal of Clinical Epidemiology,* 85: 37-44.

Verhees, B. and Verbong, G.P.J: 2015. *Users, Consumers, Citizens: A systematic review of their roles in sustainability transitions*. (ECIS working paper series); (201504). Technische Universiteit Eindhoven.

Vrbin, C.M. 2022. Parametric or nonparametric statistical tests: Considerations when choosing the most appropriate option for your data. *Cytopathology,* 33(6): 663-667.

Vujovic, A.N., Jonathan, G.M. and Hacks, S. 2024. Digitalisation and its impact on social protection programmes effectiveness: A case from South Africa. *Procedia Computer Science*, 237: 882-890.

Walker, D.A. and Smith, T.J. 2017. Computing robust, bootstrap-adjusted fit indices for use with nonnormal data. *Measurement and Evaluation in Counselling and Development*, 50(1-2): 131-137.

Wang, J., Shahzad, F., Ahmad, Z., Abdullah, M. and Hassan, N.M. 2022. Trust and Consumers' Purchase Intention in a Social Commerce Platform: A Meta-Analytic Approach. *SAGE Open*, 12(2).

Watson, S. 2023. Towards a New Project Design Methodology for Archaeological Projects in England. *Archaeological Review from Cambridge*, *38*(2).

Wiese, M., Martínez-Climent, C. and Botella-Carrubi, D. 2020. A framework for Facebook advertising effectiveness: A behavioral perspective. *Journal of Business Research,* 109: 76-87.

Wirtz, J. and Pitardi, V. 2023. How intelligent automation, service robots, and AI will reshape service products and their delivery. *Italian Journal of Marketing,* 2023(3): 289-300.

Wirtz, J., Hofmeister, J., Chew, P.Y. and Ding, X. 2023. Digital service technologies, service robots, AI, and the strategic pathways to cost-effective service excellence. *The Service Industries Journal,* 43: 1173 - 1196.

Wiśniowski, A., Sakshaug, J.W., Perez Ruiz, D.A. and Blom, A.G. 2020. Integrating probability and nonprobability samples for survey inference. *Journal of Survey Statistics and Methodology*, 8(1): 120-147.

World Wide Worx. 2024. *Online Retail in South Africa.* Available: https://www.peachpayments.com/scale/world-wide-worx-2024-online-retail-report. (Accessed 13 October 2025)

Worku, Y.B. and Muchie, M. 2019. The Uptake of E-Commerce Services in Johannesburg. *Civil Engineering Journal,* 5(2): 349-362.

Wolverton, C.C. and Cenfetelli, R. 2019. An exploration of the drivers of non-adoption behavior: A discriminant analysis approach. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 50(3): 38-65.

Wright, K.B. 2005. Researching Internet-based populations: Advantages and disadvantages of online survey research, online questionnaire authoring software packages, and web survey services. *Journal of computer-mediated communication*, 10(3): 1034.

Wu, H. and Leung, S.O. 2017. Can Likert scales be treated as interval scales? — A simulation study. *Journal of Social Service Research,* 43(4): 527-532.

Wylde, V., Rawindaran, N., Lawrence, J., Balasubramanian, R., Prakash, E., Jayal, A., Khan, I., Hewage, C. and Platts, J. 2022. Cybersecurity, data privacy and blockchain: A review. *SN Computer Science*, 3(2): 127.

Xinya, L. and Yanyun, Y., 2016. Confirmatory factor analysis under violations of structural and distributional assumptions: A comparison of robust Maximum likelihood and Bayesian estimation methods. *Journal of Psychological Sciences*, 39(5): 1256-1267.

Xuan, T.M., Alrashdan, M.T., Al-Maatouk, Q. and Alrashdan, M.T. 2020. Blockchain technology in E-commerce platform. *International Journal of Management,* 11(10): 1688-1697.

Yahia, I.B., Al-Neama, N. and Kerbache, L. 2018. Investigating the drivers for social commerce in social media platforms: Importance of trust, social support and the platform perceived usage. *Journal of Retailing and Consumer Services*, 41: 11-19.

Yang, S. and Kim, J.K. 2020. Statistical data integration in survey sampling: A review. *Japanese Journal of Statistics and Data Science*, 3(2): 625-650.

Yang, X. 2019. How perceived social distance and trust influence reciprocity expectations and eWOM sharing intention in social commerce. *Industrial Management & Data Systems,* 119(4): 867-880.

Yates, S., Kirby, J. and Lockley, E. (2015). Digital media use: Differences and inequalities in relation to class and age. *Sociological Research Online,* 20(4): 71–91.

Ye, S., Lei, S.I., Shen, H. and Xiao, H. 2020. Social presence, telepresence and customers' intention to purchase online peer-to-peer accommodation: A mediating model. *Journal of Hospitality and Tourism Management*, 42:119-129.

Yeboah, A., Agyekum, O., Owusu-Prempeh, V. and Prempeh, K.B. 2023. Using social presence theory to predict online consumer engagement in the emerging markets. *Future Business Journal*, 9(1): 69. Available: https://doi.org/10.1186/s43093-023-00250-z. (Accessed 27 April 2025).

Yohn, D.L. 2019. Why great innovation needs great marketing. *Harvard Business Review*, 2-5.

Yoo, K., Welden, R., Hewett, K. and Haenlein, M. 2023. The merchants of meta: A research agenda to understand the future of retailing in the metaverse. *Journal of Retailing*, *99*(2): 173-192.

Yu, T. K., Lin, M. L. and Liao, Y. K. 2017. Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills. *Computers in Human Behavior,* 71: 196–208.

Yu, X. and Pan, L. 2012. Electronic commerce applications based on virtual reality technology. In: *2012 International Conference on Management of e-Commerce and e-Government*. Beijing China, 20-21 October. IEEE Computer Society. Available: DOI 10.1109/ICMeCG.2012.3

Zafar, A.U., Qiu, J., Shahzad, M., Shen, J., Bhutto, T.A. and Irfan, M. 2021. Impulse buying in social commerce: bundle offer, top reviews, and emotional intelligence. *Asia Pacific Journal of Marketing and Logistics*, *33*(4): 945-973.

Zeng, F., Ye, Q., Li, J. and Yang, Z. (2021). Does self-disclosure matter? A dynamic two-stage perspective for the personalization-privacy paradox. *Journal of Business Research,* 124: 667–675.

Zhang, D., Pee, L.G. and Cui, L. 2021. Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management,* 57: 102304.

Zhang, H., Lu, Y., Gupta, S. and Zhao, L. 2014. What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences. *Information & Management*, 51(8): 1017-1030.

Zhang, K.Z. and Benyoucef, M. 2016. Consumer behavior in social commerce: A literature review. *Decision Support Systems,* 86: 95-108.

Zhang, L., Wang, Y., Anjum, M.A. and Mu, J. 2022. The impacts of point rewarding and exchanging on users' loyalty toward mobile payment applications: a dual channeling perspective. *Internet Research*, *32*(6): 1832-1861.

Zhang, M. 2015. Internet use that reproduces educational inequalities: Evidence from big data. *Computers & Education,* 86: 212–223.

Zhang, X. and Wang, T. 2021. Understanding purchase intention in O2O E-commerce: the effects of trust transfer and online contents. *Journal of Theoretical and Applied Electronic Commerce Research,* 16(2): 101–115.

Zhao, J.D., Huang, J.S. and Su, S. 2019. The effects of trust on consumers' continuous purchase intentions in C2C social commerce: A trust transfer perspective. *Journal of Retailing and Consumer Services*, 50: 42-49.

Zhou, J., Wei, J. and Xu, B. 2021. Customer segmentation by web content mining. *Journal of Retailing and Consumer Services,* 61: 102588.

Zhou, L., Zhang, P. and Zimmermann, H.D. 2013. Social commerce research: An integrated view. *Electronic Commerce Research and Applications*, 12(2): 61-68.

Zhu, H., Ou, C.X., van den Heuvel, W.J.A. and Liu, H. 2017. Privacy calculus and its utility for personalization services in e-commerce: An analysis of consumer decision-making. *Information & Management*, 54(4): 427-437.

Zhu, R., Wang, M., Zhang, X. and Peng, X. 2023. Investigation of personal data protection mechanism based on blockchain technology. *Scientific Reports*, 13(1): 21918.

APPENDIX ONE: QUESTIONNAIRE

Factors that influence consumers' non-adoption of FMCG online shopping post COVID-19 in South Africa.

Participant Information Sheet

Dear Participant

My name is Cleopatra Matli, and I am a researcher at the Durban University of Technology. I am currently embarking on a study that focuses on the factors that influence non-adoption of online shopping, especially for Fast Moving Consumable Goods (FMCG). The study is important since it will help both retailers and consumers alike on the reasons for the slow adoption of online shopping, which will in return assist in the development of a framework to improve this. I would like to invite you to participate in the research. Briefly, research is a systematic search for generalised new knowledge. Therefore, your honesty in answering the questionnaire will aid the researcher to achieve the objectives of this study.

The questionnaire should not take longer than 20 minutes to complete. All responses will be kept confidential. Please note that filling out this questionnaire is voluntary and that there are no right or wrong answers/responses to any of the questions and statements. Your assistance in completing the questionnaire will be highly appreciated. I hereby request your consent and support in conducting this research. And please note that, you may withdraw from participating in the research at any stage should you wish to do so without any repercussions. Participants will not receive any financial rewards from participating since this research is for academic purposes.

Your survey responses will be strictly confidential and data from this research will be reported only taken together in aggregate. Your information will be coded and will remain confidential. Furthermore, this study will be available online and hosted by the relevant accredited website. This research will not involve any research – risk-related issues. Data will be stored in a secure and locked location. Should you require further information, please contact me or any of the persons using the contact details provided below.

Please contact the researcher (cleopatram@dut.ac.za or 0722733910), supervisor (0313735396) or the Institutional Research Ethics Administrator (031 373 2375). Complaints can be reported to the Interim Acting Director: Research and Postgraduate Support at TtiDirector@dut.ac.za

* Indicates required question

Informed Consent

I hereby confirm that I have read and understood the information above which spells out the nature of the research project, and

- I have read and understood the above-written information regarding the study.
- Hence, I confirm that the researcher informed me about this study's nature, conduct, benefits and risks.
- In view of the research requirements, I agree that the data collected during this study can be processed in a computerised system by the researchers.
- I know that the data collected during this study, including demographic details (without any personally identifying data), will be processed, stored and

published in accredited journals, academic conferences or book chapters by the researcher(s).

- I have sufficient opportunity to ask questions and (of my own free will) declare myself prepared to participate in the study.
- I understand that significant new findings developed during the course of this research relating to my participation will be made available to me as academic material.
- I know that I may withdraw my consent and participation in the study without prejudice or retribution at any stage.

Based on the above, I. *

- [ ] Consent to participate in the study
- [ ] Do not consent to participate in the study

Screening Questions

This study is focusing on Fast Moving Consumer Goods (FMCG), also known as consumer-packaged goods. These include all consumables, such as groceries, that are purchased regularly. Examples include toiletries (such as soap, shampoo, toothpaste, etc.), detergents (such as fabric softener, dishwashing soap, floor cleaner, etc.), food (including meat, vegetables, canned goods, etc.), and household accessories. These items are meant for daily or frequent consumption.

1. Have you ever bought anything online? *

- [ ] Yes, I have.
- [ ] No, I haven't, although I have browsed some online shopping platforms.
- [ ] No, I have neither searched nor bought anything online.

2. If you answered "Yes, I have" to the above question, please indicate which of the following product categories you purchased online. Have you ever bought anything online? *

Check all that apply.

- [ ] Electronic devices, e.g., TVs, Smartphones, Sound system, laptop, etc.
- [ ] Fashion, i.e., clothing, footwear or jewellery.
- [ ] Food items, e.g., milk, meat, fruits, drinks, rice, etc.
- [ ] Beauty and personal care products, e.g., body lotion, bathing soap, body sprays, hair products, etc.
- [ ] Home hygiene products, e.g., detergents, house sprays/fresheners, etc.

- DIY and Hardware, e.g., drilling machine, spanner set, hammer, etc.
- Toys and Baby products
- Other: ____________________

3. If you answered "No, I haven't, although I have browsed some online shopping platforms" to the above question, please indicate why you did not purchase online. *

Mark only one oval.

- I would just be researching about product features, read reviews, and gather information to make informed decisions about what to buy, albeit in-store.
- I would be comparing prices so I can go and purchase in-store (physically).
- I would be checking product availability and the nearest outlet.
- I abandoned the process as I was concerned about the security of the site.
- Other: ____________________

Section A: Demographic data

4. Please indicate your gender. *

Mark only one oval.

- Male
- Female
- Prefer not to say

5. Please indicate your ethnic group. *

Mark only one oval.

- African
- White
- Indian
- Coloured

6. Please indicate your occupation. *

Mark only one oval.

- Student
- Employed

- Self-employed
- Unemployed

7. Please indicate your monthly income. *

Mark only one oval.

- Less than R5000
- R5001 - R10000
- R10001 - R15000
- R15001 - R20000
- More than R20000

8. Please indicate your highest level of education. *

Mark only one oval.

- No formal qualification
- Matric certificate or equivalent
- Diploma / Degree
- Postgraduate Qualification

9. Please indicate your age*

____

Section B: Access and Connectivity

10. Which device(s) do you primarily use to connect to the internet? *

Mark only one oval.

- Smart phone/Tablet
- Smart TV
- Laptop/Desktop
- I do not have any such device
- Other: ______________________________

11. How do you connect to internet? *

Mark only one oval.

- Mobile Data
- Private Fibre/Broadband/Wi-Fi/Cable connection (ADSL)
- Public Wi-Fi Hotspots
- Work Wi-Fi/Cable connect
- Other: ________________________________

Section C: Online Shopping Factors

12. Please rate the following online shopping performance-related statements measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I believe that online shopping is not helpful or beneficial for me in my daily life.					
2. I don't think that using online shopping platforms would improve my shopping experience or make it easier for me.					
3. Online shopping decreases my productivity in accomplishing shopping tasks.					
4. Shopping online will decrease my chances of getting better discounts.					
5. Shopping online will decrease my chances of getting quality products.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

13. Please rate the following online shopping technology ease of use-related statements measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I find online shopping to be complicated and confusing, making it harder for me to shop online.					
2. I believe that using online shopping platforms requires too much effort and learning, which discourages me from using them.					
3. I feel overwhelmed by the thought of navigating through different online shopping websites and apps.					

4. I perceive online shopping as a hassle and prefer sticking to familiar in-store shopping methods.					
5. I think that dealing with online payment processes and delivery logistics is too much of a hassle for me.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

14. Please rate the following statements of social influence about online shopping measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. People who influence my behaviour think that I should not use online platforms for shopping.					
2. People who are important to me think that I should not participate in online shopping.					
3. No one in my inner circle shops online.					
4. In general, people close to me discourage me when I attempt to shop online.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

15. Please rate the following statements about conditions for online shopping measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I do not have resources necessary for me to use online shopping platforms.					
2. I do not have necessary knowledge for me to use online shopping platforms.					
3. The device(s) I am using is not compatible with online shopping platforms.					
4. Online shopping platforms do not have consultant to assist with difficulties incurred while using the platform.					

5. My residential location is not supported by online shopping delivery services.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

16. Please rate the following statements about the effect of technophobia on online shopping measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	**SD**	**D**	**N**	**A**	**SA**
1. I feel nervous or anxious when I have to use new technology.					
2. I avoid using technology whenever possible because it makes me uncomfortable.					
3. I worry that I'll break something or mess something up when using technology.					
4. I feel overwhelmed or stressed when I have to use technology for tasks or activities.					
5. I am afraid that online shopping platforms can used to spy on people.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

17. Please rate the following statements about perceived lack of reciprocity measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	**SD**	**D**	**N**	**A**	**SA**
1. I feel that online shopping platforms will not adequately acknowledge or appreciate my patronage.					
2. I perceive a lack of effort from online retailers to understand and meet my individual needs and preferences.					
3. I do not receive personalised or targeted offers or promotions from online shopping platforms.					
4. I feel that online retailers prioritise their own interests over meeting my expectations or providing value to me as a customer.					
5. I perceive a one-sided relationship with online shopping platforms, where I invest time and					

resources without receiving sufficient benefits or rewards in return.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

18. Please rate the following statements about distrust in online payment systems measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I am concerned about the security of my financial information when making online payments.					
2. I worry that online payment systems may be vulnerable to hacking or unauthorised access.					
3. I lack confidence in the ability of online payment systems to protect my personal and financial data.					
4. I hesitate to use online payment systems because I fear fraudulent transactions or identity theft.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

19. Please rate the following statements about distrust in online shopping platforms measured on a 5-point scale from "Strongly Disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I am sceptical about the reliability and authenticity of products sold on online shopping platforms.					
2. I have doubts about the transparency and honesty of online retailers in their product descriptions and pricing.					
3. I worry that online shopping platforms may engage in deceptive practices or misleading advertising.					
4. I lack confidence in the customer service and support provided by online shopping platforms in resolving issues or concerns.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

20. Please rate the following statements about perceived lack of social presence measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA

1. I feel isolated or disconnected when shopping online compared to shopping in physical stores.					
2. I miss the social interactions and personal connections that I experience when shopping in a traditional retail environment.					
3. I find it challenging to seek advice or recommendations from friends or family members while shopping online.					
4. I perceive a lack of community or social atmosphere when browsing and purchasing products on online shopping platforms.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

Section D: Intention to shop online for the first time

21. Please rate the following statements about your behavioural intention measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I have no intention to shop online in the near future.					
2. I do not see myself exploring or trying out online shopping platforms in the future.					
3. I will always prefer traditional in-store shopping over online shopping and do not plan to change this preference.					
4. I feel more comfortable and satisfied shopping in-person rather than online.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

Section E: Moderators

22. Please rate the following statements about your digital literacy measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	SD	D	N	A	SA
1. I do not know how to solve my own technical problems.					
2. I find it difficult to learn how to use new technologies.					

3. I do not know about a lot of different technologies.					
4. I am not confident with my search and evaluation skills with regards to obtaining information from the internet.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

23. Please rate the following statements about your retailers' marketing effort measured on a 5-point scale from "Strongly disagree" to "Strongly Agree". *Mark only one oval per row.*

Items	**SD**	**D**	**N**	**A**	**SA**
1. Marketing messages from online shopping platforms are often confusing and irrelevant to my interests and needs.					
2. I am dissatisfied with the frequency and timing of marketing communications from online shopping platforms; they are either too frequent or poorly timed.					
3. Marketing efforts from online shopping platforms are not personalised and fail to engage me as a consumer.					

SD-Strongly Disagree, **D**- Disagree, **N** – Neutral, **A**- Agree, **SA** – Strongly Agree

APPENDIX TWO: ETHICS TRAINING CERTIFICATE

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Certificado

Certificat

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Ce document atteste que - this document certifies that

Cleopatra Matli

a complété avec succès - has successfully completed

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APPENDIX THREE: ETHICAL CLEARENCE

DUT
DURBAN UNIVERSITY OF TECHNOLOGY

INSTITUTIONAL RESEARCH ETHICS COMMITTEE

Institutional Research Ethics Committee
Research and Postgraduate Support Directorate
2nd Floor, Berwyn Court
Gate 1, Steve Biko Campus
Durban University of Technology

P O Box 1334, Durban, South Africa, 4001

Tel: 031 373 2375
Email: lavishad@dut.ac.za
http://www.dut.ac.za/research/institutional_research_ethics

www.dut.ac.za

27 November 2024

Ms C M Matli
2 Golden Birches
142 Entabeni Road
Paradise Valley
Pinetown

Dear Ms Matli

Factors that influence consumers' non-adoption of FMCG online shopping post COVID-19 in South Africa.

I am pleased to inform you that Full Approval has been granted to your proposal.

The Proposal has been allocated the following Ethical Clearance number **IREC 242/24**. Please use this number in all communication with this office.

Approval has been granted for a period of **ONE YEAR**, before the expiry of which you are required to apply for safety monitoring and annual recertification. Please use the Safety Monitoring and Annual Recertification Report form which can be found in the Standard Operating Procedures [SOP's] of the DUT-IREC. This form must be submitted to the DUT-IREC at least 3 months before the ethics approval for the study expires.

Any adverse events [serious or minor] which occur in connection with this study and/or which may alter its ethical consideration must be reported to the DUT-IREC according to the DUT-IREC SOP's.

Please note that any deviations from the approved proposal require the approval of the DUT-IREC as outlined in the DUT-IREC SOP's.

It is compulsory for a student or researcher to apply for recertification on an annual basis. The failure to do so will result in withdrawal of ethics clearance. It is the responsibility of the researcher and the supervisor to apply for recertification.

Please note that you are required to submit a Notification of Completion of Study form together with an abstract to the DUT-IREC office on completion of your study.

Yours Sincerely

Professor P Mashau
Chairperson: DUT-IREC

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APPENDIX FOUR: EDITORIAL CERTIFICATE

DR KAREN CORBISHLEY

B.Comm, BTech; MTech; DPhil Mngt Sci (Mktg)

Academic Consultant and Editor

karen@corbishley.co.za

083 6332257

24 October 2025

FACTORS THAT INFLUENCE CONSUMERS' NON-ADOPTION OF FMCG ONLINE SHOPPING POST COVID-19 IN SOUTH AFRICA

I, Dr Karen Corbishley, declare that I have rendered the following services as contracted by **Cleopatra Moipone Matli** for the above-mentioned paper.

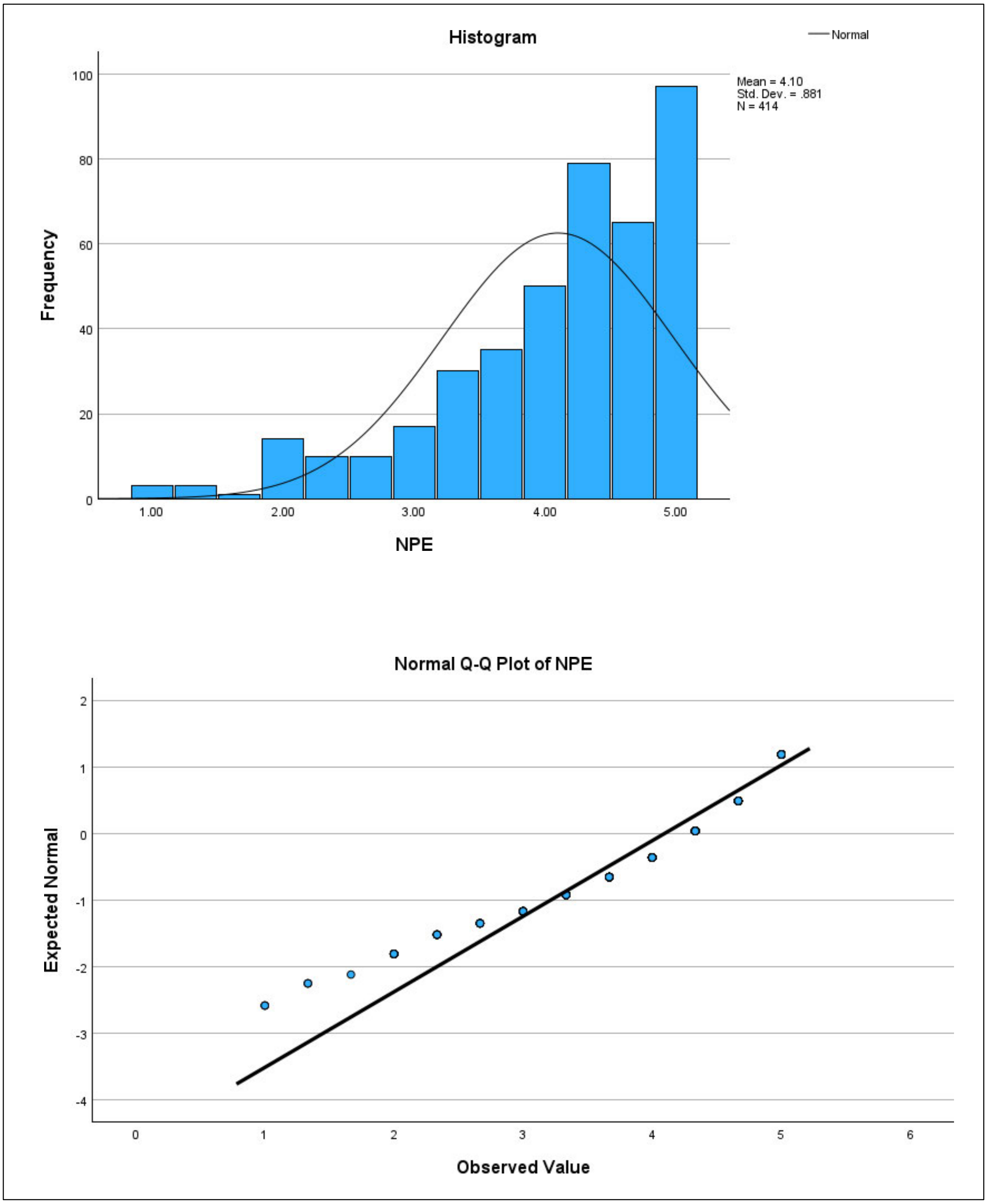
I have edited the document, checking for language, clarity, structure and flow. I have also checked and cross-checked references according to the DUT Harvard style. A number of recommendations were made in the aforementioned areas which may be accepted or rejected at the discretion of the client.

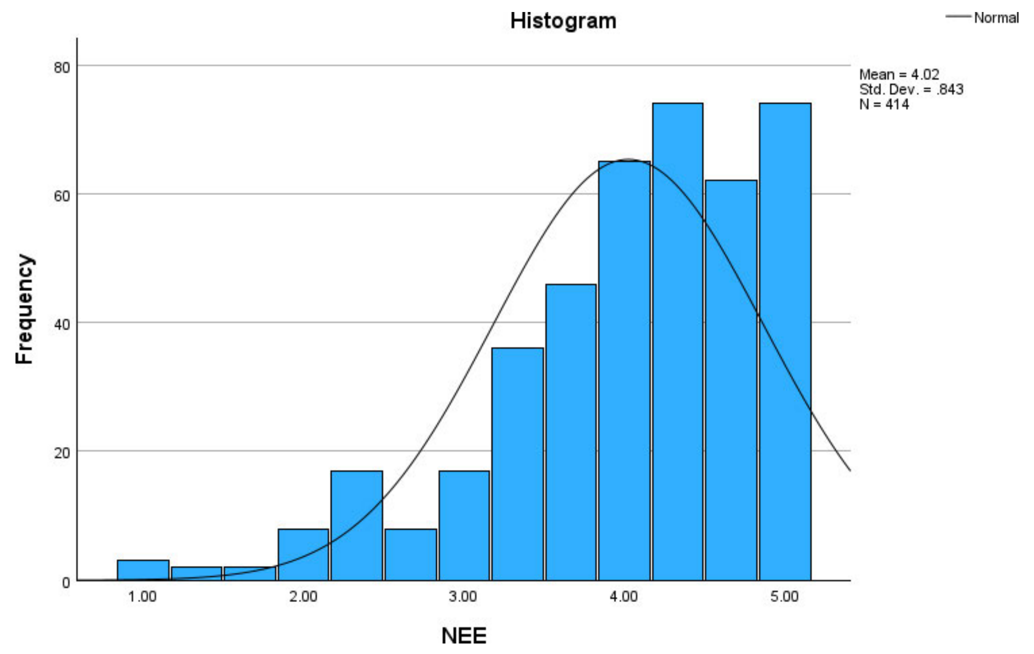
I am a freelance academic consultant and editor, with a focus on academic material in the field of Management Sciences. I am in possession of a B.Comm UNP, BTech, Master's (Cum Laude) and DPhil in Management Science (specialising in Marketing). I also hold a certificate in proof reading and copy editing from the South African Writer's College. During my 30 years at DUT (culminating in Senior Lecturer), I have supervised and examined several Masters and Doctorates, and published a number of papers in accredited journals.

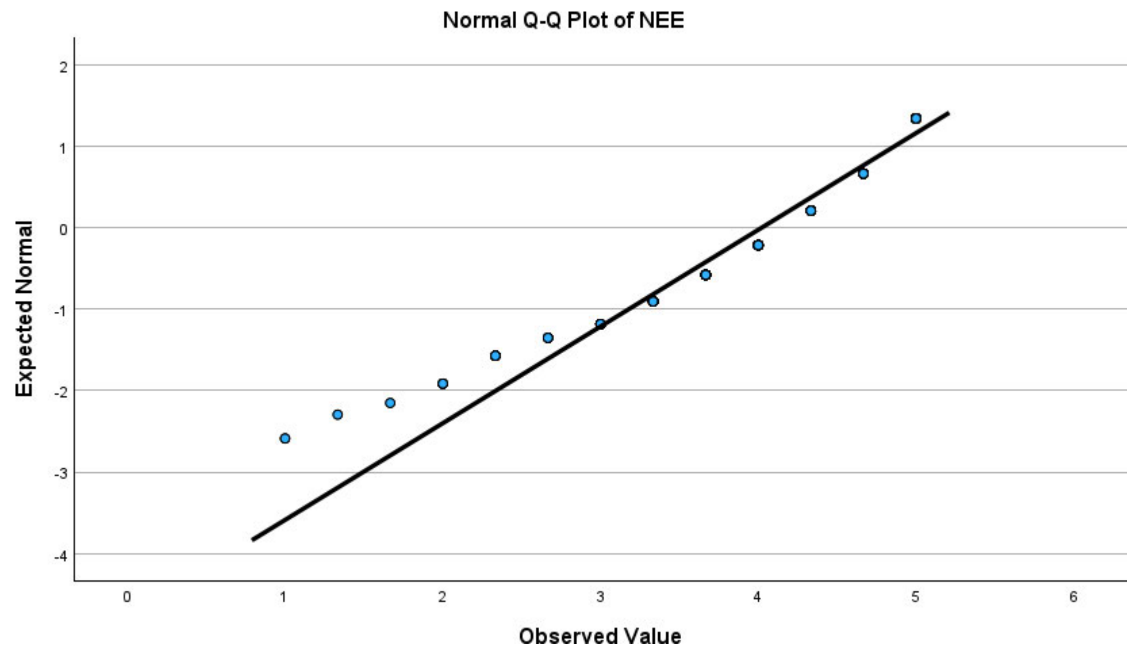
SIGNATURE:

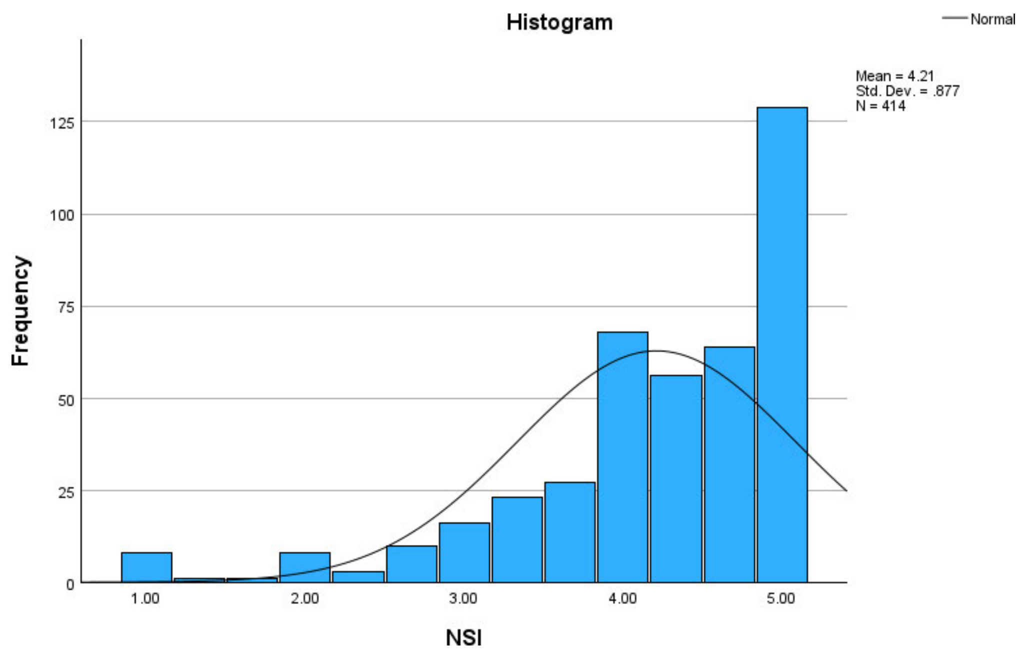
Dr Karen Margaret Corbishley

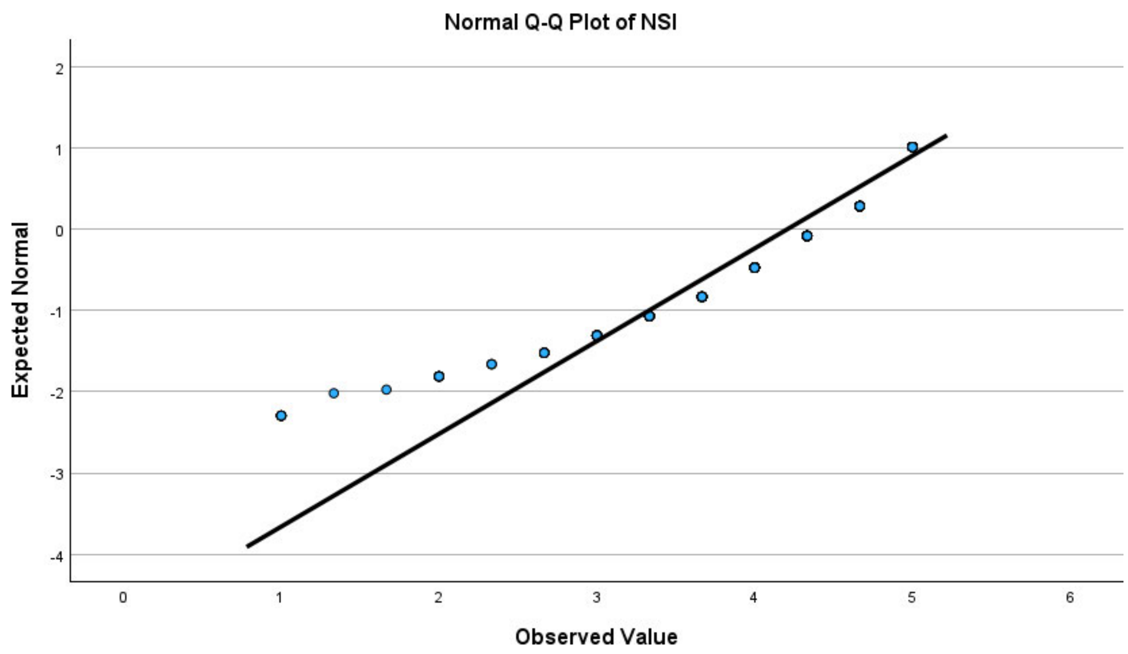
APPENDIX FIVE (A): FIGURES 5.1A-L HISTOGRAMS AND Q-Q PLOTS

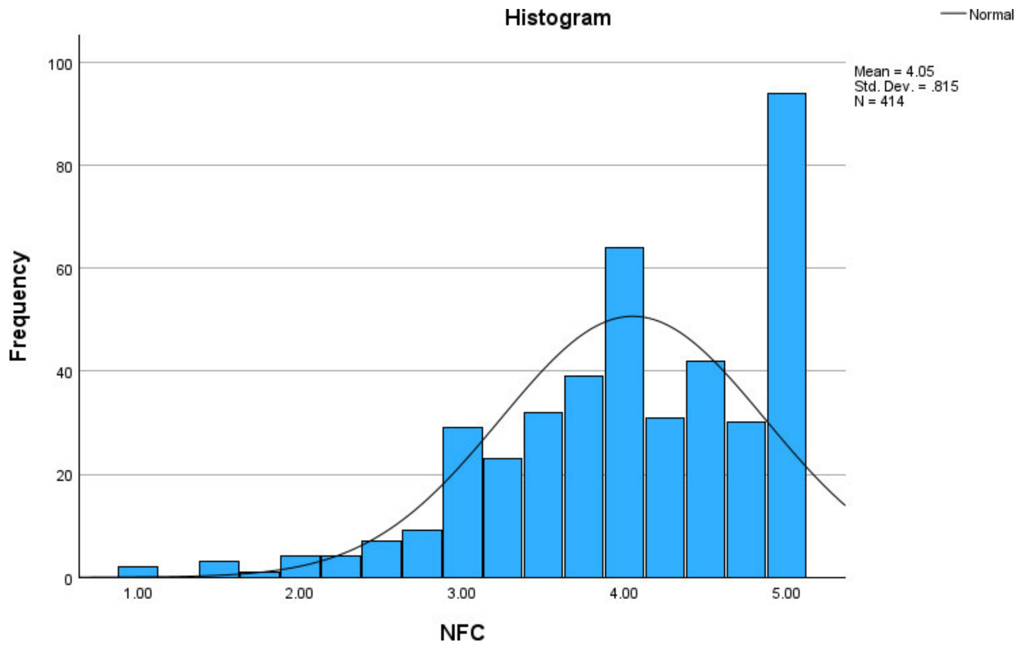


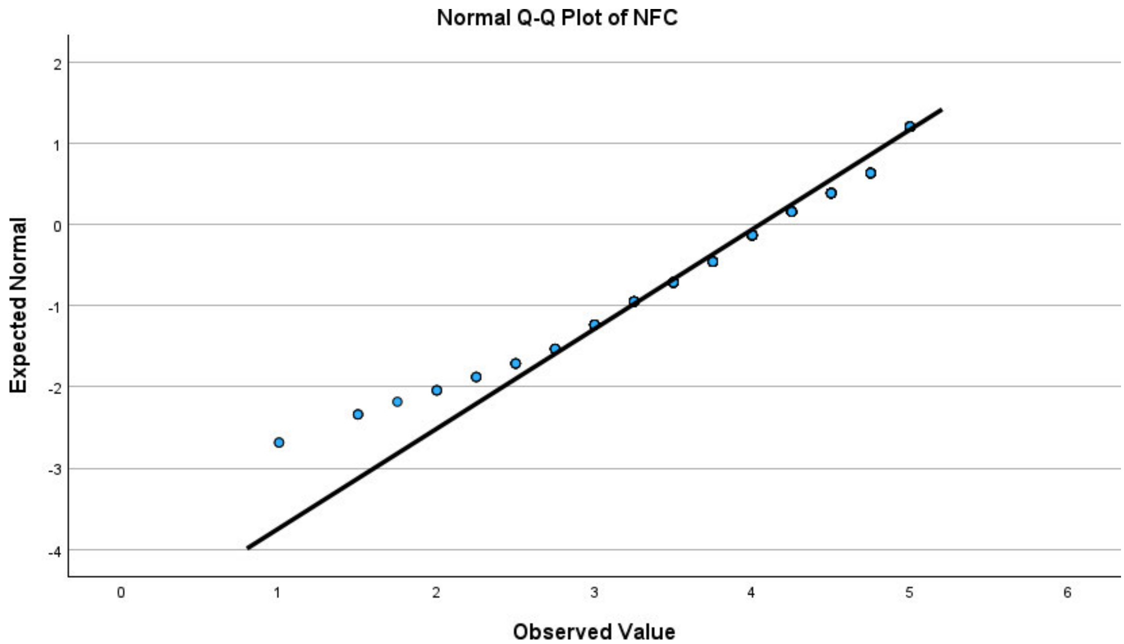

Histogram
Normal
Mean = 4.02
Std. Dev. = .843
N = 414
Frequency
80
60
40
20
0
1.00
2.00
3.00
4.00
5.00
NEE

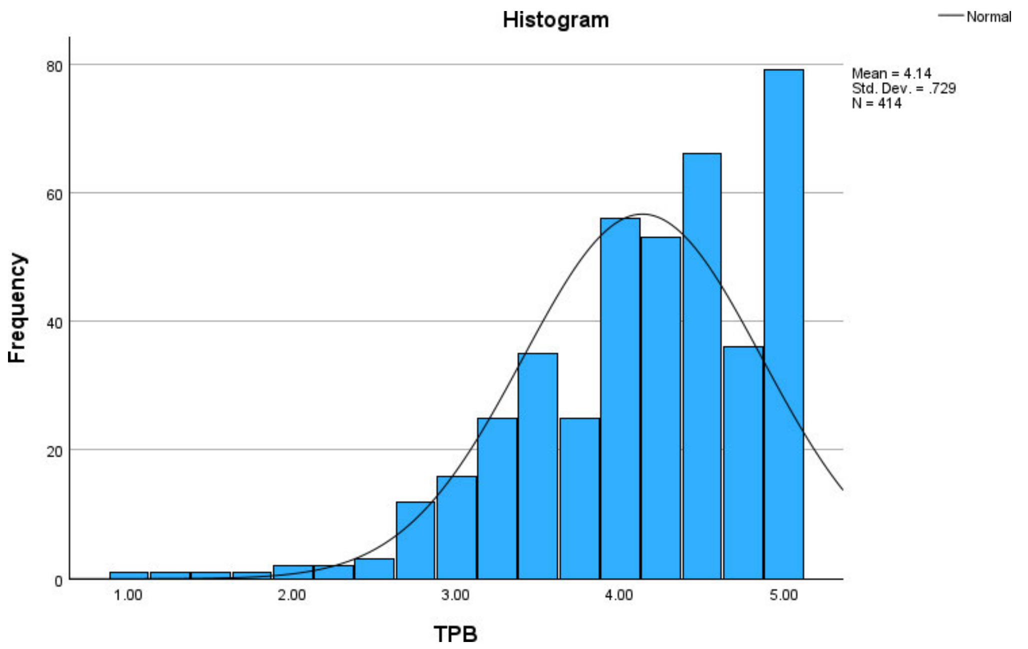

Normal Q-Q Plot of NEE
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value


Histogram
Normal
Mean = 4.21
Std. Dev. = .877
N = 414
Frequency
125
100
75
50
25
0
1.00
2.00
3.00
4.00
5.00
NSI

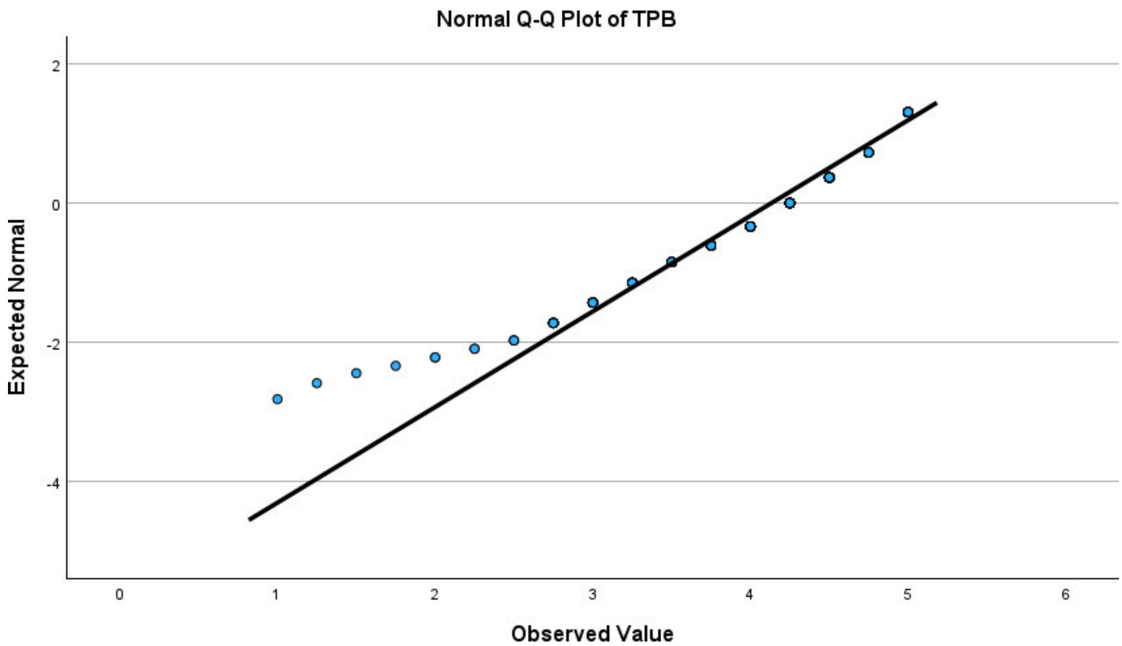

Normal Q-Q Plot of NSI
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value


Histogram
Normal
Mean = 4.05
Std. Dev. = .815
N = 414
Frequency
100
80
60
40
20
0
1.00
2.00
3.00
4.00
5.00
NFC

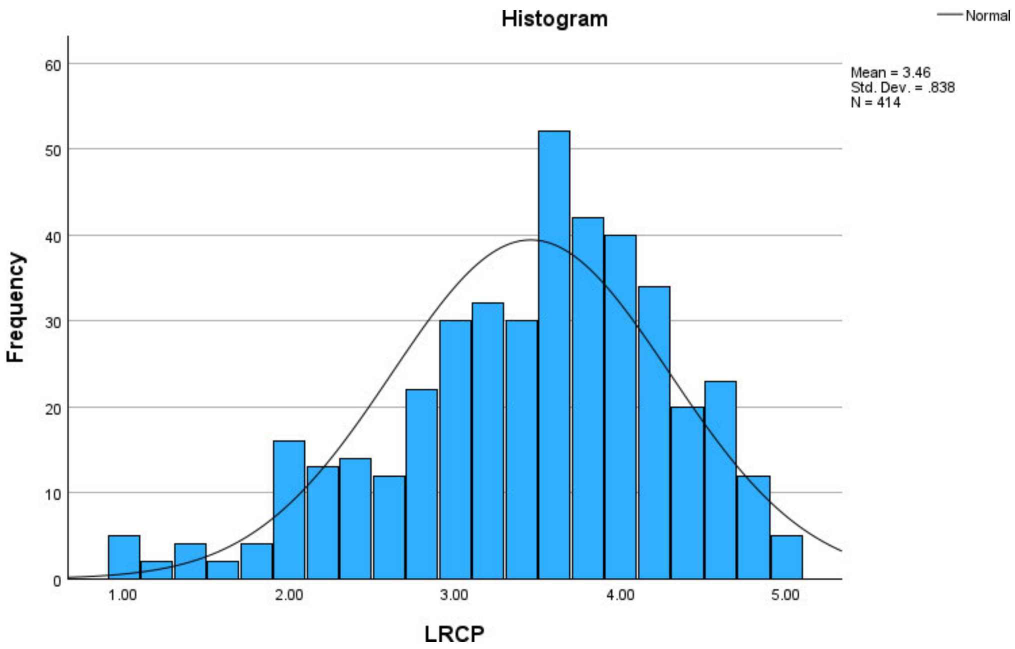

Normal Q-Q Plot of NFC
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value

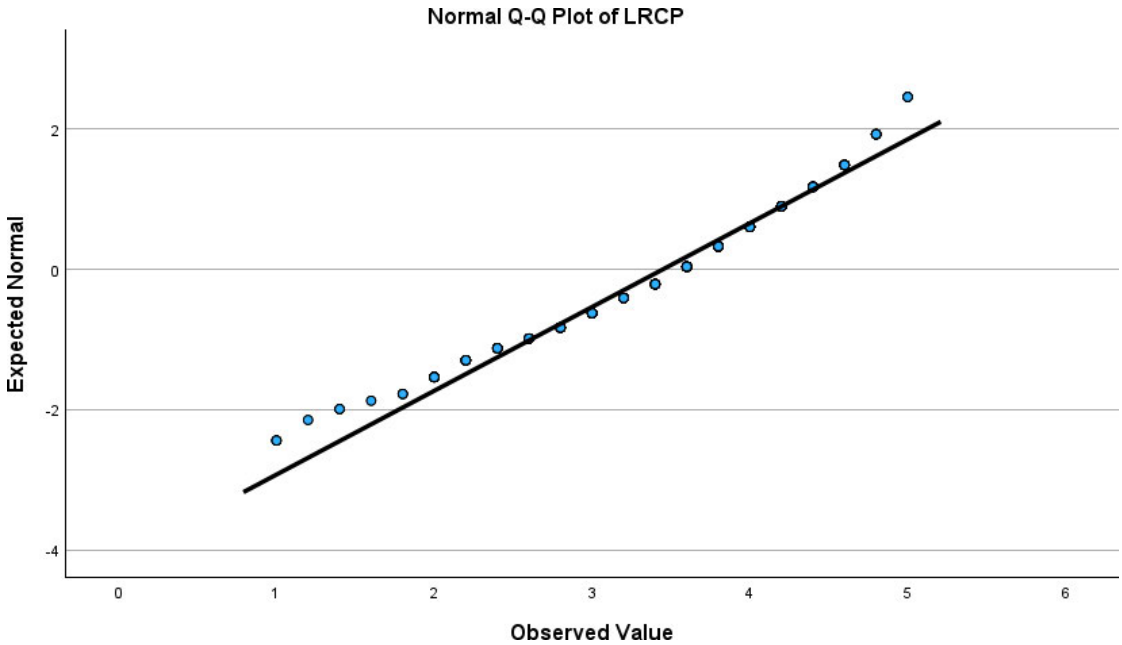


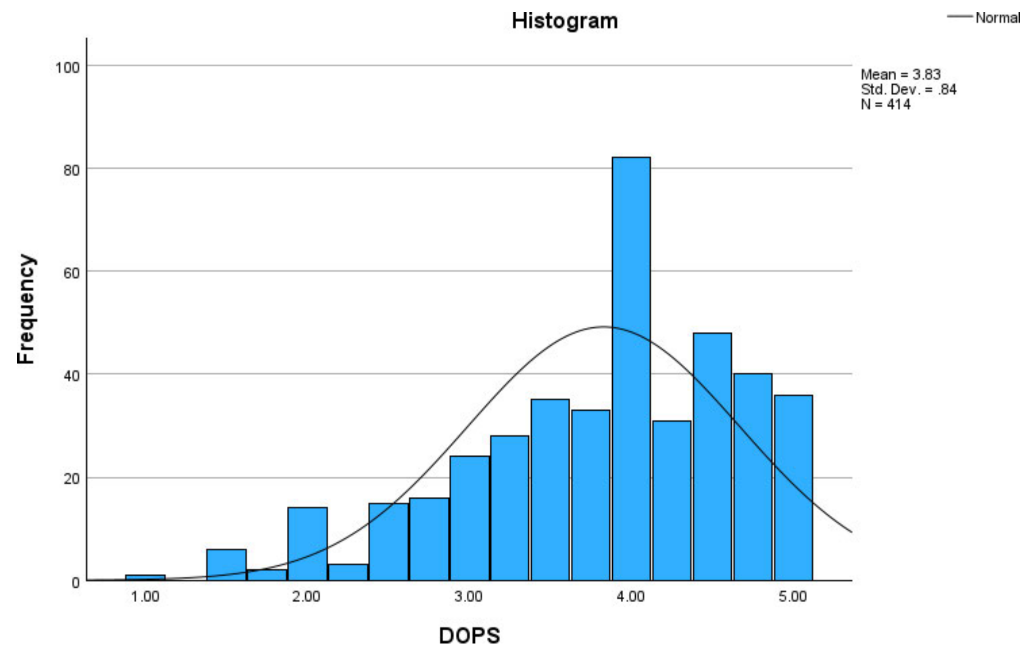
Histogram
Normal
Mean = 4.14
Std. Dev. = .729
N = 414
Frequency
80
60
40
20
0
1.00
2.00
3.00
4.00
5.00
TPB

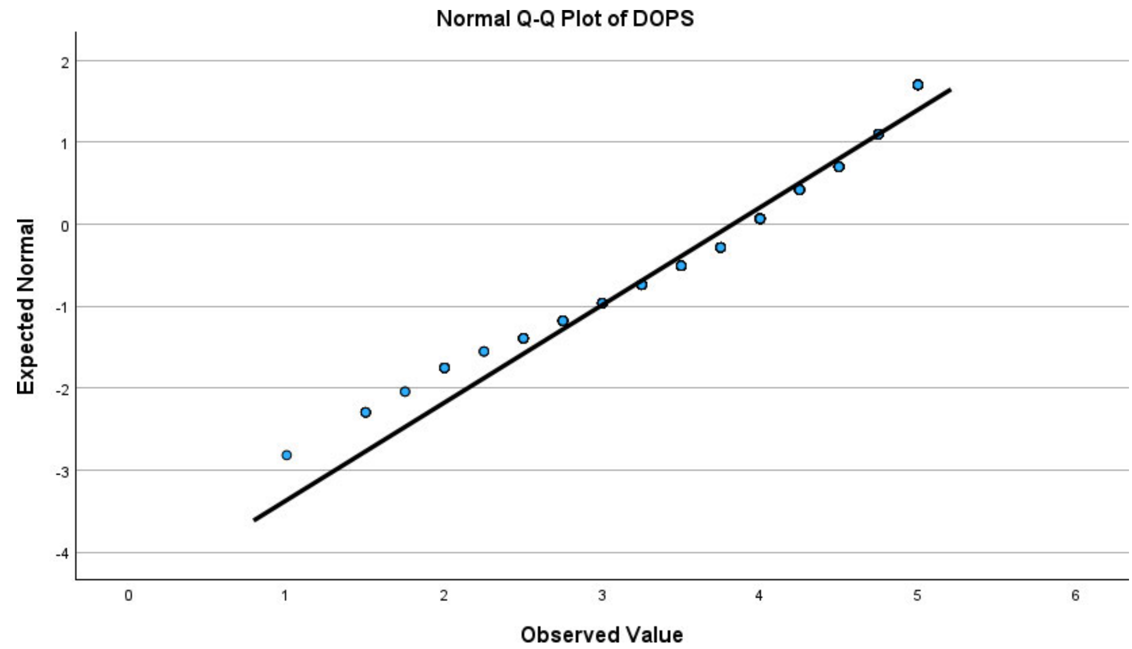


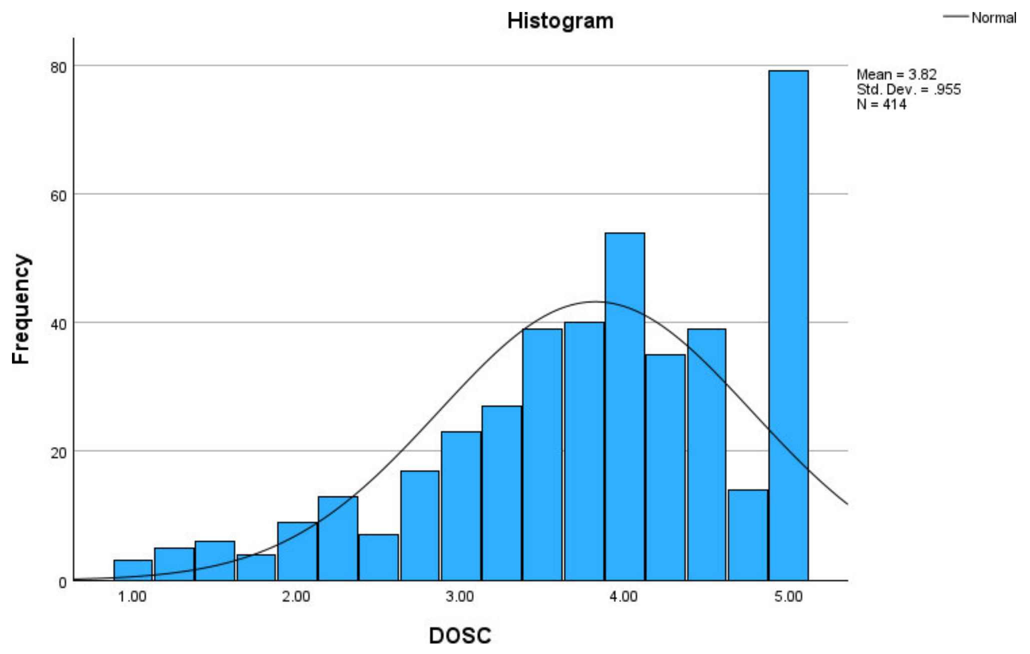
Normal Q-Q Plot of TPB
Expected Normal
2
0
-2
-4
0
1
2
3
4
5
6
Observed Value

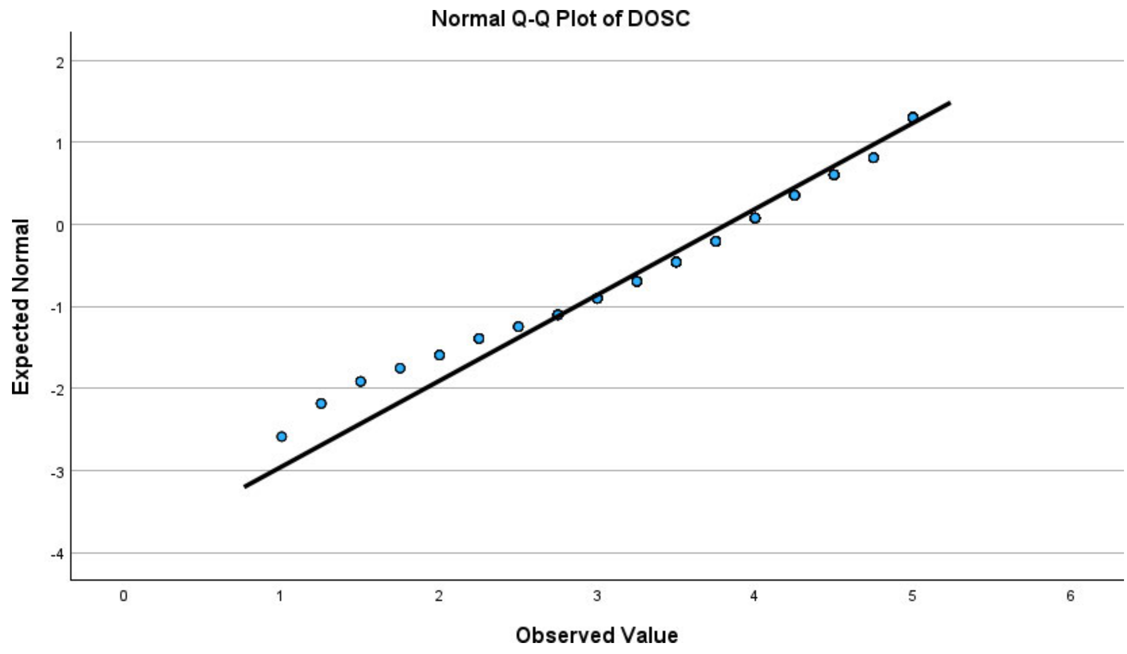

Histogram
Normal
Mean = 3.46
Std. Dev. = .838
N = 414
Frequency
0
10
20
30
40
50
60
1.00
2.00
3.00
4.00
5.00
LRCP

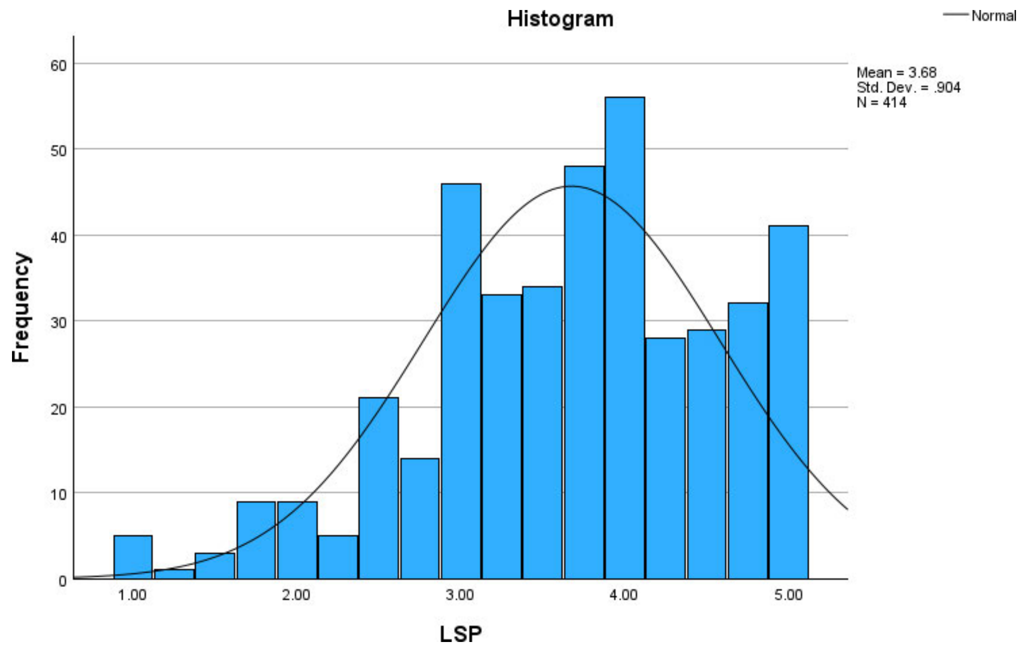

Normal Q-Q Plot of LRCP
Expected Normal
2
0
-2
-4
0
1
2
3
4
5
6
Observed Value

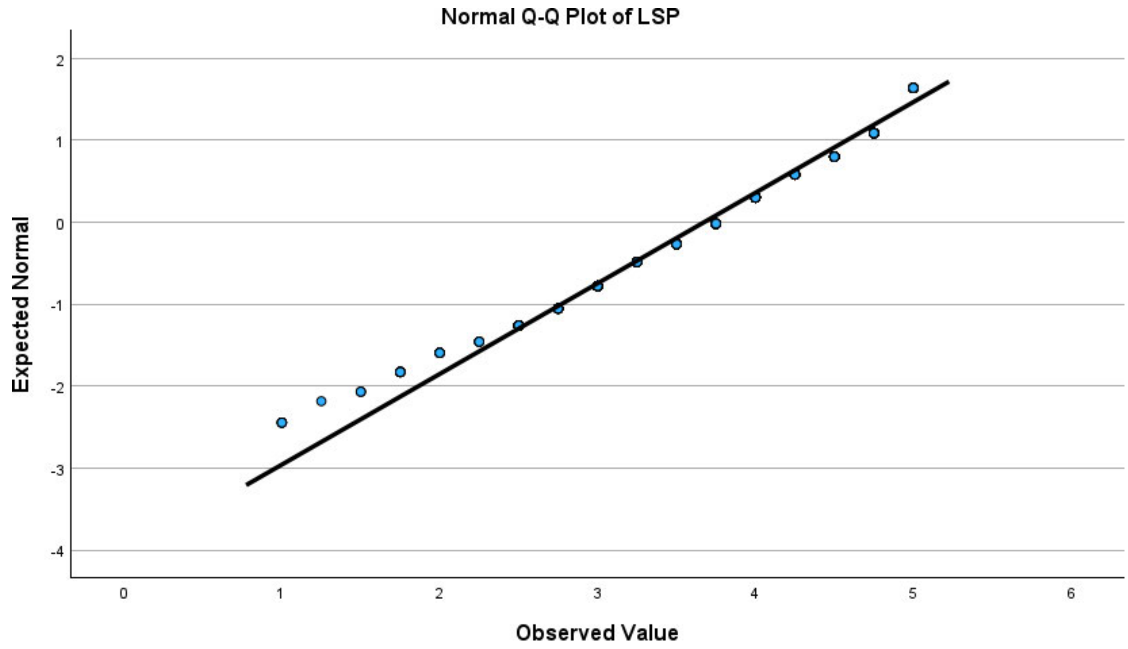

Histogram
Normal
Mean = 3.83
Std. Dev. = .84
N = 414
Frequency
0
20
40
60
80
100
1.00
2.00
3.00
4.00
5.00
DOPS

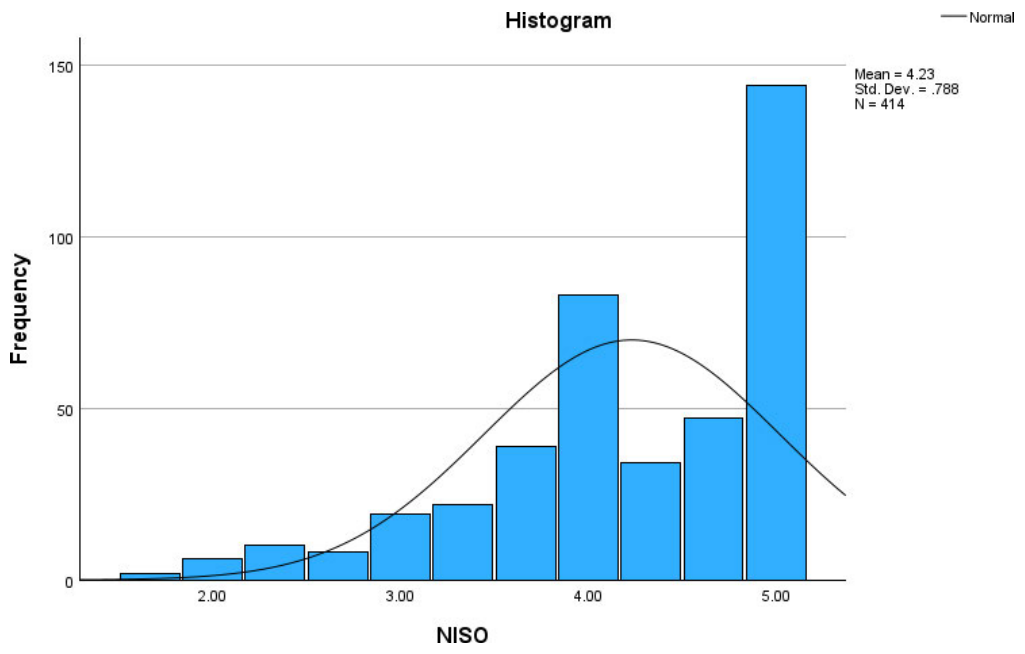

Normal Q-Q Plot of DOPS
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value

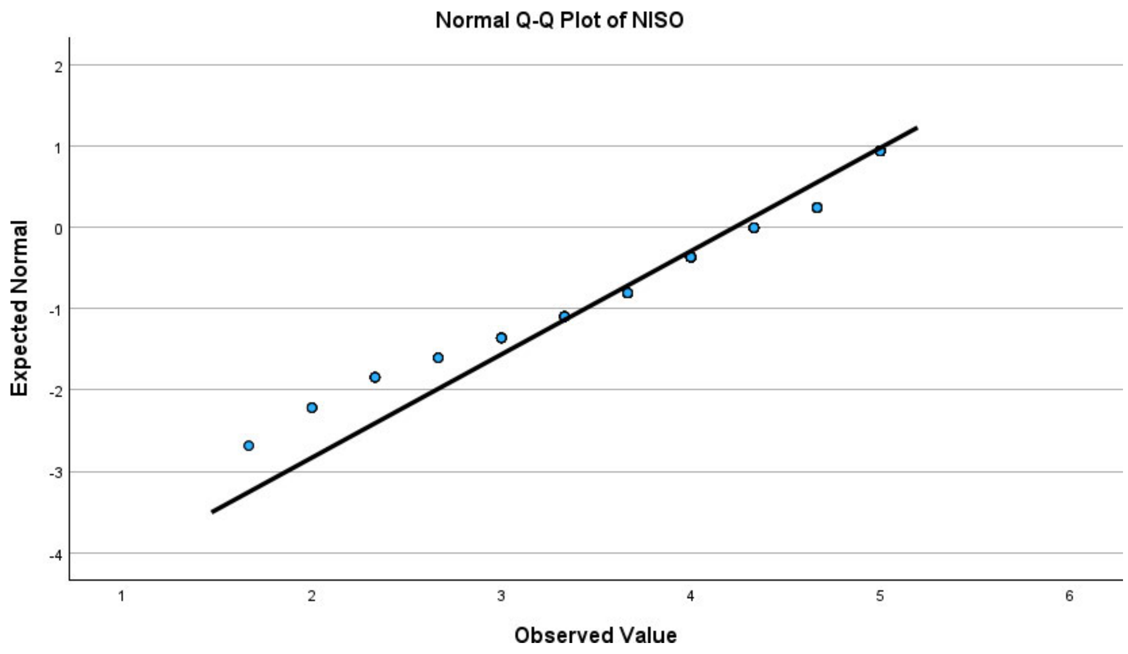

Histogram
Normal
Mean = 3.82
Std. Dev. = .955
N = 414
Frequency
0
20
40
60
80
1.00
2.00
3.00
4.00
5.00
DOSC

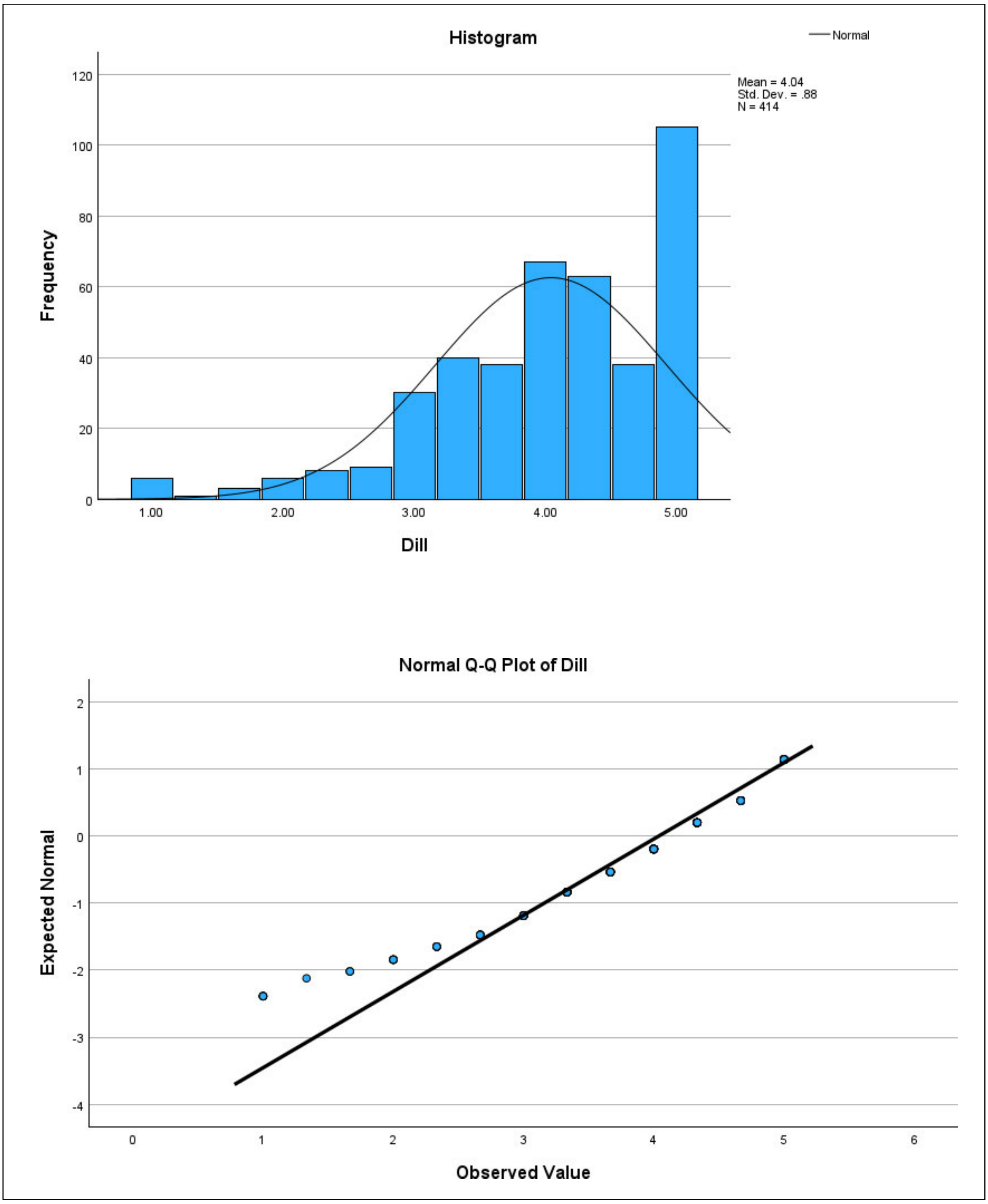

Normal Q-Q Plot of DOSC
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value

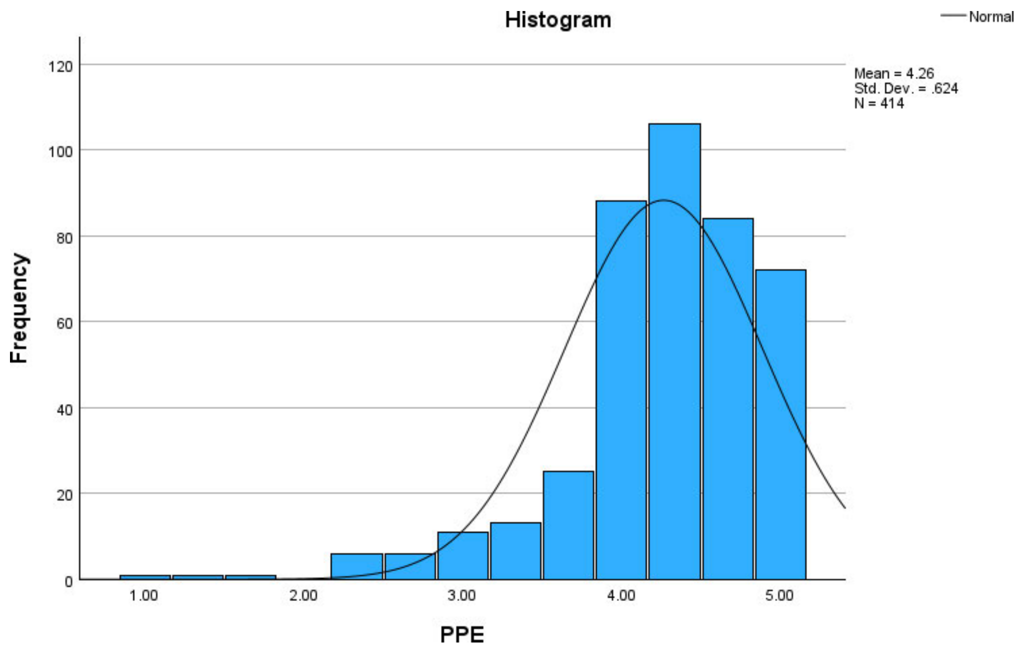

Histogram
Normal
Mean = 3.68
Std. Dev. = .904
N = 414
Frequency
LSP
0
10
20
30
40
50
60
1.00
2.00
3.00
4.00
5.00

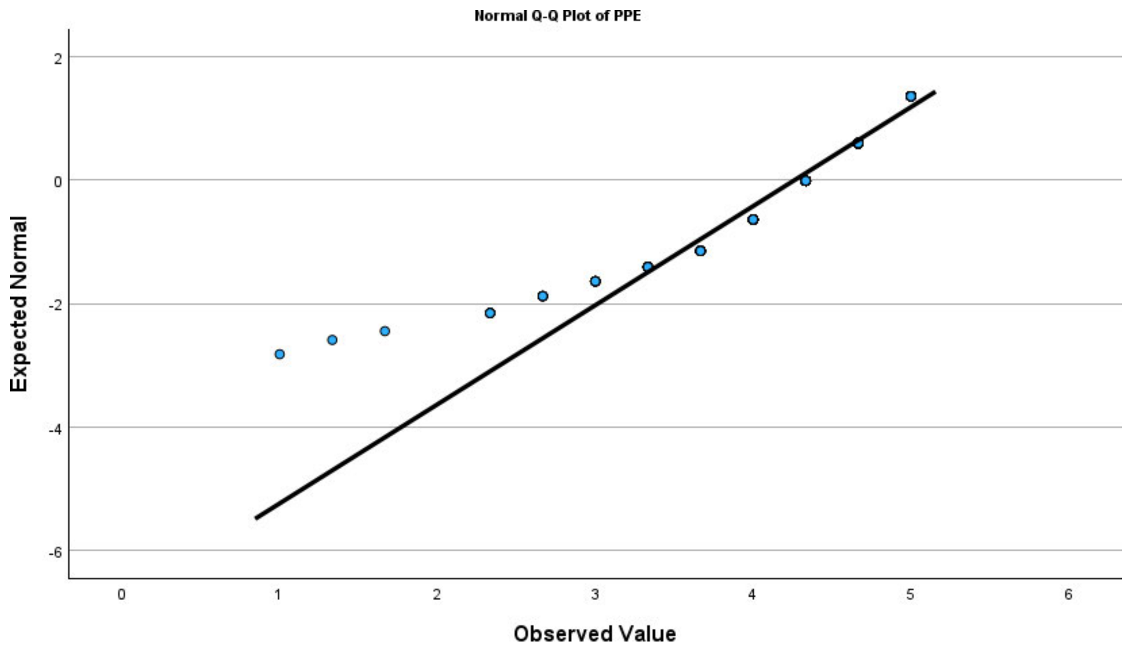

Normal Q-Q Plot of LSP
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6


Histogram
Normal
Mean = 4.23
Std. Dev. = .788
N = 414
Frequency
0
50
100
150
2.00
3.00
4.00
5.00
NISO

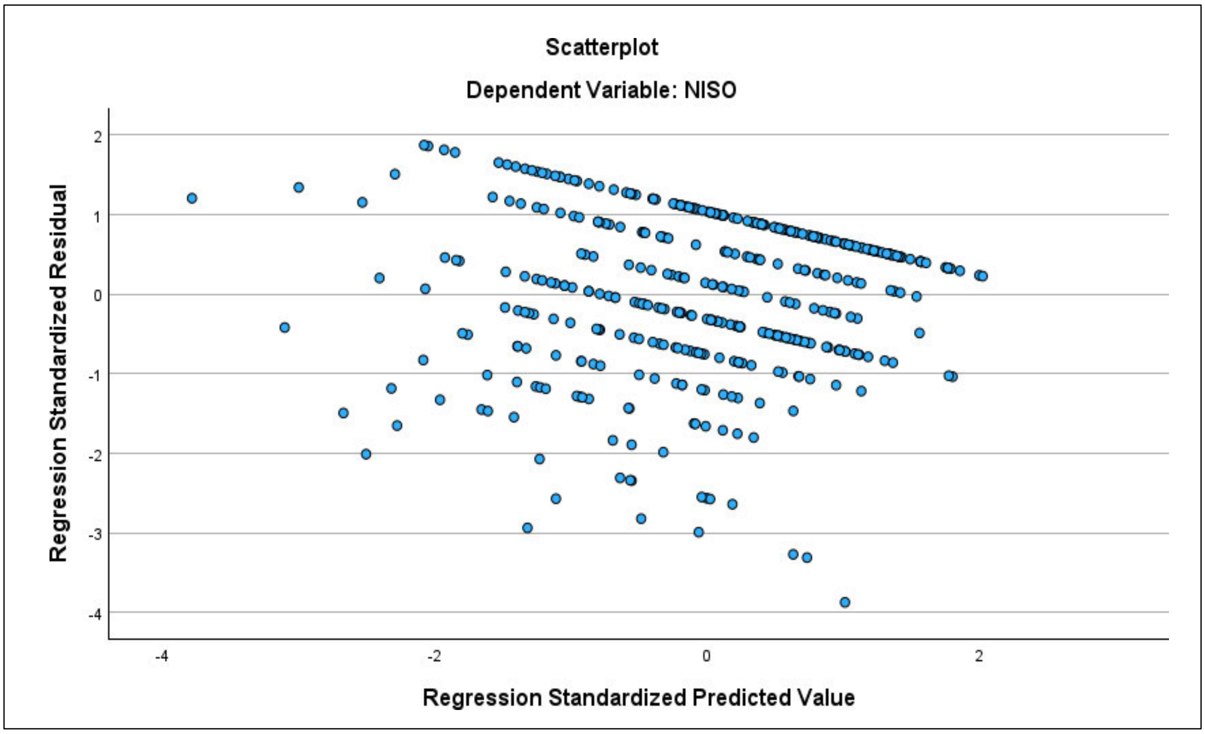

Normal Q-Q Plot of NISO
Expected Normal
2
1
0
-1
-2
-3
-4
1
2
3
4
5
6
Observed Value

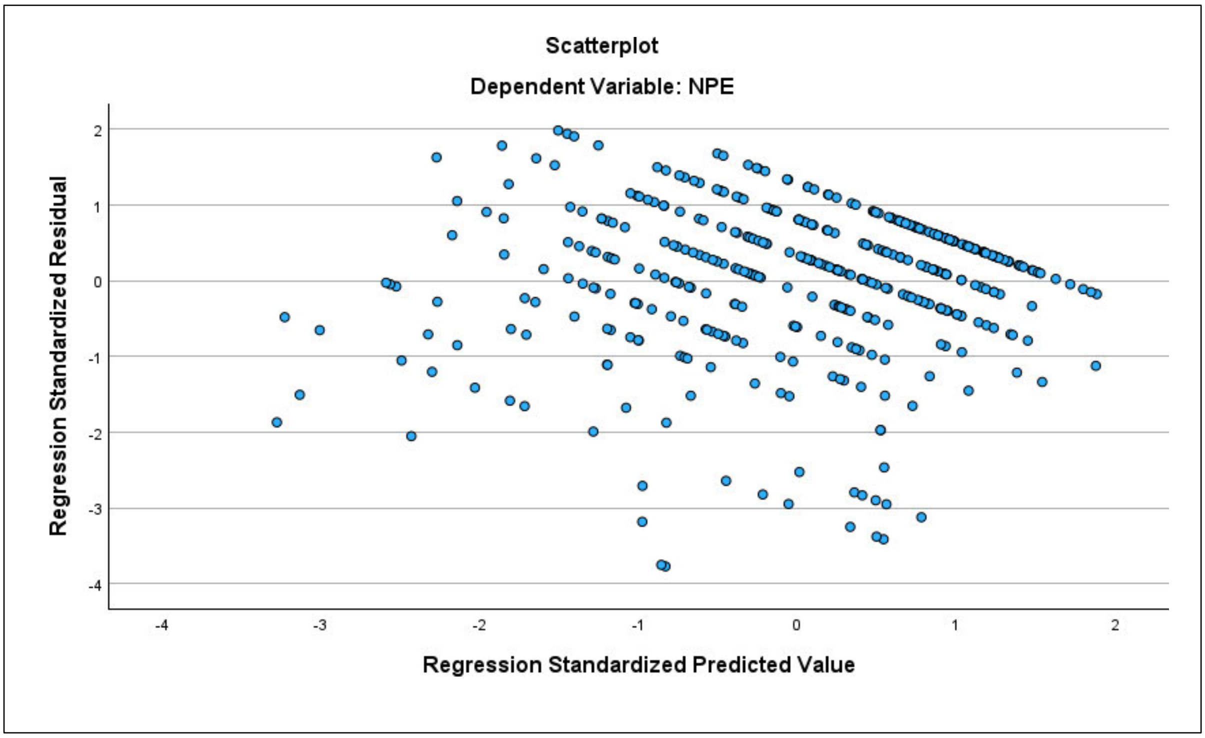

Histogram
Normal
Mean = 4.04
Std. Dev. = .88
N = 414
Frequency
Dill
Normal Q-Q Plot of Dill
Expected Normal
Observed Value

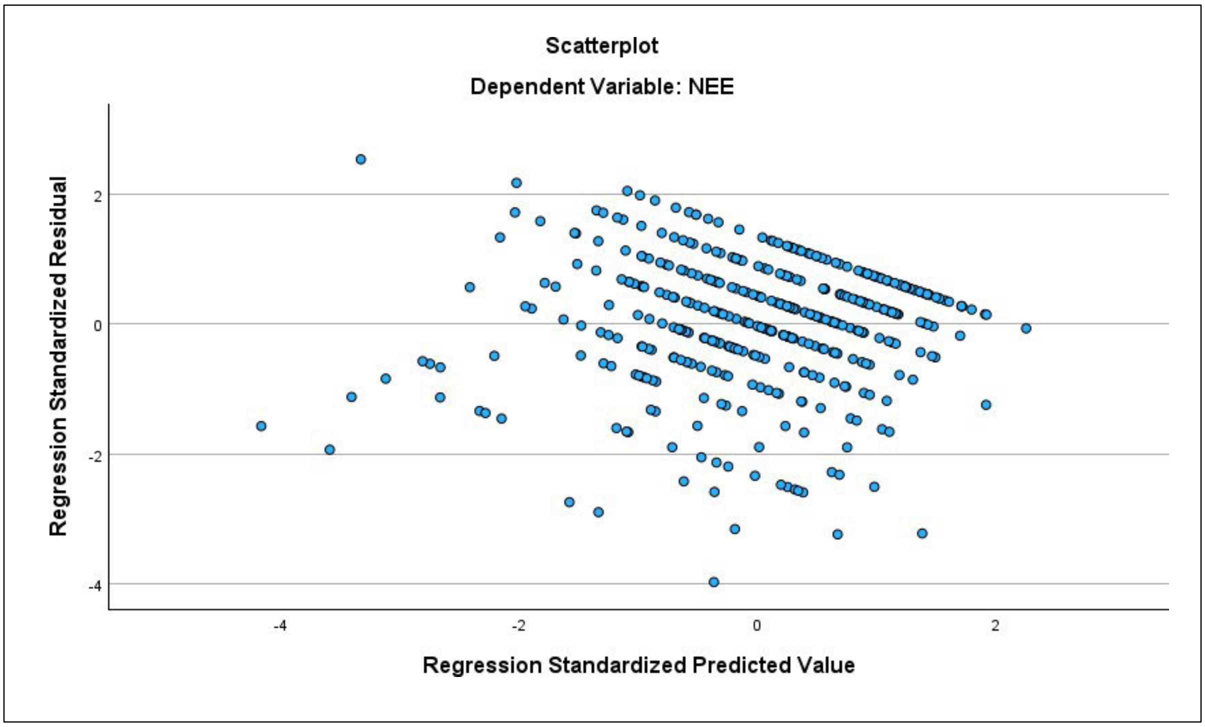

Histogram
Normal
Mean = 4.26
Std. Dev. = .624
N = 414
Frequency
120
100
80
60
40
20
0
1.00
2.00
3.00
4.00
5.00
PPE

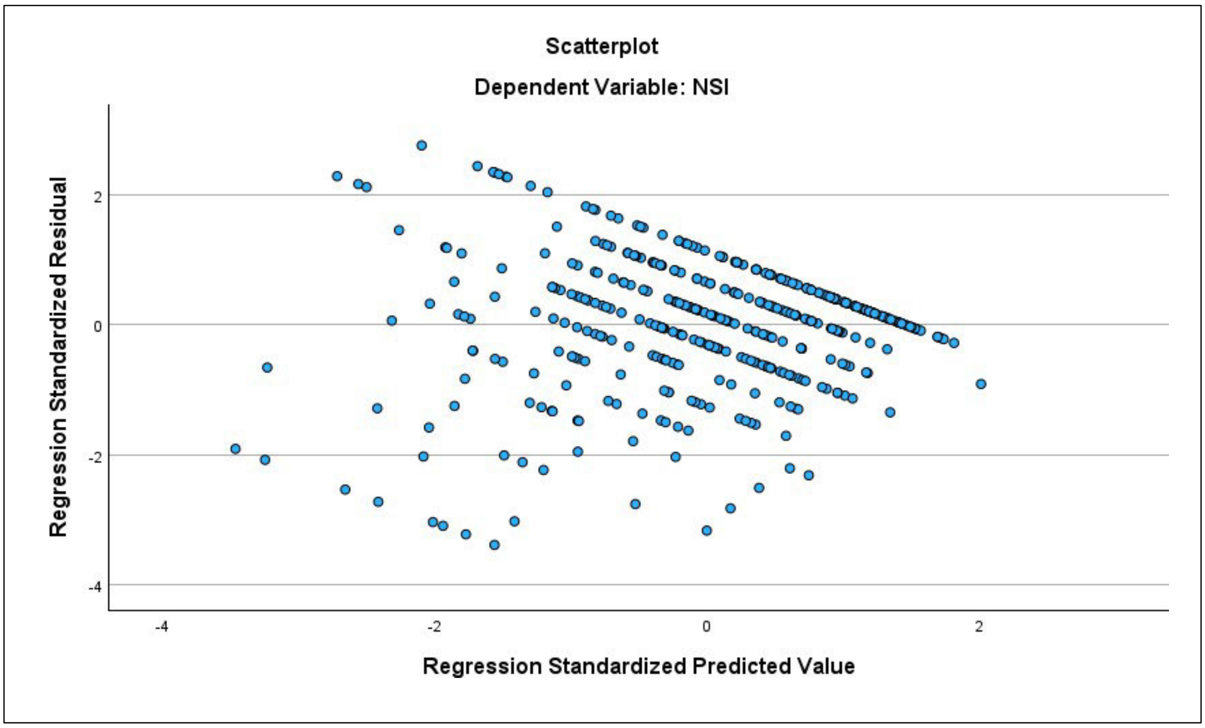

Normal Q-Q Plot of PPE
Expected Normal
2
0
-2
-4
-6
0
1
2
3
4
5
6
Observed Value

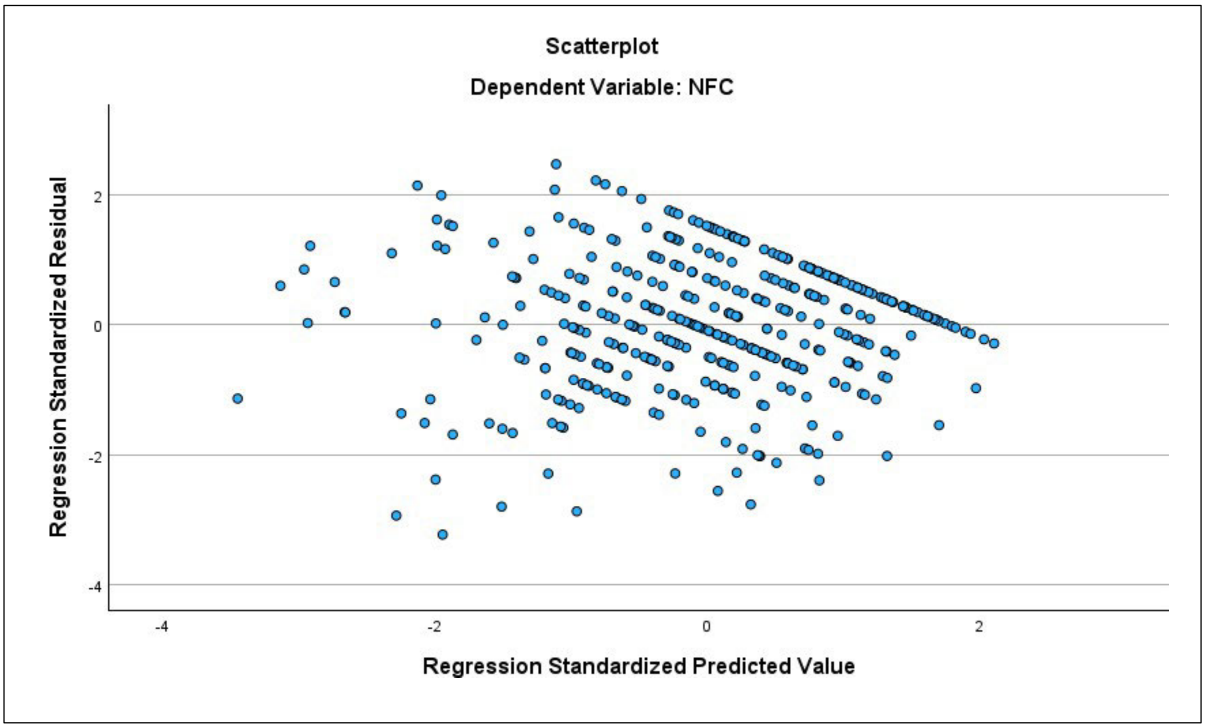
APPENDIX FIVE (B): FIGURES 5.2A-L SCATTERPLOTS

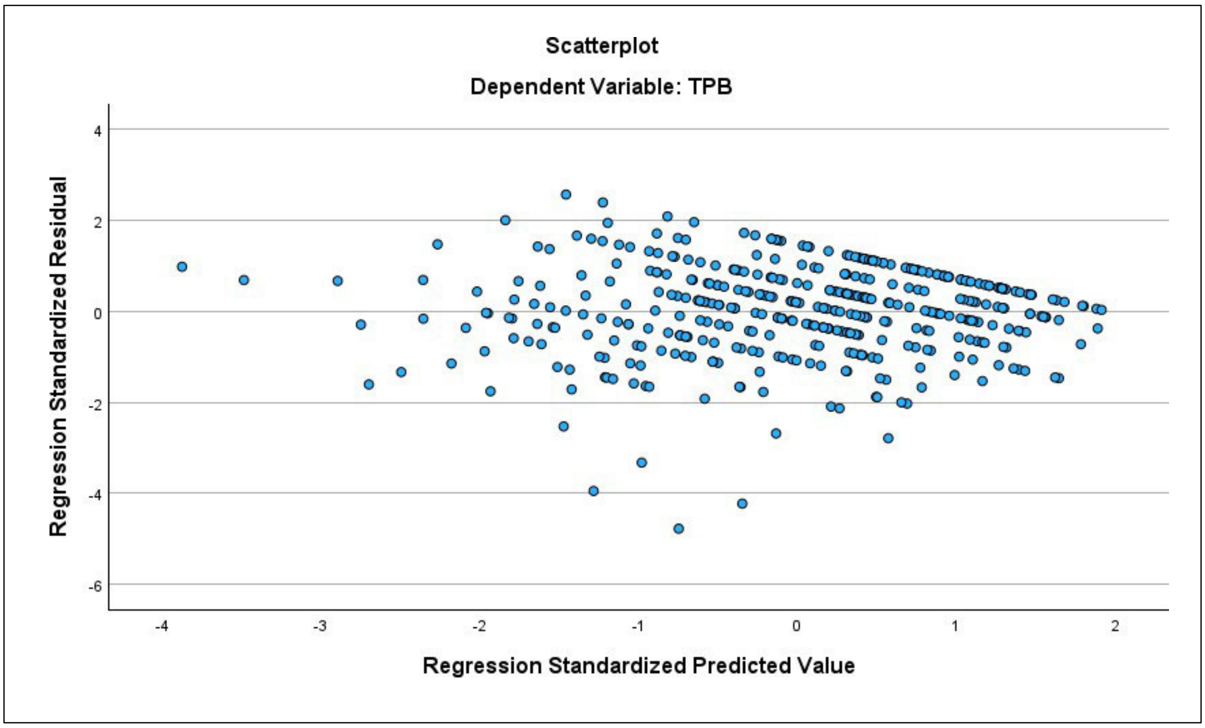


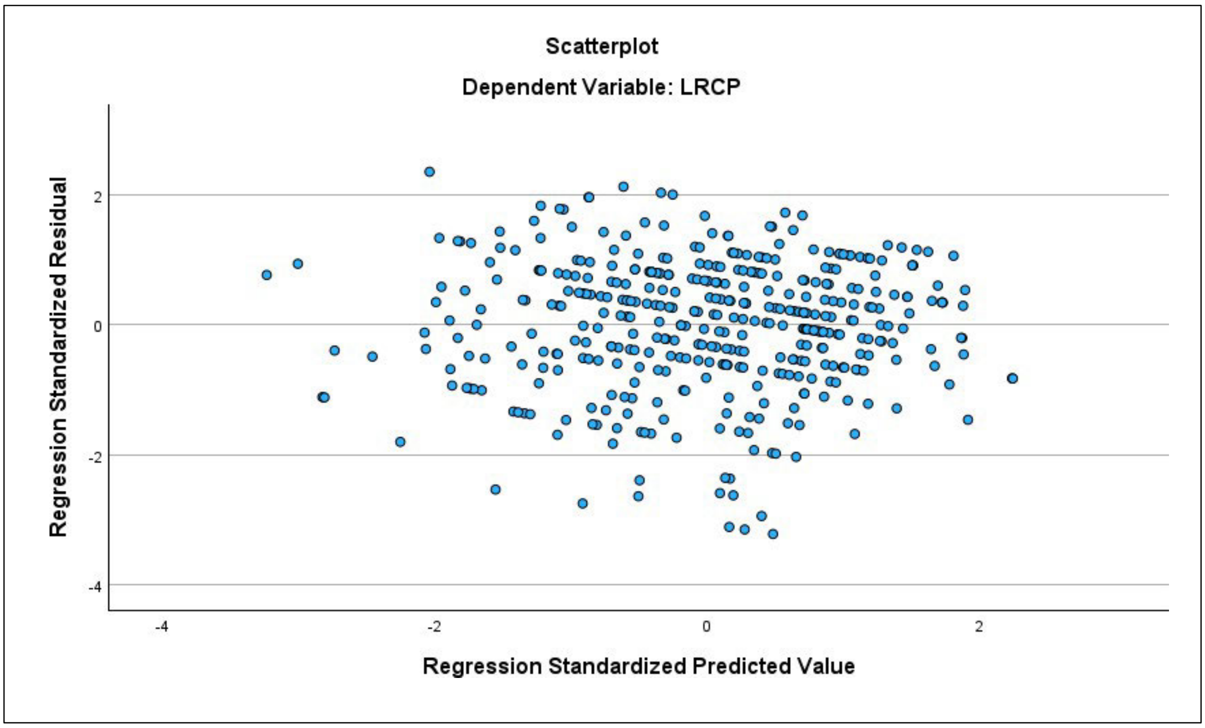


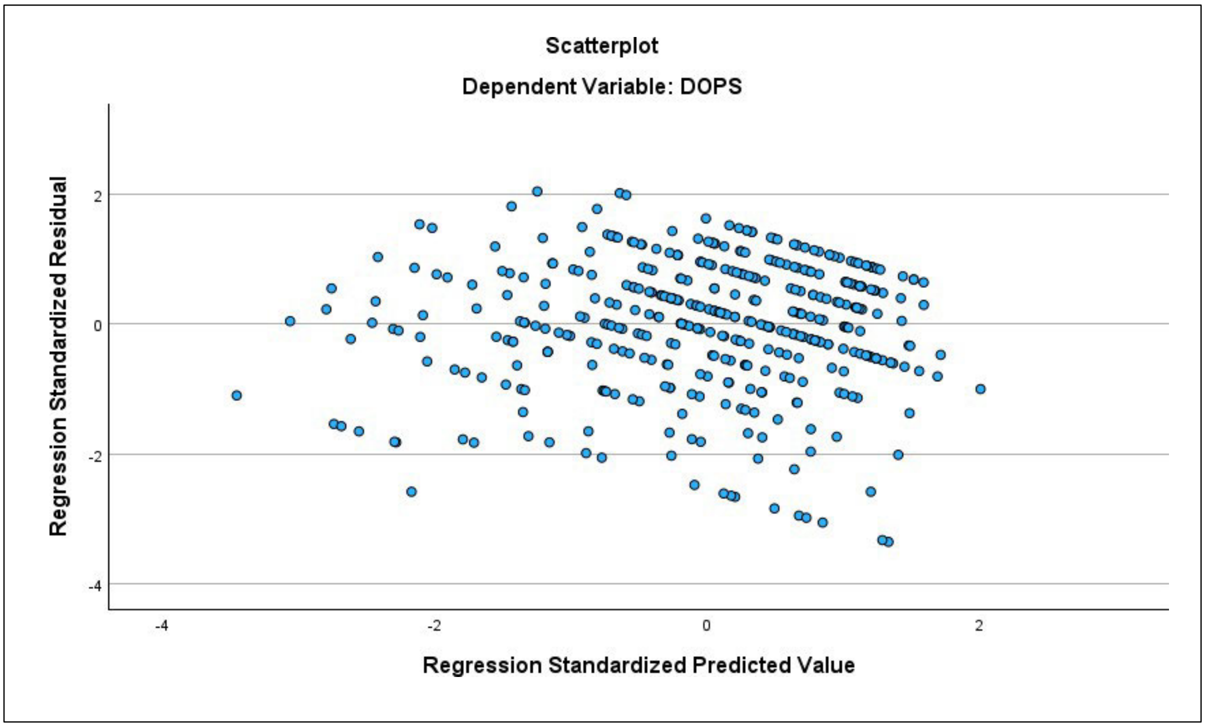

Scatterplot
Dependent Variable: NEE
Regression Standardized Residual
Regression Standardized Predicted Value
2
0
-2
-4
-4
-2
0
2

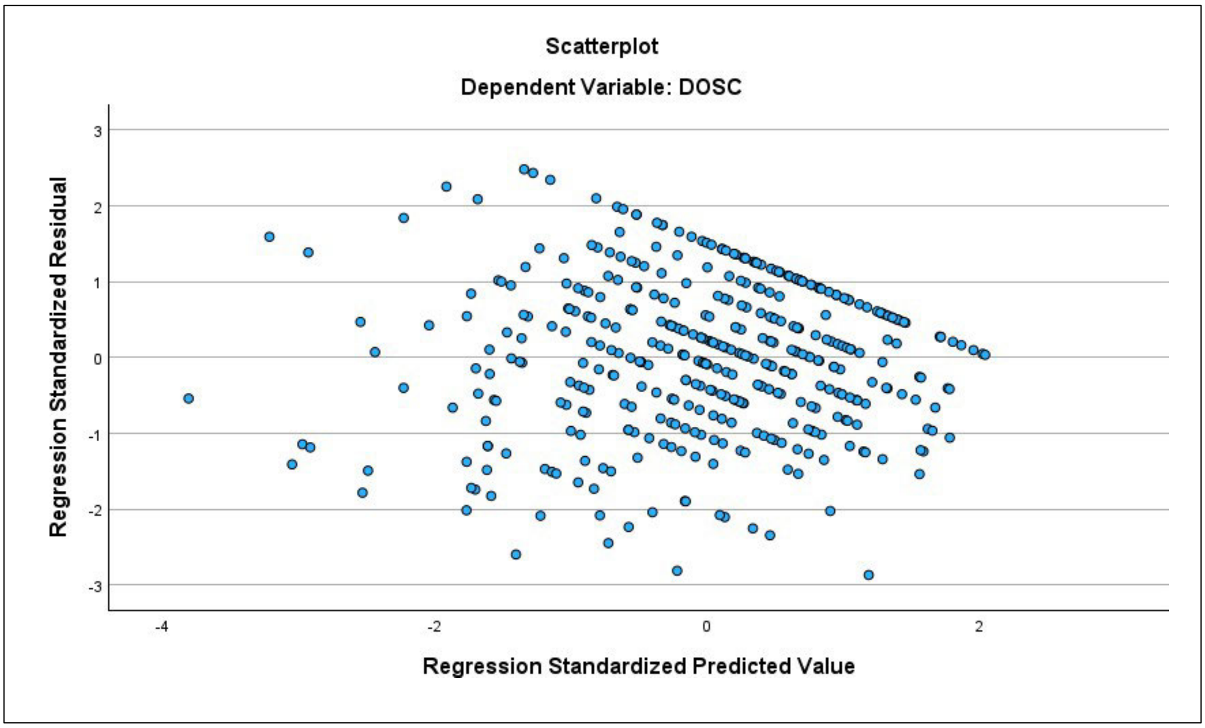

Scatterplot
Dependent Variable: NSI
Regression Standardized Residual
Regression Standardized Predicted Value
2
0
-2
-4
-4
-2
0
2

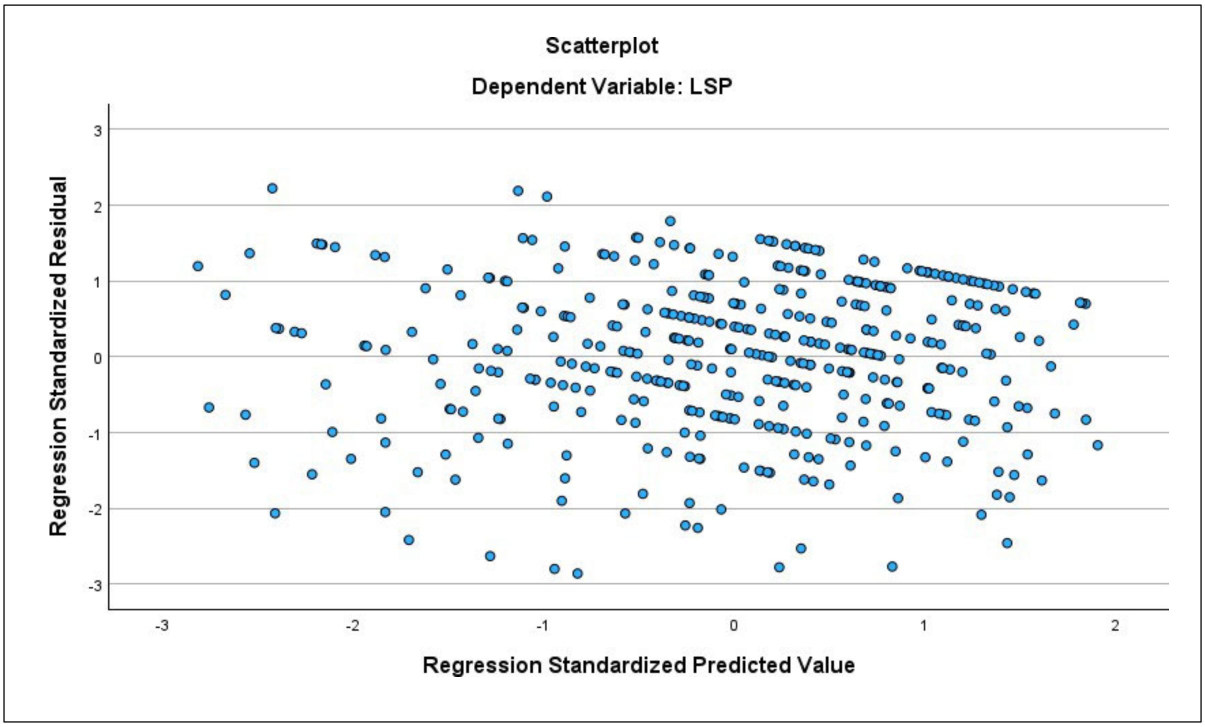

Scatterplot
Dependent Variable: NFC
Regression Standardized Residual
2
0
-2
-4
-4
-2
0
2
Regression Standardized Predicted Value

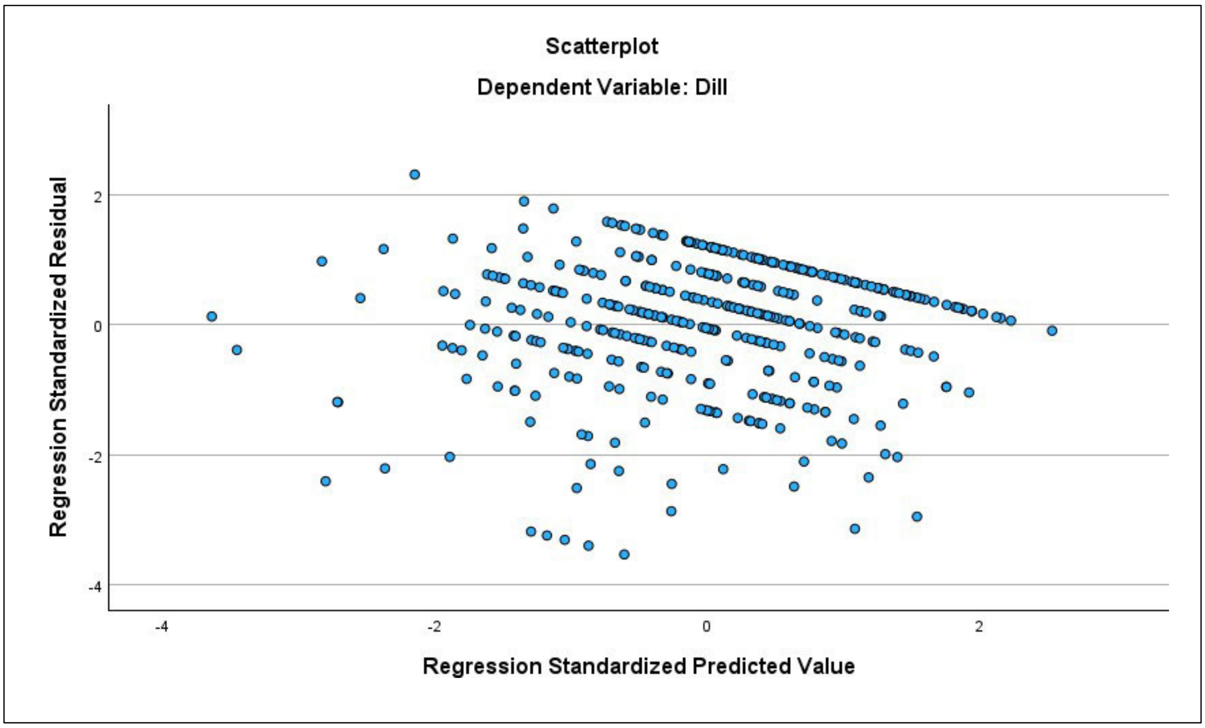

Scatterplot
Dependent Variable: TPB
Regression Standardized Residual
4
2
0
-2
-4
-6
-4
-3
-2
-1
0
1
2
Regression Standardized Predicted Value

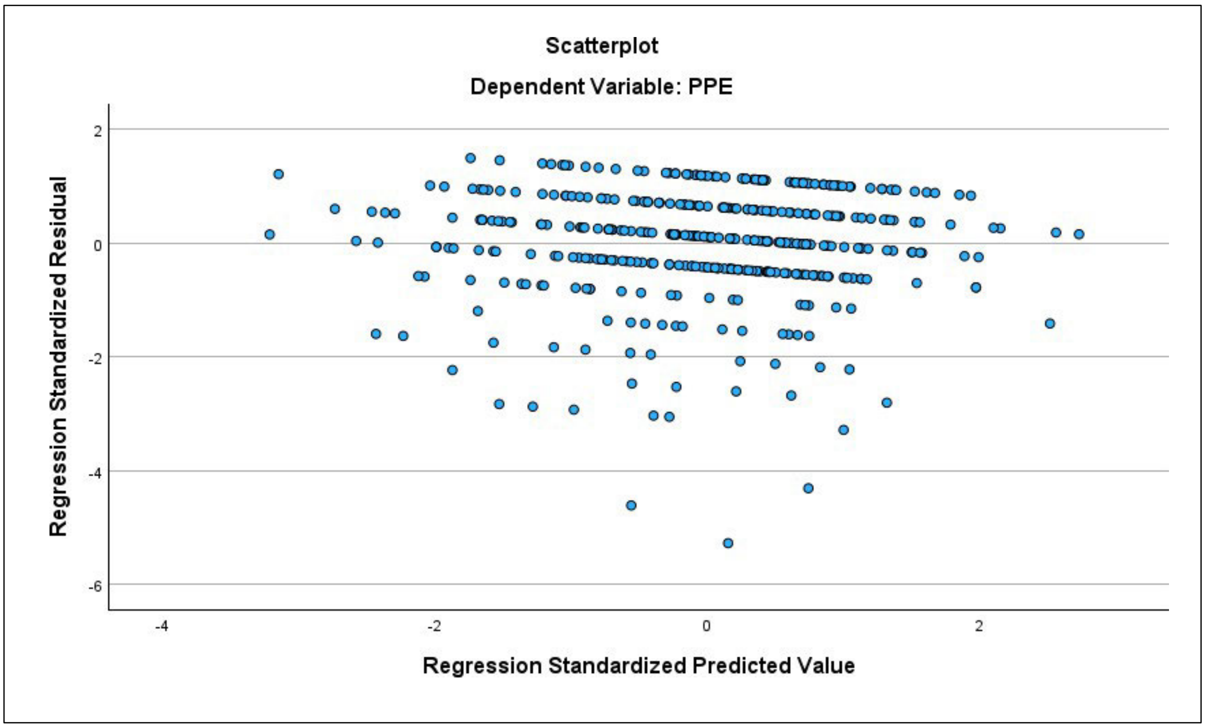

Scatterplot
Dependent Variable: LRCP
Regression Standardized Residual
Regression Standardized Predicted Value
2
0
-2
-4
-4
-2
0
2


Scatterplot
Dependent Variable: DOPS
Regression Standardized Residual
Regression Standardized Predicted Value
2
0
-2
-4
-4
-2
0
2


Scatterplot
Dependent Variable: DOSC
Regression Standardized Residual
Regression Standardized Predicted Value
3
2
1
0
-1
-2
-3
-4
-2
0
2


Scatterplot
Dependent Variable: LSP
Regression Standardized Residual
Regression Standardized Predicted Value
3
2
1
0
-1
-2
-3
-3
-2
-1
0
1
2


Scatterplot
Dependent Variable: Dill
Regression Standardized Residual
2
0
-2
-4
-4
-2
0
2
Regression Standardized Predicted Value


Scatterplot
Dependent Variable: PPE
Regression Standardized Residual
2
0
-2
-4
-6
-4
-2
0
2
Regression Standardized Predicted Value