Determinants of User Growth in B2C E-Commerce Platforms in South Africa

Liesl Viljoen-Nel

443960

A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

Johannesburg, 2024

ABSTRACT

Globally, e-commerce has grown exponentially, especially during the COVID-19 pandemic, since people were forced to stay at home and shop online. South Africa has also experienced e-commerce growth, and the e-commerce penetration rate is forecasted to accelerate from 27 million registered e-commerce users in 2022 (43.5%) to 39.7 million registered e-commerce users by 2027 (64%). These statistics show that retailers will need targeted activities to ensure user growth in their e-commerce platforms since the competition between retailers to obtain e-commerce customers will intensify as it becomes a dominant sales channel in South Africa.

This exploratory study investigated the "Determinants of User Growth in business-to-consumer (B2C) e-Commerce Platforms in South Africa" through the unique application of an academic (UTAUT2) and a practitioner model (AARRR). This study is the first South African study on e-commerce user growth. It is exclusive as existing literature mainly studies behavioural intention to use and use behaviour of information systems. However, it fails to address user growth, a critical component of information systems' retention and continuous use intention. This aim of this study was to understand the factors that impact use behaviour from a consumer perspective and, ultimately, user growth on e-commerce platforms in the fast-moving consumer goods industry specific to South Africa.

A quantitative survey was conducted through a non-probability convenience sampling process from March to July 2023. Electronic survey links were distributed via e-mails, social media posts and online messaging services to reach a sample frame of 7,386 prospective respondents. Completed questionnaires were received from 743 respondents. After a data cleansing and rescaling procedure, the data from 550 respondents were analysed in a phased approach using exploratory factor, regression, correlation and moderation analyses.

The independent variables accounted for 65.12% of the total variance in the UTAUT2 model, and performance expectancy and facilitating conditions emerged as the strongest predictors of behavioural intention. Neither age, gender, nor experience had a moderating impact on the independent variables and behavioural intention. Behavioural intention, however, significantly influenced user growth, as the customer transitioned from activation to retention to referral and the revenue phases of the user growth construct.

Retention was the dominant factor in the user growth construct, explaining 18.66% of the total variance in the data. Revenue showed the highest correlation with behavioural intention, demonstrating that consumers will use a platform if they benefit from the transaction. Customer satisfaction moderated the relationship between behavioural intention and user growth, and facilitating conditions and user growth. This result demonstrates that customer service and support are instrumental in promoting user growth in B2C e-commerce platforms.

South African customers have adopted B2C e-commerce platforms and have transitioned from the acquisition to the retention phases of the customer life cycle. However, shopping online in South Africa has not become a habitual activity or a necessity, which could be attributed to the availability of plenty of shopping malls with brick-and-mortar retailers throughout the country. It is recommended that retailers use data-driven insights to design targeted marketing activities for each phase of the purchase life cycle to strengthen behavioural intention and trigger user growth in B2C e-commerce platforms. The study makes a meaningful contribution to the South African digital commerce literature by concluding with practical recommendations that managers can apply to designing, implementing, and managing B2C e-commerce platforms in the fast-moving consumer goods or other consumer packaged goods industries.

KEYWORDS

AARRR, e-commerce user growth, e-commerce adoption, e-commerce retention, e-commerce customer satisfaction, FMCG, UTAUT2.

DECLARATION

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

Name: Liesl Viljoen-Nel Signature: Viljoen-Nel

Signed at Johannesburg

On the 29th day of February 20 24

DEDICATION

To my Mother, Elna Viljoen, and my Father, Dr Robert B Viljoen, who raised me to be hardworking, resilient and persistent in reaching my goals.

Mother, thank you for teaching me that no problem is too big to solve. Your determination, courage, and perseverance as a businesswoman gave me hope and faith to believe in my career aspirations. Thank you for being a caring and loving Mother and for always reminding me “to keep my eye on the ball”.

Father, thank you for all the encouragement and reassurance during a period of absolute turmoil in my life. Your unbelievable work ethic and commitment towards your profession is an example, not only of a passion for the theory, but an unprecedented dedication to the practice of medicine. Thank you for setting this example and inspiring me to work hard. You urged me never to say “I can not” but to always believe in myself.

To Oupa Pierrie Viljoen, I wish you were here to celebrate this milestone with me. As a construction economics and management professor, the academics were very close to your heart. You would have been so proud as I completed this academic journey.

To Oupa Fritz Schoeman, an entrepreneur and visionary businessman. Your brave and fearless endeavours have been an inspiration to me.

Lastly, but most importantly, I want to thank my heavenly Father for the opportunity to complete this qualification. Thank you for giving me hope, strength and perseverance to work hard and fulfil my dreams.

ACKNOWLEDGEMENTS

I want to thank my husband, Emile Nel, for his unwavering support throughout the 38 months of completing my degree. Thank you for all the tasty meals and countless cups of coffee served as I was working at my desk. Your love and commitment have been a pillar of strength.

Prof Nixon Ochara, my supervisor, thank you for your wisdom, guidance and mentorship during my research project.

Prof Anthony Stacey, thank you for guiding me through the data cleansing process and basic quantitative statistical techniques.

My editor, Monica Botha, thank you for the language and technical editing. The final document is very professional and can be presented with pride.

To Syndicate 2 of the MMDB 2021 class. You taught me resilience, how to work under pressure and that a team is only "as strong as its weakest link".

Lastly, I appreciate and want to thank everyone who participated in the pre-testing and final completion of my questionnaires.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

Term	Definition	Reference
AARRR	Pirate Metrics: acquisition, activation, retention, referral, revenue	McClure, 2007
ANOVA	Analysis of Variance	www.statology.org/anova
App	Application	Gillis, 2023
B2A	Business-to-Administration	Rouse, 2012
B2B	Business-to-Business	Jewels & Timbrell, 2001
B2C	Business-to-Consumer	Budree, 2023
BI	Behavioural Intention	Thompson et al., 1991
BRICS	Brazil, Russia, India, China and South Africa	Haji, 2021
C2B	Consumer-to-Business	Budree, 2023
C2C	Consumer-to-Consumer	Budree, 2023
C2M	Consumer-to-Manufacturer	Mak & Max Shen, 2021
CAC	Customer Acquisition Cost	Rosset et al., 2002
CLV	Customer Lifetime Value	Rosset et al., 2002
CMB	Common Method Bias	Podsakoff et al., 2003
CMV	Common Method Variance	Rodríguez-Ardura & Meseguer-Artola, 2020
CPG	Consumer Packaged Goods	Kenton, 2021
CRM	Customer Relationship Management	Stokes, 2018
CRO	Conversion Rate Optimisation	MacGaw, 2005
CV	Co-creation Value	Vega-Vazquez et al., 2013
ECT	Expectation Confirmation Theory	Bhattacherjee, 2001
EE	Effort Expectancy	Venkatesh et al., 2003

EFA	Exploratory Factor Analysis	Field, 2013
EFT	Electronic Funds Transfer	www.datareportal.com/reports/digital-2023-south-africa
EOU	Ease of Use	Moore & Benbasat, 1991
FAQ	Frequently Asked Questions	www.merriam-webster.com/dictionary/FAQ
FC	Facilitating Conditions	Venkatesh et al., 2003
FMCG	Fast-moving Consumer Goods	Kenton, 2021
GMV	Gross Merchandising Value	Chevalier, 2022
HM	Hedonic Motivation	Venkatesh et al., 2012
ICT	Information and Communications Technology	Armstrong, 2020
IMF	International Monetary Fund	www.imf.org
IS	Information Systems	Thompson et al., 1991
IT	Information Technology	R. Agarwal and E. Karahanna, 2000
KMO	Kaiser-Meyer-Olkin Measure	Hair, 2007
LMS	Learning Management Software	Raman & Don, 2013
LSM	Living Standards Measure	Ngqinani, 2020
MM	Motivational Model	Vallerand, 1997
MOCA	Model of E-Commerce Adoption	Guzzo et al., 2016
MPCU	Model for Personal Computer Utilisation	Thompson et al., 1991
NASDAQ	National Association of Securities Dealers Automated Quotations Stock Market	www.nasdaq.com

OGS	Online Grocery Service	Van Droogenbroeck & Van Hove, 2021
PA	Parallel Analysis	Ledesma & Valero-Mora, 2019
PBC	Perceived Behavioural Control	Ajzen, 2002
PC	Personal Computer	Thompson et al., 1991
PE	Performance Expectancy	Venkatesh et al., 2003
PEOU	Perceived Ease of Use	Davis, 1989
PU	Perceived Usefulness	Davis, 1989
PV	Price Value	Venkatesh et al., 2012
RFM	Recency, Frequency, Monetary	Lai, 2022
ROI	Return on Investment	www.investopedia.com/terms/r/returnoninvestment
SAQ	Self-administered Questionnaire	De Leeuw, 2008
SEO	Search Engine Optimisation	McGaw, 2015
SCT	Social Cognitive Theory	Compeau & Higgins, 1995
SI	Social Influence	Venkatesh et al., 2003
SME	Small and Medium sized Enterprises	Chooprayoon & Fung, 2010
SMS	Short Messaging Service	https://www.techtarget.com/searchmobile computing/definition/Short-Message-Service
SPSS	Statistical Package for the Social Sciences	www.ibm.com
Stats SA	Statistics South Africa	www.statssa.gov.za
TAM	Technology Acceptance Model	Davis, 1989

TAM2	Technology Acceptance Model 2	Venkatesh & Davis, 2000
TAM3	Technology Acceptance Model 3	Venkatesh & Bala, 2008
TBL	Triple Bottom Line	Dreher & Strobel, 2023
TBP	Theory of Planned Behaviour	Ajzen, 1991
TECTAM	Thai E-Commerce Technology Acceptance Model	Chooprayoon & Fung, 2010
TRA	Theory of Reasoned Action	Hale et al., 2002
TTF	Task Technology Fit Model	Klopping & McKinney, 2004
UG	User Growth	Researchers' own
UTAUT	Unified Theory of Acceptance and Use of Technology Model	Venkatesh et al., 2003
UTAUT2	Unified Theory of Acceptance and Use of Technology Model 2	Venkatesh et al., 2012
VIF	Variance Inflation Factor	Daoud, 2017
WBS	Wits Business School	www.wbs.ac.za
WOM	Word of Mouth	Stokes, 2018
WTO	World Trade Organization	www.wto.org

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

This research project was a quantitative study investigating the determinants that influence consumer behavioural intention and satisfaction on user growth (UG) in business-to-consumer (B2C) e-commerce platforms when purchasing fast-moving consumer goods (FMCG) online in South Africa.

The Unified Theory of Acceptance and Use of Technology model 2 (UTAUT2) (Venkatesh et al., 2012) in conjunction with the Pirate Metrics (acquisition, activation, retention, referral, revenue) (AARRR) (McClure, 2007; Zhang, 2021) was used to create a nomological framework, with the dependent construct being UG and the independent construct being the UTAUT2 variables. The moderating influence of customer satisfaction was tested between the independent and dependent constructs. The study focused on B2C e-commerce platforms of FMCG retailers in South Africa.

1.2 Background of the study

The FMCG industry in South Africa (including liquor and tobacco) grew by 13.4% to R593 billion in annual sales for the twelve months ending March 2023 (NielsenIQ, 2023b). The FMCG industry contributes more than 70% annually to the South African economy (Businesswire, 2023).

In recent years, with the expansion of internet technology, consumers have been browsing and buying more online by downloading shopping applications (apps) to facilitate their purchases. Consumers use the internet or apps as a source of information on the price and availability of products, and for the convenience of online shopping and home delivery. Retailers are eager to get consumers to use their apps/platforms to grow B2C sales due to elevated competition to obtain market share and increased rivalry in the market. There are limited data available on customer behaviours and e-commerce usage patterns of the B2C channel in South Africa, therefore the challenge for retailers is not only to determine how to acquire new users, but to maintain existing users and to stimulate continuous use of the apps/platforms, ultimately to achieve UG on the apps/platforms.

The "strategy–execution gap", identified by Feiz et al. (2021), refers not only to the confusion among start-ups or organisations on which strategies to apply to drive UG. It also relates indirectly to identifying specific factors that influence behavioural intentions, use behaviour and customer satisfaction with platforms or businesses that could foster or prohibit UG on platforms. Due to practitioners' successes with growth hacking strategies, this study selected the AARRR model (McClure, 2007) to test its applicability to B2C platforms in South Africa. The aim was to review the customer journey through a customer’s lens by applying the AARRR model (Ellis & Brown, 2017). This review intended to understand the determinants influencing customers' intention and actual online buying behaviour resulting in UG in B2C e-commerce platforms in South Africa (Feiz et al., 2021).

1.2.1 Internet statistics

The number of people using the internet is growing. There were 5.19 billion internet users by the third quarter of 2023. The most recent statistics reflect that the connected society worldwide grew by nearly 100 million users between July 2022 and July 2023. However, approximately 2.58 billion individuals are still "unconnected" to the internet. Most of the “unconnected society” lives in Africa and Southern or Eastern Asia (Kemp, 2023).

According to current projections, two-thirds of the world's population will be online by the middle of 2024, with new internet users increasing by 2% yearly. Most internet users (57%) access it via their mobile devices, although many people in developed markets still use laptops or desktops to access the internet (Kemp, 2023).

South Africa had an estimated population of 62.02 million in January 2023, with 48.8 million people being internet users (StatsSA, 2023). South Africa’s internet penetration rate was 78.6% as of January 2023 (Kemp, 2023), which is expected to grow by 10% by 2027 (Kamer, 2023). Households with no access to the internet have declined from 64.8% in 2011 to 21.1% in 2022 (StatsSA, 2023).

There were 25.8 million social media users in South Africa in 2023, who spent an average of 3 hours and 44 minutes daily on social media. With 112.7 million mobile connections in South Africa, there is an 181.7% connection rate compared to the number of residents in the country – the highest in the world (Kemp, 2023).

1.2.2 Global e-commerce growth statistics

E-commerce has experienced significant global growth since 2020, with online sales exceeding $5.7 trillion in 2022 worldwide. E-commerce growth was also fuelled by a 70% growth in online retail store visits through mobile devices by late 2022 (Pasquali, 2023).

Global e-commerce sales are projected to expand by 56% between 2022 and 2026 to reach an estimated market volume of $8.1 trillion by 2026 (Chevalier, 2022). Forecasts predict global e-commerce will have a 25.4% share of total retail sales by 2025 (Copolla, 2022). The average global revenue by a user amounted to $318.4 in 2022 (Statista, 2022).

The biggest e-commerce market by sales volume in 2022 was China, with 50% of all retail sales being conducted through e-commerce. Second was the United Kingdom with 36%, South Korea with 32% and Denmark with 20% of their retail sales online. The Philippines and India are currently the fastest-growing e-commerce markets, with sales forecasted to increase by > 25% by 2027 (Chevalier, 2022).

1.2.3 South Africa e-commerce growth statistics

South Africa is the 51st most prominent market for e-commerce in the world (eCommerceDB, 2023b). The market shows positive growth patterns, with a net e-commerce sales value of $3 billion in 2019 (Deloitte, 2020) and a forecasted sales volume of $4.961 billion for the year ending 2027 (eCommerceDB, 2023b). In 2020, e-commerce sales in South Africa accounted for 2.8% of overall retail sales; in 2022, the share of total sales increased to 6.8%. The share of total retail will continue to increase with an average of 6.5% to 8.8% by 2027 (eCommerceDB, 2023a).

The South African online retail market was expected to grow by 12.9% in 2023. E-commerce consists of the following sub-markets: electronics and media (28.1%), hobby and leisure (20.7%), fashion (19.8%), furniture and appliances (10.9%), personal care (7.5%), DIY (6.8%) and groceries (6.1%) (eCommerceDB, 2023b).

Takelot is the leader in B2C e-commerce sales in South Africa, with other leading retailers being superbalist.com, woolworths.co.za, mrp.com and homechoice.co.za. In 2021, these top five online stores accounted for 68% of sales of the top 100 online stores in South Africa (eCommerceDB, 2023a).

1.2.4 Barriers to e-commerce

According to the Institute for International Economics and Finance in Moscow in 2021, e-commerce expansion and growth are essential for the countries that are part of BRICS (Brazil, Russia, India, China, and South Africa). The Institute has determined that to facilitate the growth of e-commerce for the BRICS countries, the following issues must be addressed (Haji, 2021):

Firstly, constrained physical infrastructure requires improvement to provide essential services like electricity, transportation and logistics networks, information, and telecommunications technology. These improvements will relieve the constrained supply of goods and services due to accessibility and mobility challenges (Haji, 2021).

Secondly, the unfavourable economic circumstances should be addressed by improving skills and job opportunities across the country, especially in rural areas (31.7% of the population in South Africa) with a low population density (Kemp, 2022).

Thirdly, drive financial inclusion through education to ensure people are skilled to obtain and use epayment services. The majority of digital transactions in South

Africa are currently facilitated through credit or debit card payments (44%), electronic funds transfers (EFT) (19%), e-wallets (19%) or other payment methods (10%), leaving the remaining prospective buyers excluded due to their reliance on cash transactions (Kemp, 2023; Saleh, 2022).

E-commerce growth in South Africa can lead to opportunities to solve social and economic issues, including improving the quality of life for people living in rural areas. However, it can also cause threats or drive the expansion of the digital divide between urban and rural areas, where e-commerce is inaccessible due to the lack of information and communication technology (ICT) infrastructure, slowing down adoption. Therefore, addressing the challenges is pivotal in driving long-term e-commerce growth in South Africa (Haji, 2021).

1.2.5 E-commerce in the BRICS member countries

In the Moscow Declaration 2020, the BRICS countries recognised the importance of the growth of the digital economy to achieve their Sustainable Development Goals. The BRICS countries decided to strengthen collaboration through the BRICS E-commerce Working Group in light of the industry's quick development and rising number of online transactions globally.

With e-commerce expanding rapidly, the BRICS countries aim to adopt similar policies formulated from the best practices of the member group to address issues like consumer protection, prohibiting the sale of counterfeit goods, raising awareness of illegal goods or portals and protecting local offline retailers. The BRICS countries have subsequently agreed on a framework to ensure consumer protection amongst the BRICS member group (BRICS, 2023).

1.2.6 Opportunities for e-commerce in South Africa

SA Connect, South Africa's national broadband project as part of the National Development Plan, identified by the government in 2013, aims to create an inclusive information society by providing internet access (broadband/Wi-Fi) to all South Africans by 2024 (Mzekandaba, 2022). In phase 1, eight rural district municipalities were connected to SA Connect broadband services which includes 970 schools, health facilities and government offices. Phase 2, which is due for completion in 2025/26, aims to connect 5.8 million sites to high-speed internet (Mzekandaba, 2023).

E-commerce is in its infancy in South Africa, but with the government's support and the implementation of SA Connect (Mzekandaba, 2022), as well as continued support from the BRICS member group (BRICS, 2023), retailers have a significant opportunity to increase e-commerce, especially m-commerce, as a preferred purchasing channel in South Africa.

1.3 Research Problem

1.3.1 Main research problem

Based on the outcome of the initial literature review for this study, it was evident that previous research on the acceptance and use of B2C e-commerce platforms has mainly been conducted through the application of theoretical and scholarly models such as the Technology Acceptance Model (TAM) (Davis, 1989), Technology Acceptance Model 2 (TAM2) (Venkatesh & Davis, 2000), Task Technology Fit Model (TTF) (Klopping & McKinney, 2004), UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012).

The main focus of these scholarly models was predominantly centred around the factors influencing acceptance of technology and behavioural intention to use technology, with minimal reference to “actual use” of technology. UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) incorporated “use behaviour” as their outcome variable, but most of the studies incorporating this construct predominantly focused on measuring the variables that influence behavioural intention to use and not actual system use behaviour.

A meta-analysis of the UTAUT2 model (Venkatesh et al., 2012) found that “use behaviour” emerged as the strongest significant path in the model, but the analysis did not provide an explanation of the effects that results in this significant path (Tamilmani et al., 2021). Further research into the available literature found very limited articles on the factors or determinants that influence "use behaviour" or UG in information systems. Neither TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003) or UTAUT2 (Venkatesh et al., 2003) could address this deficiency, which was to provide practical guidance or suggestions on how actual system use, "use behaviour", or UG and eventually repetitive system usage (continuous usage) is achieved (Davis, 1987).

The proposed study aspired to address this deficiency by applying a practitioner model, the AARRR model (McClure, 2007), to investigate the factors that drive behavioural intention that results in system use and the acceleration of UG (Zhang, 2021) in B2C e-commerce platforms in the South African FMCG industry.

A 2023 study by Nielsen IQ across 12 markets, including South Africa, found that 53% of consumers have bought groceries online in the last six months, with 48% stating that they have done some shopping online. Half of the respondents (49%) also confirmed that they researched online to compare products and pricing but then completed their shopping in-store (NielsenIQ, 2023a). There was, therefore, an opportunity to understand why consumers do not consistently shop online and what would entice them to shop more online, resulting in UG in B2C e-commerce platforms.

Secondly, it was also essential to understand whether satisfaction influences a customer's behavioural intention to buy on a B2C e-commerce platform. Unfavourable experiences might impact a customer's decision to return to a platform, hampering prospective UG. Due to the limited empirical research available in South Africa, the insights recorded with this study aim to benefit the FMCG industry in South Africa by promoting UG in its B2C e-commerce platforms.

1.4 Main Research Question

What are the determinants that influence user growth in B2C e-commerce platforms in the South African FMCG industry?

1.4.1 Research question 1

Which determinants influence a customer's behavioural Intention to use B2C e-commerce platforms in South Africa?

1.4.2 Research question 2

To what extent do customers' behavioural intentions influence user growth in B2C e-commerce platforms in South Africa?

1.4.3 Research question 3

To what extent does satisfaction affect behavioural intention to use B2C e-commerce platforms in South Africa?

1.5 Research Objectives

i) To gain an improved understanding of the determinants that influence customers' behavioural intention to buy on B2C e-commerce platforms in the FMCG industry in South Africa.

ii) To investigate how customers' behavioural intentions influence user growth in B2C e-commerce platforms in the South African FMCG industry.

iii) To understand the effect of customer satisfaction on user growth in B2C e-commerce platforms in the South African FMCG industry.

1.6 Rationale

A significant volume of literature has been written on internet retailing. A study by Doherty and Ellis-Chadwick in 2006 concluded that the existing literature can be divided into three sections:

i) A retailer perspective

It mainly includes the adoption of technology from a retailer perspective and the potential to replace physical retail establishments. It also considers the management perspectives required to facilitate online retailing.

ii) A consumer perspective

This perspective examines the online behaviour of consumers and is subdivided into classification variables (remains relatively static or evolves gradually) and character variables (perceptions, beliefs, and attitudes) that impact the "ease of use" and "usefulness" of online platforms and the intention to buy online.

iii) A technology perspective

This dimension relates to technology and how it influences internet shopping. This includes website design, functioning of software applications and information technology (IT) infrastructure (Doherty & Ellis-Chadwick, 2006).

The rationale of this research study was to contribute to the literature by investigating the significance of a website or application's characteristics (technology perspective) combined with the behavioural intentions from a consumer perspective and how they influence UG in B2C e-commerce platforms. UG was analysed according to the AARRR model (McClure, 2007) to understand the determinants in each customer journey phase in B2C e-commerce platforms in the FMCG industry in South Africa. This research intended to deliver guidelines to retailers on applying the AARRR model effectively to drive UG in their B2C e-commerce platforms (Zhang, 2021).

A few studies have emerged in Asia about the tremendous success of UG strategies on major platforms like Pinduoduo and Shopee (Setiyani et al., 2023; Zhang, 2021). There was, therefore, an opportunity to replicate a UG study in South Africa since it had not been done before. Most international scholarly models focus on the explanation of the adoption of online technologies, for example, TAM (Davis, 1987), TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), UTAUT (Venkatesh et al., 2003) and UTAUT2

(Venkatesh et al., 2012). However, these models fail to address “use behaviour” and do not provide information on the factors affecting actual technology use. This research was built on the existing user adoption and UG literature to discover the determinants that facilitate use behaviour that results in UG in B2C e-commerce platforms in the FMCG industry in South Africa.

1.7 Delimitations of the Study

This study focused on UG as the primary dependent variable, initially adopted from UTAUT2 (Venkatesh et al., 2012) as “use behaviour”. The UTAUT2 model (Venkatesh et al., 2012), with all its independent variables and satisfaction, originally from the Expectation-Confirmation Theory (ECT) (Hossain & Quaddus, 2012), was incorporated into the research framework.

The study was limited to the following items:

i) The moderating effect of age, gender and experience was tested between behavioural intention (BI) and performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC).

ii) The moderating effect of age, gender and experience was not tested between BI and Habit, BI and hedonic motivation (HM) or BI and price value (PV).

iii) The UG construct was divided into five phases or measured indicator variables: acquisition, activation, retention, referral and revenue (McClure, 2007).

iv) Satisfaction was tested as a moderator between BI and the UG construct, as well as between FC and the UG construct.

v) The study narrowed down its scope to focus on the FMCG industry in South Africa. FMCG goods include a broad consumer packaged goods (CPG) range as defined in section 2.2.9. These goods are classified into premium and mainstream categories to provide different price points for various consumer groups (Gupta, 2018).

vi) The research was not limited to a specific organisation but to B2C e-commerce platforms deployed by the FMCG industry in South Africa to facilitate the selling of CPG to end consumers.

vii) The research surveyed anyone above 18 years of age who has used, tried or attempted to use a B2C e-commerce platform to order FMCG products online. Respondents were older than 18 years since it is the minimum age required to provide contractual consent in South Africa.

viii) Non-users of B2C e-commerce platforms were eliminated from the study.

1.8 Significance of the Study

This study was the first South African study that has incorporated all the variables of the UTAUT2 model (Venkatesh et al., 2012) in a research project on e-commerce UG post the COVID-19 era. The COVID-19 era saw exponential growth in e-commerce sales globally (see section 2.2.3). The study was also the first to apply the AARRR model (McClure, 2007) as a proxy for the dependent variable, UG.

1.9 Operational Definitions

AARRR is a growth hacking model/funnel first introduced in the Silicon Valley by David McClure in 2007. The abbreviation stands for acquisition, activation, retention, referral and revenue. The AARRR model is also called the “Pirate Metrics” (McGaw, 2015) by entrepreneurs who use it as guidelines to scale small businesses. This study refers to the AARRR model as the user growth (UG) construct.

An application (app) is a computer software package that serves a particular purpose directly for the end user or, in certain situations, for another application. A platform is any hardware or software used to host an application or service

(Gillis, 2023). A website is a single domain name for a set of web pages. The terms ***application/platform/website*** were used interchangeably depending on the context of the situation.

A customer is an individual or business purchasing another organisation's goods or services. Consumers are individuals who consume an organisation's goods or services. A consumer can, therefore, also be a customer (Kenton, 2023). The terms ***consumer/customer/buyer/user***/***online shopper*** were used interchangeably in this study depending on the context of the situation.

Customer experience can be defined as the overall response relating to cognitive, emotional, social, affective and physical reactions and feedback. Customer experience includes the total experience across various retail channels, including the inquiry, purchase, utilisation/use, and post-sales phases of the end-to-end experience (Verhoef et al., 2009).

Online shopping/purchasing is the action a retailer's consumer or customer takes when purchasing online products using an e-commerce platform (An et al., 2016). In return, ***online retailing/sales*** are when retailers sell their products to consumers/customers online through an e-commerce platform (Van Droogenbroeck & Van Hove, 2021).

E-commerce adoption starts when consumers initially embrace internet activities like information-gathering and product purchases from commercial websites. This leads to the consumer's participation in online trading relationships with web providers and can be described as the adoption of B2C e-commerce websites or apps (Pavlou & Fygenson, 2006).

Retention/continuance intention is defined as a person's intention to continue using apps/websites/platforms after initial use and adoption (Bhattacherjee, 2001). Retention is the consumer's continued use of a product over a period. An organisation can only deliver long-term business growth if it can extend its consumers' life cycle and retain them (Zhang, 2021).

A ***retailer*** sells goods and services to clients in modest amounts both in-person and online. Examples of retailers are pharmacies, grocery stores, and apparel stores (Sendpulse, 2023).

Subjective norm is the belief that an influential individual or group supports or opposes a specific behaviour or action (Venkatesh et al., 2003). This study measured subjective norms by measuring the impact of SI on the BI to use a B2C e-commerce platform.

The customer journey can be broken down into three phases: pre-purchase, purchase, and post-purchase. It encompasses the complete process of the total customer experience with an organisation/company over a period during a purchase cycle that includes multiple touchpoints. The phases have become more dynamic, continuous, and less linear, especially with the technology that allows easy flexibility to toggle between the phases (Lemon & Verhoef, 2016; Verhoef et al., 2009).

1.10 Assumptions

During this research project, the researcher assumed that the study's participants had access to a mobile smartphone, tablet, or personal computer/laptop with an internet connection through Wi-Fi, 3G/4G/5G, or a fixed line connection. The assumption was also made that the participants have basic English literacy to read and understand words, phrases, or instructions on a B2C e-commerce platform.

Due to high online fraud in South Africa caused by scams, impersonation and money laundering, often through e-mails or marketplaces, individuals have less enthusiasm to transact online (Tredger, 2023). These online safety and privacy concerns reduce trust and e-commerce acceptance. Therefore, this research project has assumed that all participants have accepted online risk factors when transacting online in light of publicly known risk concerns and trust perceptions (Mohammed & Tejay, 2017).

B2C e-commerce websites/apps are owned and managed by organisations, which are retailers, manufacturers or wholesalers, and either of these parties can act as the retailer or seller in this study.

1.11 Chapter Outline

Chapter 1 provides an introduction and background to the study and sets the research projects' aspirations through the purpose statement. Next, the research problem is revealed, after which the objectives are articulated.

Chapter 2 gives an in-depth summary of the literature review that concluded on the most prominent technology acceptance and psychological scholarly models between 1975 and 2016. The analytical framework is then proposed, which includes the conceptual framework, encompassing all the theoretical and empirical concepts in the scope of this study. Lastly, each research question is broken down into several hypothesis statements and explained according to the literature under review.

Chapter 3 provides a breakdown of the research methodology, including the applied research approach and design. Details on the sampling method and data collection procedure are explained. Next, quality assurance is evaluated through concepts of validity and reliability, and section 3.11 considers various ethical aspects and the study's possible impact on human participants.

Chapter 4 presents the results after the data collection was completed. The findings were delivered according to each statistical method applied through the exploratory factor (EFA), regression, correlation, and mediation analysis. Descriptive statistics were applied to the respondents' demographic profile, to provide the reader with a comprehensive overview of the individuals who took part in the survey.

Chapter 5 discusses the study's results in correlation to the literature reviewed in Chapter 2 and the results presented in Chapter 4. The results are presented for each hypothesis statement.

Finally, ***Chapter 6*** concludes the study with answers to each research question and a closing summary of the research report. Recommendations for practical application and managerial implications are discussed. Suggestions for further research opportunities are also presented.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

A literature examination was conducted for 2012 to 2023 on the following databases: Ebsco Host, Emerald, Elsevier, Science Direct, SpringerLink and Researchgate. Filters were applied to include only journal articles and conference proceedings papers. Almost 300 documents were found and sorted according to inclusion and exclusion criteria relating to keywords, title, year, and author. A process of analysis and a critical evaluation of each paper's abstract followed. Further gaps were identified, and an advanced search was conducted on Google Scholar to find suitable literature.

The literature was reviewed to identify which scholarly models and theories have been applied to B2C e-commerce studies and whether a specific study has been concluded to understand the application of the AARRR model (McClure, 2007; Zhang, 2021) on B2C e-commerce platforms. The literature found was limited to the individual determinants of the Technology Acceptance Models, with BI as the dependent variable, and very few frameworks applying use behaviour or UG as the outcome variable. Chapter 2 explores the literature in the following structure:

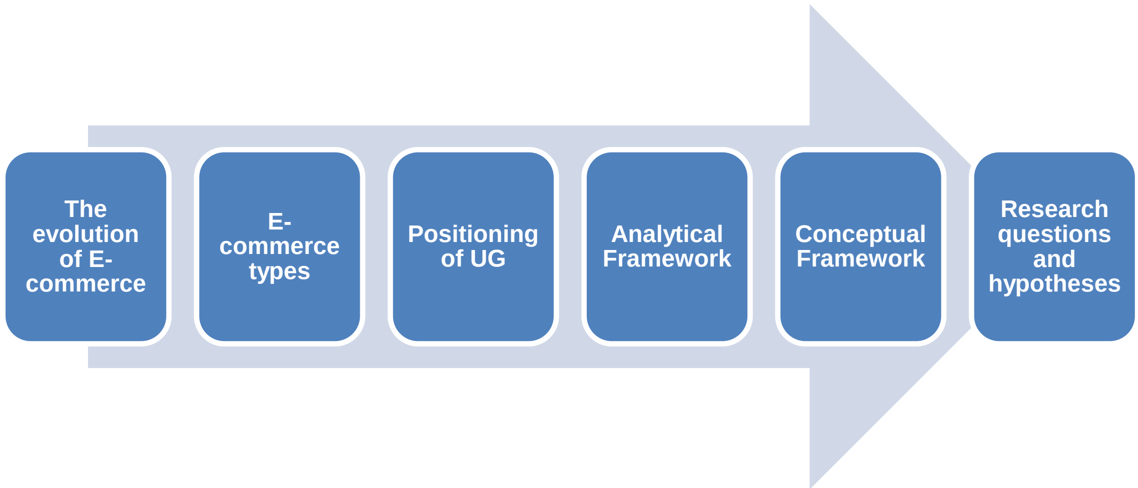


Figure 1: Structure of Chapter 2

2.2 Background: UG in B2C e-commerce platforms

2.2.1 The evolution of e-commerce

The Third Industrial Revolution, or Society 4.0, between 1980 and 2020 became the digital revolution, marking the start of electronic and information technology, otherwise known as the internet (Armstrong & Lee, 2021). The internet is a global network of computers and electronic devices linked through a network of protocols and hardware whilst being protected with authorisations. It allows users from one computer to get information from another computer (Budree, 2023).

The World Wide Web, invented by Tim Berners-Lee in 1989, is the collection of electronic information that can be accessed through the internet by using browsers (Budree, 2023). A platform resides on the internet and hosts various applications like e-commerce applications. E-commerce can also be hosted through a website, which is a collection of publicly accessible web pages on a single domain name (Gillis, 2023). The internet has connected billions of people and businesses worldwide by removing traditional geographical barriers and enabling cross-border trading.

Table 1 below summarises the most important milestones in e-commerce history. It started with a basic online commercial transaction and has grown into dynamic online stores and marketplaces facilitating worldwide trading.

Table 1: Evolution of e-commerce

Year	Event
1960	Electronic Data Interchange was invented.
1971	E-mail was invented.
1981	The first B2B transaction was processed.
1984	The first commercial online transaction. The first online shopping system.
1989	Web 1.0: The World Wide Web was invented by Tim Berners-Lee. "Read-only Web"
1995	e-Bay and Amazon were launched. Start of the "DOT-com" bubble.

Year	Event
2005	Web 2.0: Social media, blogs, video sharing, web applications, e-mails "Read/write Web"
2008	The Great Recession: Changes in consumer behaviour started with consumers shopping more online to compare prices and seek deals.
2014	Web 3.0: Blockchain, cryptocurrency, AI. Chinese Taobao.com launched livestream e-commerce. "The Semantic Web"
2016	Instagram shopping tags & TikTok shopping launched.
2019	COVID-19: E-commerce sales increased as lockdowns restricted access to traditional stores.
2022	Acceleration of social commerce with the launch of Twitter (X) Shops. NFTICally launched the first metaverse e-commerce system. Augmented and Virtual Reality integration into more e-commerce systems.

Source: (Armstrong & Lee, 2021; Budree, 2023; Solanki & Dongaonkar, 2016)

2.2.2 What is e-commerce?

E-commerce is the purchasing or selling of products and services (including money and data) via an electronic internet transaction (Budree, 2023). E-commerce can also be defined as the production, display, selling, insuring, distribution, and payment of transactions for products and services in the electronic sphere of technology (Çelik & Yilmaz, 2011). Thirdly, e-commerce sells physical goods to private end consumers through a digital channel. The sales include purchases made through mobile devices (tablets and smartphones), notebooks, laptops, and desktop computers (Statista, 2022).

Online marketplaces made up the majority of all online sales in 2022. Amazon leads the world's online retail website traffic rankings, with 5.9 billion direct visits to the Seattle-based e-commerce website in April 2023. Amazon offers digital content, computing services, consumer electronics, and e-retail. In terms of gross merchandising value (GMV), the Chinese retail giant Alibaba is currently the largest e-commerce retailer in the world, with sales exceeding $700 billion in 2022. According to analysts, Amazon will surpass Alibaba since sales are accelerating and are forecasted to reach $1.2 trillion by 2027 (Chevalier, 2022).

The largest economies in Africa, Nigeria, South Africa, Kenya, Morocco, and Egypt, are experiencing rapid e-commerce growth. Nigeria has two major online marketplaces, Jumia and Konga. South Africa's largest e-commerce platform is takealot.com, whilst Kilimall is the largest platform in Kenya (Galal, 2023). Takealot's revenue reached $827 million in 2022. In March 2023, 66% of South African consumers bought from Takealot.com, and 29% purchased from Clicks.co.za (Cowling, 2023a).

2.2.3 Why e-commerce?

The globalisation of socio-economic and demographic factors and rising consumer awareness caused the global economy to shift structurally from the old, industry-based economy to the new, information-led digital economy (Armstrong & Lee, 2021). The International Monetary Fund (IMF) (Savrul & Kılıç, 2011) contends that this change has caused the world's nations to become more economically dependent on one another due to the quick and widespread advancement of technology, rises in financial transfers across international borders, and the diversity and amount of trade in products and services. E-commerce has emerged in this shift between economies since it has eliminated the problem of "time" and "space" and, in the process, lowered production costs (Savrul & Kılıç, 2011).

Three economic tipping points, the Dot-com bubble, the 2008 Great Recession and COVID-19, have profoundly impacted the e-commerce environment as we know it today. The Dot.com bubble, from 1995 to 2000, can be attributed to the rapid rise and fall of internet start-ups. With NASDAQ crashing in 2000, most companies filed for bankruptcy. Google, eBay and Amazon survived and are still excelling as e-commerce giants today (Budree, 2023).

The Global Financial Crisis of 2008 forced some organisations to turn to e-commerce activities to become more efficient, save money, accelerate their businesses, and access the global economy. Although e-commerce is also affected during economic turmoil, the impact is less on e-commerce than other trade channels (Savrul & Kılıç, 2011).

The COVID-19 pandemic inflicted worldwide lockdowns on people, imposing a restriction on human movement, not only between countries but also within countries, provinces, towns and cities. Businesses were forced to sell their products online, and a surge in B2B and B2C sales was seen in medical supplies, household goods and food products (WTO, 2020).

FMCG e-commerce sales in the post-COVID-19 era continue to thrive, with global online sales growing four times faster than offline sales; it is estimated that by 2025, 10% of all FMCG sales will be online. This trend is driven by a higher demand for convenience in urban areas due to direct-to-consumer sales and improved technology and logistics software that enables retailers to reach broader target markets. The benefits of e-commerce for both the retailer and the consumers are outlined in Table 2 (Kumar et al., 2021):

Table 2: Benefits of e-commerce in the FMCG industry

Benefits of e-commerce in the FMCG industry:	**For the Retailer:**	**For the Consumer:**
Cut out the middleman - maximise profits/reduce costs	X	X
Overcome geographical limitations	X	X
Data collection: Consumers' buying habits	X	
Low investment: high return on investment (ROI)	X	
Open 24/7	X	X
Consumers can search and locate products quickly		X
Create a market for niche products	X	X
Scalability	X	
Use consumer data to build long-term relationships	X	
Compare competitor pricing before buying		X
Improve customer experience with customised offerings	X	X
Flexible delivery options	X	X
Immediate payment, no debt collection	X	
Availability of information to make informed purchase decisions		X
Delivery scheduling and updates		X
Improve speed to market and overall efficiency	X	
Access to customer support		X

Source: Adapted from (Irawan, 2023; Kumar et al., 2021)

2.2.4 e-Commerce types

i. Business-to-Consumer (B2C)

Business-to-consumer (B2C) transactions include exchanging products, services, and information between producers and end consumers for public consumption through the internet. The exchange process is concluded with electronic payments (Jewels & Timbrell, 2001). B2C e-commerce includes paid online services (cloud computing) and paid content (entertainment) (Budree, 2023).

ii. Business-to-Business (B2B)

The use of the internet to purchase, trade, or interchange information between two or more organisations is known as business-to-business (B2B) transactions. B2B transactions can occur directly between organisations, e.g. Walmart and Unilever (manufacturer to wholesaler or retailer), or through a third party (an intermediary) who facilitates the matching of buyers and sellers (Jewels & Timbrell, 2001).

iii. Business-to-Administration (B2A)

Business-to-administration (B2A) entails the electronic transactions of products, services and information between organisations, governments, or government agencies (Rouse, 2012). The sphere of transactions includes taxation, social care, health care and legal services (Jain et al., 2021).

iv. Consumer-to-Consumer (C2C)

Consumer-to-consumer (C2C) e-commerce is the facilitation of online sales between consumers by using third-party applications. It includes the transactions on online marketplaces, auctions and forums (Budree, 2023).

v. Consumer-to-Business (C2B)

Consumer-to-business (C2B) e-commerce entails selling products or services between consumers and businesses. Businesses, therefore, buy products from consumers (Stokes, 2018). The C2B model often includes scenarios where businesses use influencers and pay them a fee to promote their products or services (Budree, 2023).

vi. Consumer-to-Manufacturer (C2M)

The Consumer-to-manufacturer (C2M) e-commerce model is a consumer-driven and consumer-initiated business activity with a manufacturer (Li & Tran, 2021). C2M creates digital connections between end-users, upstream manufacturers and product designers to generate opportunities for several strategies to speed up the information flow process (Mak & Max Shen, 2021).

2.2.5 E-commerce channels

Transactions are facilitated through either of the following channels:

Table 3: E-commerce channels

The internet (e-commerce)	**Mobile devices (m-commerce)**	**Social Media Platforms (social commerce)**
Transactions are performed using a laptop or desktop computer (Jewels & Timbrell, 2001).	Transactions are performed via wireless mobile devices like tablets or smartphones (Statista, 2022).	Transactions are performed through social media platforms (e.g. X, Facebook, Instagram). Social networks and user contributions impact the extent to which the transactions go viral (Stokes, 2018).

Both mobile and social commerce are conducted through apps/platforms, which are characterised as software that is downloadable to a mobile device that uniquely displays a brand identity—typically through the app/platform name and the appearance of a brand logo or icon (Bellman et al., 2011).

2.2.6 What is UG in B2C e-commerce platforms?

User Growth ***(UG)*** is the process of turning passive customers into active users of a platform. The main goal of UG is to assist start-ups or businesses in rapidly acquiring a significant number of users at little or no expense (Zhang, 2021). In this study, the outcome variable, “actual system use” (Davis, 1989) or “use behaviour" determinant (Venkatesh et al., 2003; Venkatesh et al., 2012) was adopted from the UTAUT2 model and was defined as the "UG" determinant.

2.2.7 UG statistics

Global e-commerce user numbers are expected to increase by 32% to reach 3.1 billion users by 2025. Asia had 2.4 billion active online users in 2021, the most globally. Asia has an e-commerce penetration rate of 53%. However, predictions show that Africa's users will increase by 55% in 2025 to overtake Asia. Africa currently has 334 million active online shoppers, which is expected to grow to 518 million active online shoppers by 2025 (GlobalDataPoint, 2022).

Asia's success can be attributed to its technical innovation, rapid adoption of digital trends, and a large population that has become inseparable from using e-commerce to complete their daily activities (GlobalDataPoint, 2022).

Africa's e-commerce shopper penetration rate has increased from 13% in 2017 to 28% in 2022 and is expected to reach 40% by 2025 (GlobalDataPoint, 2022). South Africa's e-commerce shopper penetration rate reached 47.7% in April 2023 (± 23.3 million users). The South African growth trajectory is evident, with the latest data showing that 20.72 million people had bought online by January 2023 and 10 million people had ordered from a supermarket by April 2023. Approximately 49.1% of South African people use a banking, insurance or investment website/app. The approximate spending in South Africa in 2022 on some of the major categories was $1 billion on fashion, $534.1 million on food, and $174.8 million on beverages (Kemp, 2023).

2.2.8 The importance of UG in B2C e-commerce platforms

In 2019, Shopee, an Indonesian e-commerce platform, expanded its interactive features by adding in-app live streaming on the platform to secure user stickiness. They also enhanced their gamification proposition, the Shopee Quiz, by rewarding players with Shopee Coins. Also in 2019, another company, Lazada, an Alibaba-owned business in Southeast Asia, announced its plans to deploy in-app live streaming and consumer games (Pillai, 2019). In August 2021, JD.com, a Chinese e-commerce platform, published a 26% increase in revenue and a 16.6% increase in its share price on the Hong Kong Stock Exchange after a record-breaking increase of 32 million new users, bringing the total number of users to over 530 million (Wu, 2021).

Two recent publications on Pinduoduo (Li & Tran, 2021; Zhang, 2021), a Chinese social e-commerce platform specialising in group buying through social media transactions, discuss the exponential growth that the company has experienced since its listing on the NASDAQ Stock Exchange in 2018. Pinduoduo was founded in September 2015, and the organisation has grown the number of active annual users from 100 million in 2016 to 195 million in 2018 (+51%), to 487 million in 2020 (+40%), to 730 million users in 2021 (+66%) (Liang & Cheah, 2020; Lu, 2023).

Pinduoduo's acquisition strategies included a strategic partnership with WeChat and a user-sharing link mechanic, resulting in rapid platform UG. The introduction of a gamified shopping experience through "Duo Duo Orchard" in 2018 served as a valuable retention strategy to promote frequent usage of the platform. By 2021, an average of $300 was spent per user per annum (Liang & Cheah, 2020). Pinduoduo reached a GMV of $1.5 billion in 2017 and $15 billion in 2019, recording a 90% growth rate. Pinduoduo has reached a total market value of $200 billion by 2020, growth figures that Pinduoduo's competitors took 5 to 10 years to achieve (Li & Tran, 2021).

Another business, Pinterest, was not so fortunate since they recorded UG declines for two quarters in a row for the year ending 2021. The active user count was 478 million and declined to 431 million users (-9%) by November 2021. That is 47 million fewer users that create content and stimulate purchase decisions. Pinterest responded to this situation with an expansion strategy to 13 new international markets (outside the United States) and a creator funding programme for their regular Pinners. Pinterest also introduced some enhancements to their application to keep the regular users, attract new users, and invite advertising spending (Hutchinson, 2022).

UG strategies have been pivotal in the success of growing e-commerce giants like Pinduoduo, Shopee, JD.com, Lazada and the social media platform Pinterest. To grow sales volume, revenue, and shareholders' return, businesses need strategic and efficient plans to drive UG and repurchase rates on their e-commerce platforms while continuously improving the user experience and keeping consumers engaged.

2.2.9 The Fast-moving Consumer Goods Industry (FMCG)

This research paper focuses on FMCG retailers' selling or reselling processes through B2C e-commerce platforms. The FMCG industry is part of a broader industry called the consumer-packaged goods' (CPG) industry which consists of durable and non-durable products and services. The FMCG industry falls under the section of non-durable goods of CPG. This includes low-value items that consumers consume regularly in the following categories: processed, dry, fresh, baked and frozen foods, pre-packed meals, beverages, medication, cleaning products, self-care products and stationery (Kenton, 2021).

FMCG companies manage the production, distribution, and marketing of their products (Kenton, 2021). Online grocery shopping (OGS) falls under the term FMCG, describing the action where consumers buy groceries online (Klepek & Bauerová, 2020). Some examples (but not limited to) of retailers with platforms that consumers use to buy FMCG products in South Africa are:

Table 4: Examples of South African Retailers with platforms

	Retailer	**Platform name (mobile)**	**Platform name (web)**
1.	Checkers	Checkers 60Sixty	www.checkers.co.za
2.	Clicks	Clicks SA	www.clicks.co.za
3.	Dis-Chem	Dis-Chem	www.dischem.co.za
4.	Makro	Onecart/Makro Shopping	www.makro.co.za
5.	Massdiscounters (Pty) Limited	(not applicable)	www.game.co.za
6.	Pick 'n Pay	Pick 'n Pay asap!	www.pnp.co.za
7.	Shoprite	Shoprite SA	www.shoprite.co.za
8.	Woolworths	Woolies DASH	www.woolworths.co.za

2.3 Factors Influencing UG in B2C E-commerce Platforms in the FMCG Industry

2.3.1 Factors influencing non-adoption of B2C e-commerce platforms

There is a significant difference between general e-commerce and OGS adoption rates. Worldwide, OGS is experiencing slower adoption rates than other categories of products. In 2023, consumer electronics online sales are expected to grow by 39% and household appliances by 31%, while OGS is projected to grow by only 3% (Van Droogenbroeck & Van Hove, 2021). Therefore, the adoption of online sales is very product-specific.

A web-based survey in the Czech Republic confirmed that non-online buyers prefer to see and choose their own finest and freshest groceries before purchasing; they distrust the return policy and are not prepared to pay for delivery (Klepek & Bauerová, 2020). They perceive online shopping as slow due to the order delivery time gap. Non-online buyers also experience hedonic stimulation from the in-store shopping experience and prefer contact with the seller established through habit (Van Droogenbroeck & Van Hove, 2021).

According to the literature on technology adoption, consumers actively consider various elements before making an adoption decision as part of a cognitive elaboration process that informs BI. However, the upfront evaluation of OGS does not translate into BI for many non-users. These non-users require a trigger to transition from the non-adopter to the adopter stage. The cause of a trigger is often situational, like a sudden change in health or the lack of transport, which fulfils the missing element from the initial evaluation to conclude the decision to start using the app (Van Droogenbroeck & Van Hove, 2021).

A Belgian study on two supermarkets found that HM, habit, perceived time pressure, and innovativeness are the determinants that influence non-adopters to buy groceries online. These reasons for not buying online, combined with the triggers that call for action, need to be considered by retailers to improve their online shopping offerings (Van Droogenbroeck & Van Hove, 2021).

2.3.2 Factors influencing adoption of B2C e-commerce platforms

One of the few studies published in South Africa found that the primary reasons why consumers buy online are because it is convenient, saves time, and a delivery is offered. However, the factors influencing a consumer’s satisfaction when purchasing online are security (protection of private information), knowledge of pricing and product variety, convenience and logistics arrangements (Rudansky-Kloppers, 2014).

Other studies have been concluded by incorporating the UTAUT2 model (Venkatesh et al., 2012) to better understand the factors influencing BI to use, adoption, and actual usage of different e-commerce platforms:

Human et al. (2020) completed a study in Mauritius on consumers' intentions to adopt OGS. The results are consistent with previous studies in developed and developing countries and show that PE, HM, PV, and habit positively impact BI to buy online. However, EE, SI and FC did not show a compelling impact on BI. SI usually has a dual effect on BI through either the media, the information provided, or opinions from friends, family and peers.

However, given that Mauritius is a developing market, it seems that the exposure to the media is limited, and due to other reasons (e.g. culture), views from others are not considered. Although the impact of FC on BI has been proven in most studies worldwide, this study could not establish a positive relationship. Age showed a notable moderation between EE and BI, and FC and BI. Gender, experience, human settlement and education did not reveal any moderating effect on BI. As expected in a developing country, income strongly affects the relationship between habit and BI and HM and BI (Human et al., 2020).

An OGS study published in 2021, conducted in Belgium, a developed country, found that habit and PE mainly influence adopters or users. Neither EE, SI, FC, PV, perceived risk, perceived shopping enjoyment, or service quality significantly impacted the adoption of the OGS app. An important conclusion from this study is that marketing strategies should be formulated to drive OGS to become a habitual activity that is convenient, saves time and money and is available 24/7. Since habit is the most important predictor of intention to reuse an application, retailers should frame strategies that stimulate habit formation (Van Droogenbroeck & Van Hove, 2021).

In 2021, Kartikasari et al. (2021) studied the intention to use e-commerce to buy green cosmetics online. They found that PE, SI, FC, Habit, PV and perceived playfulness have influenced BI to use e-commerce. EE and HM did not impact the intention to use the e-commerce platform (Kartikasari et al., 2021).

A Chinese study on consumer preferences and BI to buy fresh products online found that PE and SI had a positive impact, while perceived risk negatively impacted BI to buy online. EE had no significance due to consumers with online shopping experience being accustomed to the platform (Chen et al., 2021).

Two studies on Shopee, an Indonesian e-commerce platform, reported the following results. Firstly, in 2021, investigating the factors influencing the use of Shopee found that habit and trust positively impacted BI to use Shopee. Habit and BI also influenced use behaviour of Shopee. PE, SI, PV, HM, EE and perceived transaction risk did not significantly impact BI to use Shopee. The moderators, age, gender and experience did not influence the BI or use behaviour of the Shopee platform (Maulidina et al., 2020). Secondly, in 2023 another study on the BI of Shopee e-commerce users found that SI and habit positively impacted BI to use the platform. PE, EE, FC, HM, and PV did not influence the BI to use Shopee (Setiyani et al., 2023).

In aligning the 2021 and 2023 studies on the Shopee e-commerce platform, the key finding is that habit impacts online shopping intentions positively and significantly. Based on this data, the conclusion is that shopping on Shopee has become a habit for their consumers (Setiyani et al., 2023). This conclusion is confirmed by their UG statistics, which show that Shopee users increased from 34.51 million in Q1 2018, to 75 million in Q1 2019 (+46%), to 71.53 million in Q1

2020 (- 4.62%) (COVID-19 impact), to 127.4 million in Q1 2021 (+78.1%) and 132.7 million in Q1 2022 (+ 4.16%) (Nurhayati-Wolff, 2023).

In conclusion, studies from developing and developed markets confirm that different UTAUT2 variables impact BI to use an e-commerce platform. Habit is the only variable that has consistently emerged in all the studies to influence BI positively to use and continuously use an e-commerce platform.

2.4 Analytical Framework

The adoption of technology, starting with technology adoption in the workplace, has been studied by various researchers and has been prefatory in understanding e-commerce adoption. The most popular model and the foundation for many other models was introduced in 1987 by Fred D. Davis, the Technology Acceptance Model (TAM) (Davis, 1987). TAM is an improved version of the Theory of Reasoned Action (TRA) (Hale et al., 2002). TAM introduced two fundamental determinants of attitude towards using technology in the workplace named "perceived usefulness" (PU) and "perceived ease of use" (PEUO) (Davis, 1989), which have remained foundational in technology adoption research to date. TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) contributed to the acceptance of technology in the workplace. Still, it was only in 2002 that Koufaris established the link between the computer user and online shopper (Koufaris, 2002).

Other theories in the literature that also influenced technology acceptance and adoption were the Motivational Model (MM), which considers the influence of intrinsic and extrinsic motivation on performing an activity (Davis et al., 1992; Vallerand, 1997). The Diffusion of Innovation theory (DOI) explores the rate of adoption and the potential relative advantage that innovation has in a social system due to its compatibility, complexity, trialability and observability (Rogers, 1981). DOI also argues that the “tipping point” at which innovation spreads exponentially is becoming faster and faster due to technological advances (Orr, 2003).

One model that specifically reviews e-commerce adoption is the Thai E-commerce Technology Acceptance Model (TECTAM), which presents a model for technology adoption for Thai SMEs (Chooprayoon & Fung, 2010). Another model is the Model for E-commerce Adoption (MOCA), which presents a circular model in which a customer's favourable or unfavourable e-commerce experiences are reflected through reviews, face-to-face suggestions and social media, which indirectly affects the frequency of use by others (Guzzo et al., 2016).

The following section outlines a summarised version of 16 theoretical models and theories published between 1989 and 2016. After this, a more detailed analysis of the UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) models and the AARRR model (McClure, 2007) that formed a focal point in this study are provided.

2.5 Theoretical Framework

Several growth hacking theories have emerged worldwide as growth hackers try to scale their businesses quickly. A popular model, the AARRR model(McClure, 2007), is reviewed in the next section to gain an insight into this UG construct in relationship to the theoretical underpinnings of the UTAUT2 model (Venkatesh et al., 2012).

2.5.1 Origination of the Pirate Metrics (AARRR)

The Pirate Metrics (McGaw, 2015) or AARRR model (McClure, 2007), which is short for acquisition, activation, retention, revenue and referral, is critical to monitor any startup or business to drive UG and long-term success. The metrics were initially designed for business owners or managers requiring a framework to grow the number of customers visiting their e-commerce platforms and buying their products. As the customer progressively transitions through the funnel phases, the organisation should aim to retain as many customers as possible to achieve UG on a platform.

The acquisition of a platform corresponds with awareness and how a consumer initially develops a need to use a platform, often linked to its simplicity or affected by a need statement or a social engagement (occasion) with a trusted person/people who recommends the platform (Verhoef et al., 2009). Awareness pushes the consumer to become aware of available platforms in the digital environment that could potentially fulfil this needs statement or resolve a problem (McGaw, 2015).

Adopting a platform relates to activation, which is the initial engagement in the online exchange relationship by downloading the application and subsequent interaction with the platform, like signing up for a newsletter or registering an account. The next step is retention, which includes the consumer’s first and consecutive purchases. Online retention should be driven by comprehending the consumers' underlying expectations concerning the product or service value, resulting in satisfaction and continuous use intention (Bhattacherjee, 2001).

Once the consumer is retained, the retailers count on the consumer to refer to the platform, especially after successfully fulfilling the purchasing process. Revenue will follow as a natural result of referral for the consumer and the business, as part of the co-creation of value process, and the perceived satisfaction of outcome expectations (Vega-Vazquez et al., 2013).

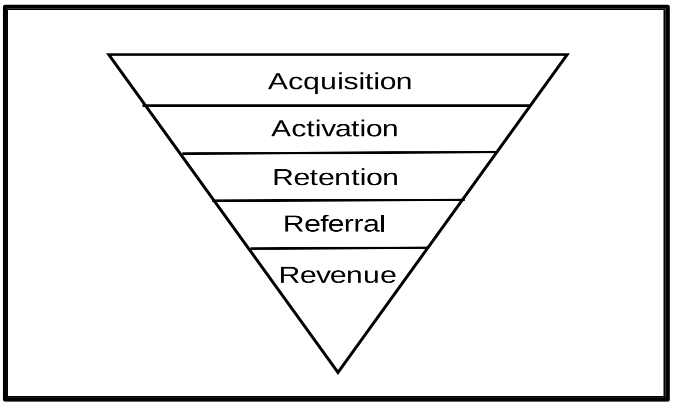


Figure 2: AARRR Model (McClure, 2007)

2.5.2 The Growth Hacking Taxonomy

Growth hacking, a buzzword invented by Sean Ellis in 2010, can be defined as a process across the entire customer journey that involves rapid experimentation to increase customers and accelerate revenue growth. Growth hacking differs from marketing since it entails science, data and processes. From a commercial standpoint, growth hacking is the practice of quickly testing and implementing low-resource, low-cost strategies to help attract and keep active users, promote products, and grow the organisation profitably (Bargoni et al., 2024).

Growth hacking is not only for marketers but for anyone, from product developers, engineers, salespeople and managers, to promote new product innovation and to continuously improve existing products by expanding the customer base (Ellis & Brown, 2017). Growth hacking focuses on UG and uses a variety of strategies to expand the user base by determining which channels and non-traditional marketing approaches best fit the marketing of the business's products and services. The key to growth is driving user conversion by delivering goods to the right clients and establishing methods of communication to interact with customers (Feiz et al., 2021). Any organisation – big or small - can apply growth hacking strategies. Organisations can set themselves up for growth hacking by following four steps (Bargoni et al., 2024):

i) Utilise big data to ensure the platform the business is attempting to develop, the target market, and the product they wish to sell are a good fit.
ii) Identify the "hack" in your organisation by effectively focusing on the appropriate clients at the right time and in the right location.
iii) Drive virality of the product or platform through social media and digital channels.
iv) Encourage customer retention using data-driven customer relationship management (CRM) systems and streamlining the organisation's marketing initiatives by introducing rewards and loyalty schemes.

With the potential for nonlinear increases in utility and value, platforms bring people and organisations together to enable innovation or interaction in ways that would otherwise be impossible. Platforms also bring people and groups together to exchange resources or fulfil a common demand. The goal of both B2B and B2C sales cycles is to guide potential customers through a series of (specific) communications and content that begins with establishing brand awareness and may end with a sale. This sale can also result in customer loyalty and encourage customers to promote the brand if it is accompanied by outstanding customer service. This process completes the growth hacking cycle (McClure, 2007).

Growth hacking in platforms can be practically achieved by applying the AARRR model (McClure, 2007), and it can be demonstrated through a growth hacking taxonomy, which leverages specific mechanisms to strengthen business value along each stage of the AARRR model. These mechanisms include innovation, marketing metrics and customer-focused tactics (Bohnsack & Liesner, 2019).

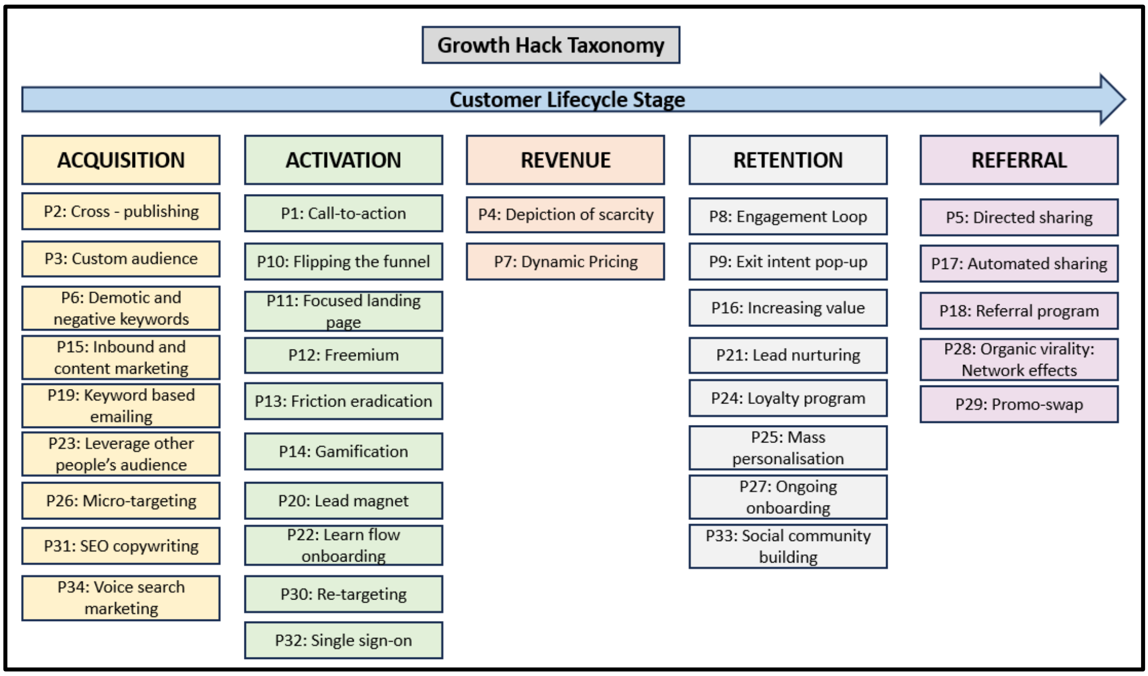


Figure 3: Growth Hacking Taxonomy (Bohnsack & Liesner, 2019)

2.5.3 Technology Acceptance Models – Summary

An analysis of the major technology acceptance models and theories found during the literature review is presented in Table 5. The table contains the details of each model, including the author and year published. In addition, the constructs on which each model is built are presented chronologically by year, illustrating the evolution of the research concerning technology adoption and the correlation to various psychological theories. This table shows the comprehensive and extensive literature review that was concluded to enable the researcher to take a world view towards understanding e-commerce acceptance and adoption through the application of scholarly models.

Table 5: Summary: Technology Acceptance Models and Theories

Number	Model	Author	Constructs	Key Findings
1.	Technology Acceptance Model (TAM)	Davis, 1989.	PEOU and PU	The key conclusion is that usefulness has a more convincing link to usage than ease of use. Users are motivated to adopt an application due to the activities it performs for them (usefulness) and secondarily for how difficult or easy it is to perform the activities on the system.
2.	The Model of PC Utilization (MPCU)	Thompson et al., 1991.	Social factors, the relationship between work and PC capabilities, long-term importance and complexity.	MPCU forecasts individual acceptance and actual personal computer (PC) utilisation. Behavioural intention and habit are excluded from the proposed model. Results confirm that social factors, long-term consequences, job fit and complexity impact PC utilisation.
3.	Theory of Planned Behaviour (TPB)	Ajzen, 1991.	Perceived behavioural control (PBC).	Extending TRA by adding perceived behavioural control (PBC) as a new variable. PBC is found to have a direct influence on actual behaviour and implied responses towards behavioural intentions. The TPB model, therefore, presents three factors affecting BI - perceived behavioural control, subjective norm, and behavioural attitude.
4.	Motivational Model (MM)	Davis et al., 1992.	PEOU, perceived enjoyment.	System use is determined by intrinsic and extrinsic motivation. The extrinsic motivation is defined as the perception that users will want to perform an activity because it is perceived to be useful in achieving specific outcomes. Still, it is unrelated to the activity itself, such as

Number	Model	Author	Constructs	Key Findings
				improved job performance. Intrinsic motivation is defined as the completion of the activity without any supplementary intention.
5.	Social Cognitive Theory (SCT)	Compeau et al., 1999.	Self-efficacy identifies four sources of perceptions: actual experience, vicarious experience, social persuasion, and physiological states.	These perceptions have ramifications for training as well as end-user support in organisations. End-user support should not only focus on technical guidance but also on promoting self-efficacy levels in individuals to improve overall technology engagement and results.
6.	Extended Technology Acceptance Model (TAM2)	Venkatesh and Davis, 2000.	PEUO, PU, SI processes, cognitive instrumental processes.	Extended TAM evaluates the impact of social influence and cognitive instrumental processes on PEUO and PU. It explains the impact of experience gained by the user over time on PU intention compared to the initial impact of subjective norm and image.
7.	The Expectation Confirmation Theory (ECT)	Bhattacherjee, 2001.	Information Systems (IS) continuance intention, satisfaction, PU, confirmation.	User satisfaction has a stronger impact on continuance intention than PU. User satisfaction is determined based on the confirmation of expectations established in prior use but secondary to the PU.
8.	Theory of Reasoned Action (TRA)	Hale et al., 2002.	BI, subjective norm, beliefs and attitude.	BI is driven by voluntary behaviour as the strongest predictor. Individual and standard conditions impact BI. Individual influences are attitude (favourable or unfavourable as expressed as a feeling of the individual towards the behaviour), social norms (SI), and intentions (individual's decision to act on behaviour or not).
9.	TAM/Flow Theory	Koufaris, 2002.	Product involvement, web skills, value-added search mechanisms, challenges, perceived control, shopping enjoyment, concentration, unplanned purchases, PU, PEOU and intention to return.	Identify a correlation between the online shopper and computer user. Measures the impact of consumer behaviour on the intention to return to online shopping or conduct unplanned purchases. PU is a strong motivator for consumers to return to online shopping.
10.	Unified Theory of Acceptance and Use of Technology Model (UTAUT)	Venkatesh et al., 2003.	EE, PE, SI and FC. Additionally, four moderating variables were identified: gender, age, experience,	Integrating eight models establishes the UTAUT: TAM, C-TAM-TPB, IDT, TRA, TPB MM, MPCU, SCT.

Number	Model	Author	Constructs	Key Findings
			and voluntariness of use.	
11.	Task Technology Fit Model (TTF)	Klopping and Mckinney, 2004.	The Fit-usefulness relationship is established.	This study found that use depends on both usefulness and task fit. Secondly, perceptions of usefulness are mostly related to use and should be addressed with the user.
12.	Technology Acceptance Model 3 (TAM3)	Venkatesh and Bala, 2008.	Computer self-efficacy, computer anxiety, computer playfulness, perception of external control, perceived enjoyment, and objective usability.	TAM3 presents experience as a new moderating variable. It found that with increased experience, the reaction towards PEUO and PU will increase. The opinion on PEUO remains an important factor despite increased experience.
13.	Innovation Diffusion Theory (IDT/DOI)	Rogers, 2010.	The adoption rate is impacted by the following attributes: relative advantage, complexity, compatibility, observability and trialability.	The relative speed at which an innovation is embraced by members of a social system is known as the adoption rate. The diffusion theory suggests that change can be promoted rapidly in society through the impact of a “domino effect” (Orr, 2003). The diffusion theory describes attributes that drive innovation to reach the “tipping point”, which causes rapid adoption of change.
14.	Thai E-Commerce Technology Acceptance Model (TECTAM)	Chooprayoon and Fung, 2010.	PEUO, PU.	Establish relationships between the public industry, SMEs and online customers in terms of perceived ease of use and usefulness in adopting e-commerce.
15.	Extended Unified Theory of Acceptance and Use of Technology Model (UTAUT2)	Venkatesh et al., 2012.	All the variables from UTAUT are incorporated plus hedonic and utilitarian benefits, habit and PV. And additionally, the moderators age, gender and experience.	Both hedonic and utilitarian benefits are essential motivators in consumer technology use. They are moderated by age, gender and experience. PV has a vital impact on the adoption and continued use of consumer technology, with moderating effects of gender and age influencing the relationship between PV and BI. In a consumer context, FC influences actual behaviour and BI whilst being moderated by gender and age. The original constructs of the UTAUT Model (Venkatesh et al., 2003) were supported, with experience being introduced as an intermediating factor in the consumer technology context. Consumer individual differences moderate habit and have direct and mediating effects on technology use.

Number	Model	Author	Constructs	Key Findings
16.	Model of eCommerce Adoption (MOCA)	Guzzo et al., 2016.	Actual use, SI, usability, usefulness, risk, trust.	These results present a circular model indicating that SI is a moderator for eCommerce adoption. Continuous online purchase intention is driven by positive online experiences, reinforced by the users' degree of satisfaction, which recommences the process again. Consumers can also refrain from continuing to buy online depending on their positive or negative experiences with the product or services and their feedback delivered through reviews (online/offline).

2.5.4 Technology Acceptance Models

The following section contains an overview of TAM, UTAUT and UTAUT2 and their major constructs as identified during the literature review.

i. The Technology Acceptance Models (TAM/TAM2/TAM3)

The foundational determinants of TAM (Davis, 1987), PU and PEOU were further studied in TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008). They presented some findings that became decisive in technology acceptance research.

The research on PU and PEOU has found that PU is a person's expectancy that using a respective application/platform would improve their work and career achievements. Secondly, PEUO is the extent to which a person thinks using a specific platform or application will be straightforward or effortless (Davis, 1989).

Both PU and PEOU are strong factors that predict a user's attitude towards system use and determine the user's attraction towards using the system. Furthermore, BI is affected by the attitude of the user and PU of the system, which in return predict the actual use of the system (Malhotra & Galletta, 1999). All of these determinants, primarily PU (Venkatesh & Davis, 2000), are inclined to play a vital role in system use intention (Nyoro, 2015).

Comprehensive studies by Venkatesh and Davis (2000) have concluded that usefulness was a more dominant driver than PEOU. However, PU could also transform as time lapses and the user gains more experience, which would cause usage intentions to increase as the dominant driver of technology acceptance (Venkatesh & Davis, 2000).

It could, therefore, be summarised that TAM (Davis, 1989), TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) emphasise mainly two determinants, PEUO and PU, based on the adoption of technology in the work environment. However, TAM2 introduced cognitive determinants, additionally to TAM (Davis, 1989), which are established over time through experience, and the perception of usefulness that could be formed based on whether job goals can be achieved as a result of productivity that is generated through system use (Venkatesh & Davis, 2000).

The TAM (Davis, 1989), TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) models mainly focus on the adoption and compulsory use, as well as the frequency of use, of modern technologies in the work environment (Koufaris, 2002). This implies that the empirical findings presented by Davis (1989), Venkatesh and Davis (2000), and Venkatesh and Bala (2008) have limited application to e-commerce applications, which by nature are voluntary to use and reuse by consumers. However, in 2002, a new study was concluded that has proven the dual application of TAM to the workplace and online shopping environment.

ii. Application of TAM to e-commerce

Koufaris (2002) analysed new customer retention, where consumers aim to return and conduct unanticipated purchases on B2C e-commerce platforms. This study found that how products are presented online impacts the entire shopping experience, affecting customers' attitudes towards shopping and their potential to buy online (Koufaris, 2002).

Website visit experiences can be reviewed by analysing the cognitive and emotional responses towards these encounters, which will support a retailer in determining future online consumer behaviour and intention to return and possible unanticipated purchases by the consumer. The study confirms that online consumers can be seen as computer users and conventional shoppers (Koufaris, 2002).

Koufaris (2002) found that enjoyment of and the perceived usefulness of online shopping drive the intention to return to online shopping, demonstrating the dual application of TAM (Davis, 1989) between the workplace and online shopping. Although the initial results from TAM (Davis, 1989) are endorsed, PEUO is less critical than PU in predicting the intended future use of the system.

The online shopper and computer user relationship is further elaborated by findings that a user-friendly interface and browsing functionalities are as crucial as efficient customer service and reasonable prices. Consumers are not seeking online amusement, but having a good emotional experience will drive shopper retention. Users adopt an e-commerce platform more overwhelmingly for its valuable activities rather than for how effortless it is to perform the activities on the B2C e-commerce platform (Koufaris, 2002).

iii. Application of TAM: Model of E-Commerce Adoption (MOCA)

MOCA made a significant theoretical contribution to the online shopping (e-commerce) literature by constructing and testing a model to strengthen the understanding of existing literature on e-commerce adoption and predicting consumers' online behaviour and, in particular, the consequence of SI (Guzzo et al., 2016).

The study’s results have shown that physical use is influenced by connectivity and broadband availability, which also informs the frequency and duration of use. SI is driven indirectly by opinions when the consumers change their minds based on advice from others (family, peers or colleagues) or online information. SI is also driven more directly when consumers' post-purchase satisfaction influences their future purchasing decisions, reconfirmed through verbal consultation or online reviews and ratings from other consumers. SI is, therefore, an indirect motivator to accept and adopt e-commerce platforms.

Usability is analysed and is predominantly (40% of respondents) impacted by PEUO of the e-commerce website. Consumers recognise risk, but it does not affect e-commerce adoption. Risk and trust are mainly driven by online payments, information security and reliable and safe delivery services and indirectly impact PU and usability (Guzzo et al., 2016).

These results present a model circular in nature, indicating that SI is a moderator for e-commerce adoption. Continuous online purchase intention is driven by positive online experiences, reinforced by the users' satisfaction, which recommences and loops the process. Consumers can also refrain from continuing to buy online depending on their favourable or unfavourable experiences with the product or service or assessments of reviews (online/offline). Consumers' verbalisation of their perceptions will directly impact other consumers' decision-making. Indirectly, they will affect their own actual frequency of use (Guzzo et al., 2016).

iv. Unified Theory of Acceptance and Use of Technology (UTAUT)

According to Venkatesh et al. (2003), UTAUT suggests three direct determinants of intention to use IT, two direct determinants of usage behaviour and one construct with no direct influence:

Direct determinants of user acceptance and BI to use technology:

a) ***Performance Expectancy*** (PE) is a metric that measures how confident a person is that using an application/platform would increase their job performance. PE is the most powerful construct of intention to use and is compelling in compulsory and voluntary systems operations (Venkatesh et al., 2003).

PE consists of five constructs from existing models: PU (TAM/TAM2/C-TAM - TPB) (Davis, 1989; Taylor & Todd, 1995; Venkatesh & Davis, 2000), extrinsic motivation (MM) (Vallerand, 1997), job-fit (MPCU) (Thompson et al., 1991), relative advantage (IDT) (Moore & Benbasat, 1991), outcome expectations (SCT) (Compeau et al., 1999; Compeau & Higgins, 1995).

Moderators: age, gender

b) ***Effort Expectancy*** (EE) is the degree to which ease of use is concurrent with using the application/platform. For first-time use, the expectation of effort is compelling in both voluntary and compulsory usage scenarios. However, the effort becomes non-significant with continuous and uninterrupted use (Venkatesh et al., 2003).

EE consists of three constructs from existing models: PEUO (TAM/TAM2) (Davis, 1989; Venkatesh & Davis, 2000), complexity (IDT) (Thompson et al., 1991), ease of use (SCT) (Moore & Benbasat, 1991).

Moderators: age, gender, experience

c) ***Social Influence*** (SI) is the degree to which a person believes that other people think they should consider to adopt a platform, application, or technique. SI is presented as a subjective norm and a direct BI determinant. SI is two-fold; firstly, individuals believe that the perspectives of others will influence their image in reaction to using technology, especially in a compulsory environment.

Secondly, individuals are also more likely to adhere to others' views if these individuals can reward or disapprove of their performance. SI is imperative in adopting technology, but the impact eventually decreases as users become more accustomed to the system (Venkatesh et al., 2003).

SI consists of three constructs from existing models: subjective norm (TRA, TAM2, TPB/IDTPB, and C-TAM-TPB) (Ajzen, 1991; Al-Suqri & Al-Kharusi, 2015; Davis et al., 1989; Taylor & Todd, 1995), social factors (MPCU) (Thompson et al., 1991), and image (IDT) (Moore & Benbasat, 1991).

Moderators: age, gender, experience.

Direct determinants of technology use behaviour:

d) ***Facilitating Conditions*** (FC) depend on the individual's expectations and refer to the extent to which support exists for application or platform usage (technical or organisational). FC was introduced to address the significance of outside variables (Venkatesh et al., 2008). The mere awareness of FC's presence (or absence) is not anticipated to significantly impact how the system is used. Instead, system utilisation depends on how much an individual believes that FC will make it possible for them to use the system, given other potential behavioural barriers (Venkatesh et al., 2008). In the presence of EE and PE constructs, FC becomes unimportant in forecasting BI (Venkatesh et al., 2003).

FC consists of three constructs from existing models: perceived behavioural control (TPB/DTPB, C-TAM-TPB) (Ajzen, 1991; Taylor & Todd, 1995), facilitating conditions (MPCU) (Thompson et al., 1991), and compatibility (IDT) (Moore & Benbasat, 1991).

Moderators: age, gender, experience.

e) ***Behavioural Intention*** (BI) reflects a person's internal belief system. It does not depict the outside forces that could affect how well a behaviour is performed. As a result, BI does not adequately account for the influence of external events that may help or hinder the conduct of the behaviour. According to empirical data, e.g. (Agarwal & Karahanna, 2000; Venkatesh & Davis, 2000; Venkatesh et al., 2003) BI is driven by and reflects various internal aspects. This implies that BI and use duration have a positive linear connection. External circumstances can also influence use duration, and behavioural expectation considers these aspects. Behavioural expectation will contribute to length of use prediction, but less so than BI (Venkatesh et al., 2008).

The role of major moderators:

Future research should challenge the current comprehension of demographic moderators to understand the influential underlying patterns better. According to Venkatesh et al. (2012), age, gender, and experience will harmonise to moderate various relationships in the UTAUT2 model.

a) Age and Gender

The age of users could indicate the users' tech savviness and susceptibility to adopt and use technology. The moderating effect of age between PE and BI and FC and BI has different intensity levels for older than younger users.

Gender roles and stereotypes, as socialised from birth, play a fundamental role in understanding the moderating effects on the direct determinants of technology adoption and use. Men are more task-orientated, and PE will be more pertinent to men than women. Contrarily, women are more interested in the effort required to complete a task; thus, EE will be a more remarkable consideration for women (Venkatesh et al., 2003).

b) *Experience*

Experience is defined as the time between using a technology for the first time and the current time. Experience is a skill an individual gains with time, starting from the moment the individual first uses the technology. If consumers do not develop their abilities and skills, the impact of gender and age will be more significant on their continuous learning to use technology. Experience is a required but not a satisfactory condition for forming a habit. The lapse of chronological time can impact the levels at which patterns can be established through engagement and knowledge of the technology in question (Kim et al., 2005; Venkatesh et al., 2012).

c) Voluntariness

In an organisational use setting, superiors often mandate technology acceptance, and usage becomes involuntary. Voluntariness is the extent to which technology adoption is voluntary or optional and not instructed (Agarwal & Prasad, 1997).

v. Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

Despite the wide acceptance of UTAUT (Venkatesh et al., 2003), the model was extended to establish another model, UTAUT2 (Venkatesh et al., 2012), to expand the original field of study from the workplace to the consumer context and to improve on the original model's results that demonstrated a variance in BI and technology use in the workplace.

UTAUT2 was established by integrating three additional constructs, Hedonic Motivation (emotional affect), Price Value (financial constraints), and Habit (routine), into UTAUT (Venkatesh et al., 2003). The three moderating characteristics, age, gender and experience, are carried over from UTAUT. Meanwhile, voluntariness is omitted from UTAUT2 (Venkatesh et al., 2012).

a) Hedonic Motivation (HM) is the amusement emanating from using technology. HM impacts substantially on BI to use technology, which relates to the usefulness or enjoyment that emphasises the serviceability of technology use. HM has been found to affect consumer technology acceptance and use significantly but declines with increased experience levels (Brown & Venkatesh, 2005).

Moderators: gender, age and experience.

b) Price Value (PV) is the transaction cost of using technology compared to the benefits derived therefrom (TingPeng & JinShiang, 1998). The consumer use environment imposes costs of use compared to a mandatory use environment (e.g. the workplace), which exempts the user from charges for using the technology. As a result, the consumer trades off the application's alleged advantages against the costs associated with using the technology. In a consumer context, women are more price-sensitive than men, primarily informed by their social roles as caretakers (Alalwan et al., 2018).

Moderators: gender and age.

c) Habit is the motive to use technology. Habit promotes BI of how people perform/behave due to their historic training or availability of information. Habit could be considered as the accumulation of past behaviour or the extent to which the behaviour is performed naturally and regularly. Habit influences use behaviour through two separate paths: firstly, through the processing of clues or suggestions, and secondly, through the availability of Information (Venkatesh et al., 2012).

Repeated actions or attitudes lead to the formation and strengthening of the connection between experience and habit. Habits are learned over time and stored in a person's memory; they can override behavioural motives over the long term. Routine practices become automatic with experience and are more influenced by the accompanying clues (Venkatesh et al., 2012).

In summary, Venkatesh et al. (2012) conclude that HM, habit, and PV play important roles in forecasting continued use and are integral in validating UTAUT2 in the context of consumer intention to use and usage of IS.

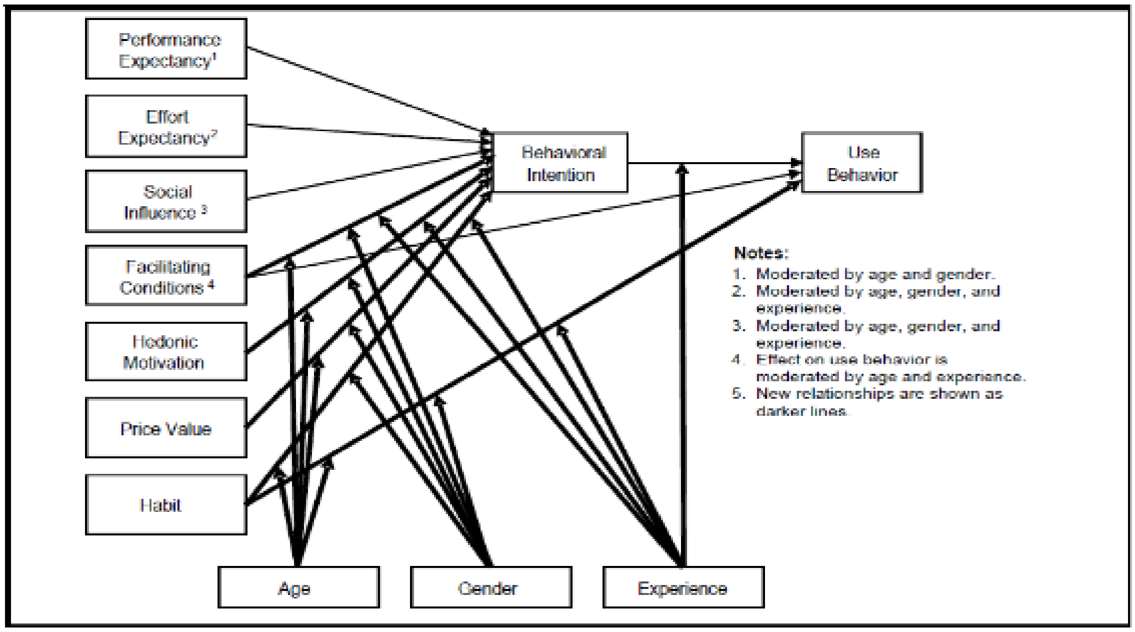


Figure 4: UTAUT2 Model (Venkatesh et al., 2012)

Table 6: Summary of the UTAUT2 constructs

Summary of the UTAUT2 Constructs		
Performance Expectancy (PE)		
Construct	**Definition**	**Original Model**
Perceived Usefulness (PU)	A particular system would enable the user to execute their tasks quicker / easier.	TAM & TAM2 (Davis, 1989; Venkatesh & Davis, 2000)
Extrinsic Motivation (MM)	Users want to perform a task to achieve a particular outcome.	Motivational Model (Vallerand, 1997)

Job-Fit	System capabilities enhance the completion of tasks/shopping objectives.	MPCU (Thompson et al., 1991)
Relative Advantage	Shopping online has more advantages than shopping in-store.	IDT (Moore & Benbasat, 1991)
Outcome Expectations	The expected outcome of performing a specific behaviour - a task or personal activity.	SCT (Compeau & Higgins, 1995)
Effort Expectancy (EE)		
Construct	**Definition**	**Original Model**
Perceived ease of Use (PEUO)	The degree to which using a system is effortless.	TAM & TAM2 (Davis, 1989; Venkatesh & Davis, 2000)
Complexity	Shopping online is perceived as being difficult to understand and use.	MPCU (Thompson et al., 1991)
Ease of Use (IDT)	Using innovation is perceived as being problematic.	IDT (Moore & Benbasat, 1991; Rogers et al., 2014)
Facilitating Conditions (FC)		
Perceived Behavioural Control	Reflects perceptions of internal & external constraints that lead to self-efficacy (a person's ability to believe that they will succeed in a particular situation).	PBC (Ajzen, 1991; Davis, 1989
Facilitating Conditions (FC)	Factors in the environment, like computer support, make an act easy to do.	MPCU (Thompson et al., 1991)
Compatibility	The degree to which the innovation aligns with potential adopters perceived beliefs, needs and experiences.	IDT (Moore & Benbasat, 1991)
Social Influence (SI)		
Subjective Norm	People important to a person think that they should perform a particular behaviour.	TAM & TAM2 & TPB (Ajzen,1991; Davis, 1989; Venkatesh & Davis, 2000)
Social Factors	The internalisation of the reference groups' subjective culture/ or specific interpersonal agreements.	MPCU (Thompson et al., 1991)
Image (IDT)	The use of an innovation will improve one's standing or reputation within a community or the extent to which technology use will enhance someone's reputation or social standing in society.	IDT (Moore & Benbasat, 1991)

2.5.5 The Expectation Confirmation Theory (ECT) and the Information System Continuance Theory

Oliver published the Expectation Confirmation Theory (ECT) in 1980. The term "confirmation of expectations" describes how a person's pre-judgments (initial expectations) regarding a product or service are confirmed or disproven. This confirmation is positive when a product or service exceeds a person's initial expectations. This leads to increased product purchases, which can be attributed to post-adoption satisfaction. Otherwise, when the confirmation is negative, dissatisfaction is experienced and the post-adoption rate declines (Oliver, 1980).

Expectation differs and could change depending on whether the consumer is in the pre-purchase phase with potentially higher expectations, impacted by subjective norms and the opinion of others or information in the media, compared to the post-purchase phase with different expectations relative to the satisfaction that was delivered during the use of the product in the purchase phase (Bhattacherjee, 2001).

According to ECT, a consumer’s intention to continue using a service or make another purchase is mainly based on their satisfaction with the product or service they had previously used. Satisfaction is characterised by a psychological or dynamic condition resulting from a mental and subjective assessment of the expectation-performance gap (confirmation). A buyer's level of satisfaction is determined by comparing their post-purchase experience with their purchasing experience and their perceived expectations (Bhattacherjee, 2001).

Higher achievement and lower expectations impact positively on consumer satisfaction and continuance intention, leading to improved confirmation related to perceived performance. However, high expectations and poor achievement lead to dissatisfaction and unperceived usefulness, which are determinants of information system discontinuance (Kim et al., 2009). Customer satisfaction is therefore determined by previous experiences, which are critical in motivating, retaining, and assessing consumers' future propensity to buy (Oliver, 1980).

The ECT framework outlines the process steps by which consumers reach repurchase/continuance intention:

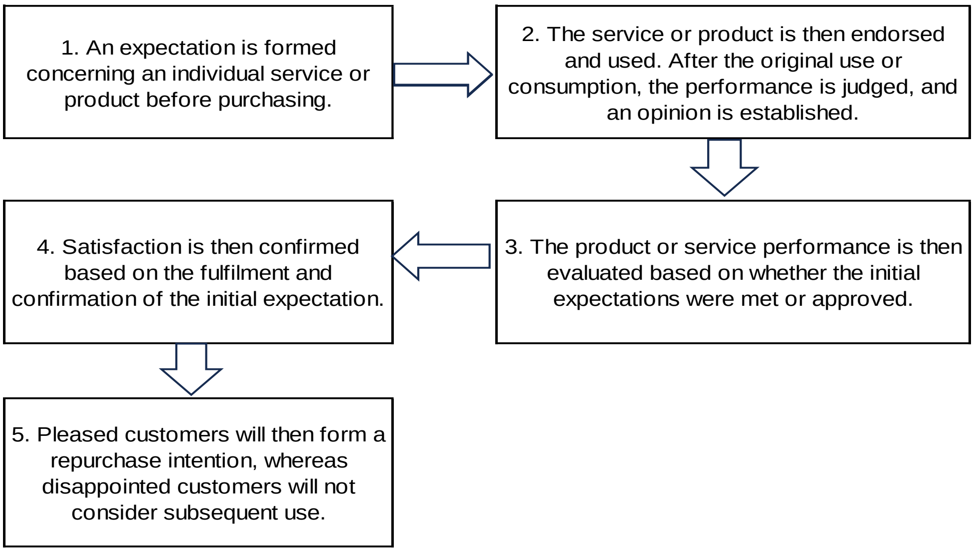


Figure 5: ECT Framework (Kim et al., 2009)

Due to high search expenses and the complexity of establishing new customers, the continuance of information systems is vital to the survival and growth of businesses. ECT confirms that repurchase and continuance use intention is mainly established through previous satisfaction with a product or service. Satisfaction is the strongest predictor of continuous use intention, with perceived usefulness a secondary factor but more applicable to the adoption of information systems (Bhattacherjee, 2001).

2.5.6 Co-Creation Value

The traditional market was organisation-centric. Markets thrived on value exchange and extraction. Organisations used to concentrate on the exchange in the market as the centre of economic value extraction. In recent times, with the start of the Fourth Industrial Revolution, well-informed, dynamic, educated and engaged customers have realised that they, too, can extract value at the traditional point of exchange (Prahalad & Ramaswamy, 2004).

Organisations are still in charge of the overall experience, but the organisation and the customer must jointly create value. A customised co-creation experience considers how the customer engages with the experience environment that the company facilitates. The information infrastructure must be consumer-focused and promote active involvement in all facets of the co-creation experience, such as information search, product and service configuration, fulfilment, and consumption (Prahalad & Ramaswamy, 2004).

Finally, the customer-organisation interactions lead to the convergence of the roles of the customer and the organisation in a market that simulates a forum for co-creation experiences. The organisation and the customer are partners and rivals in co-creating value and competitors in pursuing economic value extraction (Prahalad & Ramaswamy, 2004).

Value co-creation in B2C e-commerce is facilitated through gamification, mainly through loyalty programmes and rewards. Gamification is the process of adding aspects of game design to non-gaming services in order to maximise the value that is produced for users. Digital transformation has evolved traditional loyalty programmes into interactive experiences and services. As a result of this, gamified activities made available through online loyalty programmes boost customer interactions and encourage value co-creation. Organisations that strive to create value have a better triple bottom line (TBL) and customer satisfaction (Dreher & Ströbel, 2023).

Perceived value is another antecedent of repurchase intention and an essential element of the exchange transaction. Perceived value is a customer's perceived benefit between what they pay (price and sacrifice) and what they get (quality, benefits and services). Customers' perceptions of value thereby encourage exchange transactions. At the same time, customer value perception supersedes actual product value. Many shoppers prioritise saving time when they go shopping for food. When an online shopping platform cuts down on a customer's purchasing time, it improves their perception of value and fosters a long-lasting relationship with them (Miao et al., 2022).

Customer satisfaction must, therefore, increase if we view customers as active players in co-creating value. It has been confirmed that customers' motivation and commitment to co-creation increases with improved participation. They can recognise a higher quality of service because of their participation. This element has a direct impact on satisfaction. Customers will be less dissatisfied with the product or service if the final product or service is tailored to their needs (Vega-Vazquez et al., 2013).

2.5.7 Utilising AARRR to Achieve UG

According to Lee et al. (2003), the TAM Model (Davis, 1989) contributed significantly to the literature. Still, it omits addressing the issues or challenges that impact an organisation's revenue generation or information system sustainability (Lee et al., 2003). UTAUT (Venkatesh et al., 2003) was empirically tested, and strong support emerged for the two direct determinants, intention to use and usage behaviour (Venkatesh et al., 2003). To improve the generalisability of UTAUT, UTAUT2 (Venkatesh et al., 2012) was introduced with three additional variables and moderators, enhancing its application to the consumer technology environment.

However, one of the significant shortcomings of TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) is the limited research findings on factors that influence "use behaviour". Most of the research published addresses "behavioural intention to use" with limited data available on the catalysts of "use behaviour". Examples include elderly and internet banking (Arenas Gaitán et al., 2015), the use of fitness centre apps (Ferreira Barbosa et al., 2022), user acceptance of mobile apps for restaurants (Palau-Saumell et al., 2019), factors influencing online hotel booking (Chang et al., 2019), and acceptance of mobile learning and mobile shopping (Arain et al., 2019; Huang, 2023).

These examples and much other published literature fail to address the factors that influence and promote "use behaviour" or, in the case of an e-commerce business model, "UG". The concept of UG is derived from the AARRR model

(McClure, 2007). UG is a direct result of customer retention derived by organisations when they have a thorough understanding of their markets and have strategies to strengthen loyal customer foundations to build sustainable profitability (Wirtz & Lihotzky, 2003). UG could be aided by applying “growth hacking strategies”, which were successfully implemented by Pinduoduo (Jinling, 2021; Li & Tran, 2021) along with the AARRR model to drive UG from a retailer perspective (Wirtz & Lihotzky, 2003).

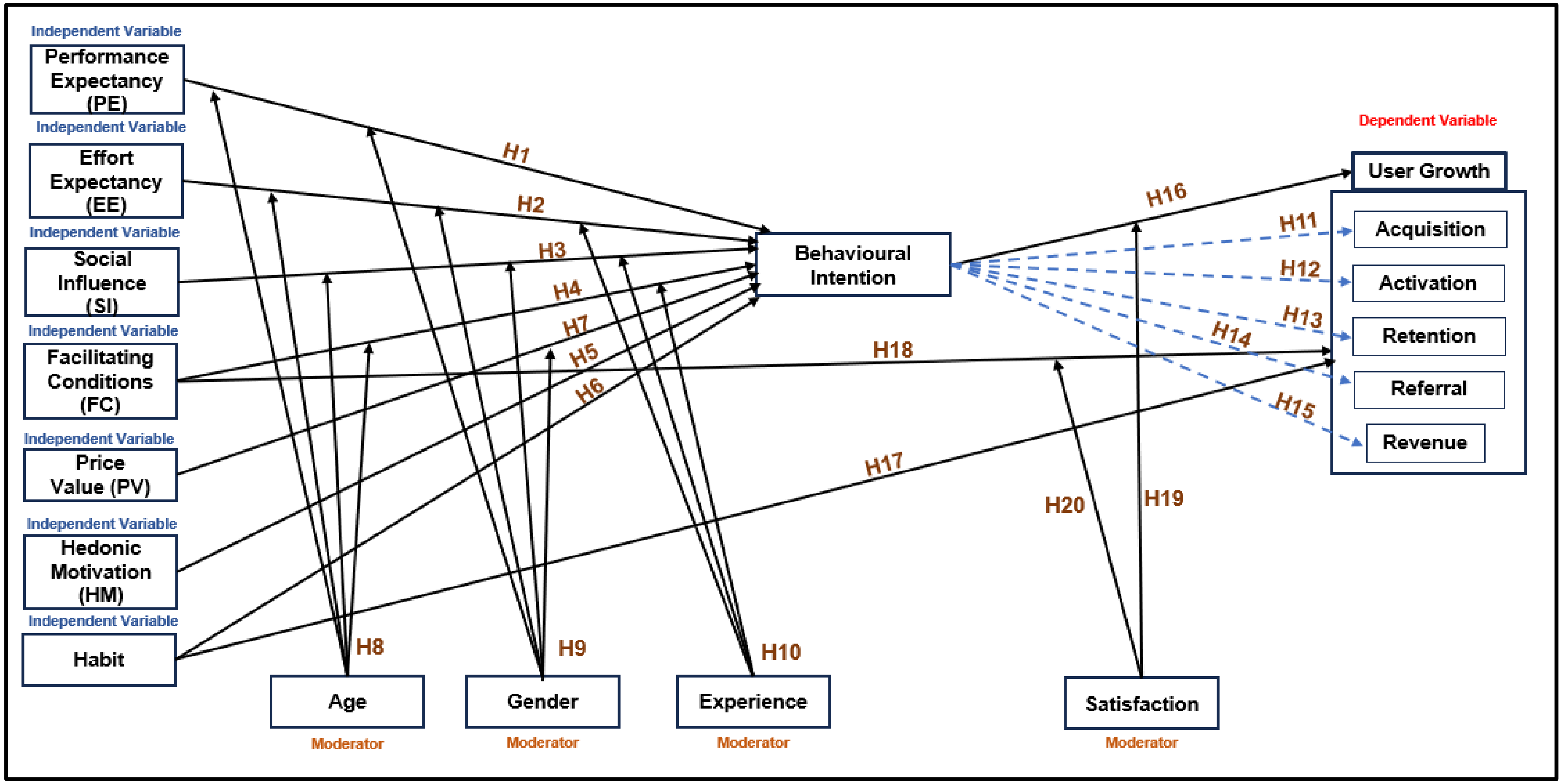
An opportunity exists to research “UG” from a consumer perspective by incorporating the variables from the technology perspective by applying the UTAUT2 model (Venkatesh et al., 2012). This lens will enable the research study to uncover the determinants influencing UG in B2C e-commerce platforms that ultimately foster organisational value and future success.

2.6 Conceptual Framework

This research study had the objective of determining the interrelationships between the UTAUT2 model (Venkatesh et al., 2012), a theoretical model, and the AARRR model (McClure, 2007), a practitioner model to conclude on the determinants of UG in B2C e-commerce platforms.

The model's exogenous variables or independent variables were PE, EE, SI, FC, HM, PV and habit. The exogenous variables always have arrows pointing from them to another variable. BI was both a dependent and independent variable in the construct. BI was considered a dependent variable as the seven independent variables predict their effect, and an independent variable (exogenous), as it predicts the effect on UG, the dependent (endogenous) variable (Hair et al., 2019).

To elaborate on the effect of BI on technology use in the consumer technology environment, use behaviour from the UTAUT2 model in Figure 4 was adapted to become UG, the dependent or endogenous variable, and it was also considered to be the outcome construct. UG is divided into five phases, or measured indicator variables – acquisition, activation, retention, referral and revenue. FC and habit were tested for their direct effect on BI and UG. The three moderators, age, gender and experience, harmonised under the UTAUT2 construct, and their moderating effect was tested between BI and PE, EE, SI and FC in various combinations (Hair et al., 2019).



Direct effect		Direct effect: Measured Indicator Variable	

Figure 6: Proposed Conceptual Framework

2.7 Primary Research Question

What are the determinants that influence user growth in B2C e-commerce platforms in the South African FMCG industry?

With the application of the UTAUT2 model (Venkatesh et al., 2012), the exogenous variables of intention to use were used to formulate the first research question. The second question was defined based on the relationship between BI and UG, and the third research question was derived based on the moderating effect of satisfaction between BI and UG, and FC and UG.

2.8 First Research Question

Which determinants influence a customer's behavioural intention to use B2C e-commerce platforms in South Africa?

2.8.1 PE (perceived usefulness/job-fit outcome expectations/task-fit) influences customers' BI to use B2C e-commerce platforms

PE is the extent to which technology will assist users in carrying out specific tasks (Venkatesh et al., 2003). In the scenario of e-commerce, PE is the degree to which the e-commerce transaction is useful for the consumer (Tang et al., 2021), or in the case of e-grocery shopping where the use of the application leads to time-saving (Van Droogenbroeck & Van Hove, 2021). PE is a more aggressive determinant of use intention than EE, especially in the adoption stage of an application (Liew et al., 2014).

The choice to use e-commerce applications is also influenced by the extent to which online purchasing activities are helpful (task-fit) to complete consumers' shopping needs and support personal capabilities (Goodhue & Thompson, 1995). The more valuable the platform is in fulfilling consumer expectations and requirements, the higher the likelihood of reusing it for future purchases. PE also measures the level of satisfaction compared to historical expectations and how it impacts continuance intention (Venkatesh et al., 2003).

Hypothesis 1

H_1: PE influences customers' BI to use B2C e-commerce platforms.

2.8.2 EE (PEOU) influences customers' BI to use B2C e-commerce platforms

EE is the perceived ease (PEOU) with which a consumer can use technology (Setiyani et al., 2023). The desire to adopt and utilise technology is higher when less effort is required to comprehend and use it. Multiple research studies demonstrate explicitly that future purchase intentions are negatively correlated with the level of expected effort and perceived complexity of online grocery services (Van Droogenbroeck & Van Hove, 2021). In the beginning, consumers' intent to utilise technology is influenced positively by simple technology. Conversely, users are less likely to stick with an app over time if they exert more effort to use it (Ferreira Barbosa et al., 2022).

In this context, during the pre-purchase phase, the consumer will evaluate the condition of the website/app, the variety of information, customer service and the technology to determine whether the purchase process can continue easily (Çelik & Yilmaz, 2011). Platform characteristics like product information and pricing search should be frictionless to promote the acquisition of the platform through downloads or website visits (Klopping & McKinney, 2004).

Hypothesis 2

H_2: EE influences customers' BI to use B2C e-commerce platforms.

2.8.3 SI (social factors/subjective norm) influences customers' BI to use B2C e-commerce platforms

The consumer is affected by the perceptions and views of others towards a B2C e-commerce platform. People in similar social networks establish norms and values through their interactions, and the use of a platform is evaluated in terms of its identification with the group's unique culture (Venkatesh et al., 2003).

Most people compare their opinions with those of others before making an online purchase. They also use social media to search for information and consider suggestions from forums, blogs, and people who have completed related purchases. SI plays a crucial role in adopting e-commerce with direct and indirect effects on e-commerce intensity and frequency of use. Social networks are becoming one of the most influential and recognised sources of information on goods and services pertaining to a community's area of interest. This can encourage information sharing among users, whether positive or negative, impacting customer sentiment and their willingness to facilitate online transactions. Online businesses must understand this notion since the findings of MOCA show that companion/associate/family influence may shape some attitudes towards adopting technology (Guzzo et al., 2016).

Hypothesis 3

H_3: SI influences customers' BI to use B2C e-commerce platforms.

2.8.4 FC (customer support) influences customers' BI and usage of B2C e-commerce platforms

FC refer to users' perception that they possess the information, tools, and resources needed to engage in a particular behaviour (Ferreira Barbosa et al., 2022). FC include external factors that enable consumers to fulfil tasks quickly, gather information or seek customer support. FC consist of a query handling process mainly used when the customer needs support whilst placing the order, after it is placed, or after delivery. This process could be provided online (instant messaging/e-mail) or telephonically (Kumar & Anjaly, 2017).

The consumer should be comfortable that the organisation/company can execute their commitments between payment and delivery of the goods or services. Consistent customer service and support will facilitate product or service delivery to complete the customer journey (Venkatesh et al., 2003). This indicates that technology acceptance depends largely on how people view the resources and assistance available for adopting an application. The role of FC is more dominant in using a platform than in the intention to use it (Palau-Saumell et al., 2019). The

UTAUT2 model (Venkatesh et al., 2012) creates a new relationship and establishes that FC is moderated by age, gender and experience.

Hypothesis 4

H_4: FC influence customers’ BI to use B2C e-commerce platforms.

Hypothesis 18

H_{18}: FC affects UG in B2C e-commerce platforms.

2.8.5 HM influences customers’ BI to use B2C e-commerce platforms

HM is the amusement or entertainment derived from the use of technology (Venkatesh et al., 2003). People will only use an application if they enjoy it and feel satisfied after using it (Castanha et al., 2023).

When shopping online, consumers seek utilitarian (PEOU or satisfactory results) and hedonic gains (enjoyment of the encounter), which are achieved by flow (Bridges & Florsheim, 2008). Flow is an unusual dynamic condition that people experience holistically when they behave fully engaged (Hoffman & Novak, 1996). When consumers are in a flow state, their actions and awareness are similar, and their focus is so intense that they barely have time to think about anything else. Therefore, facilitating the flow condition is essential to building a website that appeals to potential customers (Bridges & Florsheim, 2008).

Utilitarian principles of flow directly impact purchasing, whereas hedonic principles aid internet use and indirectly impact purchasing. Hedonic value is created through fun, playfulness and enjoyment, fulfilling a pathological use purpose rather than task accomplishment. E-commerce platforms can increase hedonic value by forming attachments to their platforms, but it could negatively impact task-orientated users by preventing them from achieving utilitarian value (Bridges & Florsheim, 2008).

Hypothesis 5

H_5: HM influences customers' BI to use B2C e-commerce platforms.

2.8.6 Habit influences customers' BI to use B2C e-commerce platforms and habit affects UG in B2C e-commerce platforms

The degree to which people perform behaviours instinctively as a result of earlier learning is known as habit (Venkatesh et al., 2003). Habit could be measured by considering past conduct (Chang, 2012). Habit is an important determinant of customer retention and repurchase behaviour. The frequency of previous behaviours determines the strength of habit; but it is not necessarily formed by repetition but through automaticity. Routine behaviours only become habits if the person performing the routines is satisfied with them, then forming habits becomes automatic (Khalifa & Liu, 2007).

Previous use experience serves as a proxy for online shopping habits and is a component of establishing online shopping habits. Whilst habit is the cognitive component of behaviours, experience is formed through actual use behaviour. In addition, perceived usefulness plays an integral role in habit formation, as a consumer will not use the platform continuously if it does not have a useful purpose. Good experiences when performing specific actions are essential for developing habits since they make people more likely to do the same thing repeatedly (Limayem et al., 2007). Without habit formation, satisfaction might not be the primary determinant in returning to an online store (Khalifa & Liu, 2007).

Hypothesis 6

H_6: Habit influences customers' BI to use B2C e-commerce platforms.

Hypothesis 17

H_{17}: Customers' habits affect UG in B2C e-commerce platforms.

2.8.7 PV influences customers' behavioural intention to use B2C e-commerce platforms

PV is the financial trade-off between an application's advantages and the cost incurred from using it (Venkatesh et al., 2003). Consumers will be encouraged to use an application which will have a favourable effect on behavioural intention if the perceived benefits obtained from the application outweigh the financial cost (Castanha et al., 2023).

Transaction costs are categorised as i) search costs - searching for information or comparing attributes, ii) product inquiry costs, iii) costs incurred during the agreement of payment terms, iv) product payment costs, v) delivery costs, and vi) after-sales service costs. Consumers will likely select a channel with lower rather than higher transaction costs. Consumers will determine the compromise between the perceived benefits of using applications and the transaction costs incurred by using e-commerce applications (TingPeng & JinShiang, 1998).

Transaction costs could be lowered or overthrown by investing in IT capabilities, improving internet connection barriers, lowering mistrust in e-payments and reducing financial constraints to promote e-commerce adoption, use and continuance intention (Yang, 2010).

Hypothesis 7

H_7: PV influences customers' BI to use B2C e-commerce platforms.

2.8.8 Age will moderate the effect of PE, EE, SI and FC on customers' BI to use B2C e-commerce platforms

Older consumers tend to learn slower due to the difficulty in processing new and complex information because of the effects of the ageing process on cognitive and memory functions. As consumers age, they rely more on support (FC) (Venkatesh et al., 2012).

2.8.9 Gender will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms

Women typically focus more on the amount of work required and the method by which goals are accomplished. In contrast, men are more willing than women to put in greater effort to overcome various obstacles and challenges to pursue their goals. Therefore, men prefer to rely less on FC when using new technology, while women tend to rely more on FC. This can also be partially explained by the ideas that society has about gender roles, with males typically being more task-oriented. The conventional gender roles in society also considers the significance of elements relating to one's profession which can change over time and impact an individual’s technology adoption patterns (Venkatesh et al., 2012).

2.8.10 Experience will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms

Though it will eventually diminish, more experience provides a stronger instrumental (as opposed to social) foundation for an individual's purpose in using a system. Greater expertise can result in an improved understanding of the technology and knowledge structures to speed up user learning, lowering the need for external support. As experience increases, there is less focus on the nonutilitarian aspects like EE or SI to influence BI and more on utilitarian elements like PE to influence use intention (Kim et al., 2005; Venkatesh et al., 2012).

Hypothesis 8

H_8: Age will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms.

Hypothesis 9

H_9: Gender will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms.

Hypothesis 10

H_{10}: Experience will moderate the effect of EE, SI and FC on customers' BI to use B2C e-commerce platforms.

2.9 Second Research Question

To what extent do customers' behavioural intentions influence user growth in B2C e-commerce platforms in South Africa?

2.9.1 A customer's BI to acquire a platform is influenced by awareness of the platform

Consumer awareness is the initial step in consumer behaviour, which leads to consumer interest, followed by some additional exploratory steps, like clicking on images or visiting a website, that serve as micro-conversions during the purchasing process of the customer journey (McGaw, 2015). In the awareness stage, consumers start to develop an interest in online shopping once they understand its advantages in terms of variety, affordability, and ease of purchasing (Shih-Chih et al., 2009).

Acquisition is when a potential consumer finds and becomes aware of an organisation or a business. Marketers apply different methods through search engine optimisation, banner ads, TV advertising and social media to drive awareness of platforms during the acquisition phase (McClure, 2007). If consumers are satisfied with their visit, they will become more active and enter the activation phase.

Hypothesis 11

H_{11}: Customers' BI influences acquisition in becoming aware of B2C e-commerce platforms.

2.9.2 A customer’s BI influences activation in the adoption of a platform

Activation is when prospective consumers convert to the organisation/company's platform by downloading the app or registering to use a website. The consumer then starts interacting with the platform through browsing (increased click-through rate), analysing product and price information, completing a form, signing up for a newsletter or making an online appointment. The ultimate activation measure for CPG would be customer registration; this will show the consumer's potential commitment to purchase and continue purchasing from the platform (McGaw, 2015).

Technology adoption is the conversion of activation determined by how well modern technology (web or mobile application) meets the user requirements and expectations to fulfil a specific task or need (Klopping & McKinney, 2004).

Hypothesis 12

H_{12}: Customers’ BI influences activation in the adoption of B2C e-commerce platforms.

2.9.3 A customer’s BI influences retention in the continuous use of a platform

Retention starts with the customer’s first purchase. It then includes all subsequent processes of fostering brand loyalty among customers to encourage them to gradually make additional purchases of the retailer's goods or services. More precisely, customer retention refers to a customer's sustained loyalty to a brand they have chosen because of favourable past experiences and satisfaction (Pink & Djohan, 2021).

Retention is synonymous with continuance intention. Continuance intention (CI) is a person’s motive to continue using technology. Social relationships, attitudes and feelings impact CI and customers' behaviour. CI is also influenced by customer experience; the less experience a customer has, the lower the potential CI (Yan et al., 2021).

Customer retention results from customer satisfaction, which impacts CI more substantially than perceived usefulness. User satisfaction is determined based on the affirmation of expectations established in prior use but secondary to the perceived benefit of the platform (Bhattacherjee, 2001).

Retention is critical for business growth and is achieved by an organisation or company when existing customers continue to purchase from the organisation and become regular customers. Serving returning customers is less expensive than acquiring new ones, and it also has the added benefit that returning customers can influence others by recommending the business to others (Zhang, 2021).

Hypothesis 13

H_{13}: Customers' BI influences retention in reusing B2C e-commerce platforms.

2.9.4 A customer's BI influences referral in recommending a platform

A referral is generated when existing customers are pleased with the organisation or company and then recommend the product or service to their social network after purchasing it. This recommendation creates network effects as the referral goes viral. Referrals can also be triggered through marketing campaigns by rewarding existing customers for referring new customers (McGaw, 2015).

Hypothesis 14

H_{14}: Customers' BI influences the referral to B2C e-commerce platforms.

2.9.5 A customer's BI influences the revenue received from reusing a platform

Successful organisations/companies measure their revenue per customer and channel to improve budgeting and the allocation of marketing spend. In this study, revenue represents the revenue (benefits) received by the customers based on their satisfactory experience with a B2C e-commerce platform. Benefits form part of the co-creation value between the retailer and the customer and are often presented through loyalty points, rewards, and savings programmes to the customer (Ellis & Brown, 2017; Prahalad & Ramaswamy, 2004).

Hypothesis 15

H_{15}: Customers' BI is influenced by the revenue received (benefits) from reusing B2C e-commerce platforms.

2.9.6 A customer's BI influences UG in an e-commerce platform

BI is the perceived probability that a person will undertake some behaviour (Ferreira Barbosa et al., 2022). A behaviour is distinct from an intention. However, it might be interpreted as measuring a person's willingness to engage in a specific action (Ajzen, 1991). BI can be divided into an intention to use technology at present, an intention to use technology in the future, and the action to start using technology in the present time (Tang et al., 2021).

BI is high when a new technology is viewed as valuable and capable of helping users achieve their goals and boost productivity. PE is a key factor that influences BI to use technology, whilst BI is the critical predictor of use behaviour of a technology (Artana et al., 2022).

Hypothesis 16

H_{16}: Customers' BI influences UG in B2C e-commerce platforms.

2.10 Third Research Question

To what extent does satisfaction affect behavioural intention to use B2C e-commerce platforms in South Africa?

2.10.1 Satisfaction influences the customers' intention to use B2C e-commerce platforms

Satisfaction can be described as the process when a person compares a product's actual performance or results to the anticipated performance or results; they may feel satisfied or disappointed. Satisfaction is experienced as a result of the upfront expectations about a product or service that have been met (Ratih et al., 2021). Managers must pay close attention to the elements that impact customer satisfaction most, which is crucial to customer retention (Ferreira Barbosa et al., 2022).

The circular nature of the online purchase journey is driven by customer satisfaction as experienced by the users during the online purchasing lifecycle (Guzzo et al., 2016). Satisfaction is divided into three types according to the online purchase journey: a) pre-purchase satisfaction, b) purchase satisfaction, and c) post-purchase satisfaction. Pre-purchase satisfaction relates to the consumers' experience with online activities before order placement, e.g. product search and comparison, browsing, and availability of information. Purchase satisfaction arises with order placement and payment. Post-purchase satisfaction is related to after-sales services like refunds and returns and customer queries and complaints handled through online customer support (Khalifa & Liu, 2007).

User satisfaction is determined based on the affirmation of expectations established in prior use but secondary to the platform's PU, which is confirmed when purchasing online (Bhattacherjee, 2001). Evaluation of satisfaction is wholly subjective and personal. User satisfaction induced by better performance and more usefulness substantially impacts repurchasing and CI. Satisfaction is an antecedent of CI and habit development and affects CI positively (Khalifa & Liu, 2007).

Hypothesis 19

H_{19}: Customers' BI to use B2C e-commerce platforms is moderated by satisfaction.

Hypothesis 20

H_{20}: The effect of FC on UG in B2C e-commerce platforms is moderated by satisfaction.

2.11 Conclusion of the literature review

After presenting the background of the study, which includes the evolution of e-commerce and e-commerce types, the concept of UG was introduced. The factors influencing non-adoption and adoption of platforms were then discussed since user adoption is transcendental to UG.

After that, the analytical framework was presented, which consists of the literature review on the scholarly technology models and psychological theories analysed to determine the hypothesis statements in relationship to the research objectives of this study. The conceptual model was constructed by combining the UTAUT2 model (Venkatesh et al., 2012) with a practitioner model, the AARRR model (McClure, 2007). Each hypothesis statement was discussed based on the supporting literature presented in Chapter 2.

Many studies have been concluded and are summarised in Chapter 2. However, none of the studies considered UG in B2C e-commerce platforms as the primary dependent variable of the study. Furthermore, most studies are fragmented and only review sections of the customer journey, failing to address authentic business problems related to challenges in the end-to-end customer journey. These studies omit specific situational issues like minimal awareness, a lack of adoption and poor customer retention. By applying UG strategies (Zhang, 2021) as articulated by the founder of growth hacking, Dave McClure (2007), organisations can promote the conversion of visitors to users on their platforms, as well as ensure that the registered users become "most often" users.

In South Africa, where most FMCG retail sales are still channelled through traditional brick-and-mortar outlets, retailers must understand the factors customers consider when evaluating online purchases. By understanding these elements, retailers could create more effective approaches to activate and retain customers and convert them to regular online customers.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

The research process is detailed by nature, and one can only succeed by following a meticulous planning process. Chapter 3 outlines the study's research methodology concerning the approach and design. It describes the researcher's procedures to organise and plan the data collection process. Lastly, quality assurance procedures are presented, and possible ethical issues are considered.

3.2 Research Approach

This research project applied a positivist paradigm as the research approach. According to positivism, the world is objective but can be explained through knowledge. As a result, positivist researchers typically look for information regarding the facts in the relationships among variables. A positivist approach uses observation and logic to explain behaviour, and a scientific definition is foundational in the explanation process. According to positivism, science offers us the purest possible ideal of knowledge (Cohen et al., 2002).

Positivists concentrate on quantitative techniques involving valid variables for hypothesis testing and verification. Given the complexity of the subject matter, there could also be more emphasis on falsification than verification. The typical research method for this paradigm is Likert-scaled questionnaires, secondary data analysis and experiments. The challenge lies in evaluating every critical factor to confirm that a relationship exists under similar circumstances (Holton & Burnett, 2005).

This study followed a quantitative, non-experimental, correlational approach (Creswell & Creswell, 2017). This approach aimed to identify the characteristics of the observed phenomenon by exploring possible associations among the constructs. This approach was suitable for the suggested conceptual model because it emphasized quantification in the collection and analysis of data by:

- Applying a deductive and analytical approach in the relationship between research and theory by testing hypothesis statements.
- Deploying the scientific model's criteria and standards pertaining to a positivist position.
- Measuring the degree of association or relationships between two or more variables.
- The study incorporated the external social reality.

Data in this study were analysed through a regression, correlation and moderation analysis. A rigorous approach was applied with internal and external validity and reliability testing to generalise findings from meticulous sampling (Holton & Burnett, 2005). The study's final results will enable the researcher to develop knowledge about the reality to support the identification of the determinants of UG in B2C e-commerce platforms in the FMCG industry in South Africa (Apuke, 2017; Bell et al., 2022; Creswell & Creswell, 2017; Leedy & Ormrod, 2015).

3.3 Research Design

A survey research method, in combination with a cross-sectional design, was used in this study. Survey research is a technique for obtaining data from people by asking them questions about their opinions, characteristics, attitudes, or historical experiences and then recording their answers. The survey research method in this study was descriptive and exploratory since the research involved an existing theory (UTAUT2) (Venkatesh et al., 2012), of which recent research has not been conducted in South Africa, as well as a practitioner theory (AARRR) (McGaw, 2015), of which very little literature has been produced globally. Hypothesis statements were derived from these theories to measure the research questions. Questionnaires were then developed from the hypothesis statements and were distributed online to respondents (Hair et al., 2019).

For this study, the survey research cross-sectional design had the benefit of collecting data from a large number of participants, which allowed for data variability. Secondly, the method is relatively easy to design, cost-effective, and quick to administer (Leedy & Ormrod, 2015). Thirdly, because the data are quantitative, it enabled the researcher to apply systematic and standardised methods to statistically analyse the relationships between the variables. In addition, this cross-sectional approach linked the outcome of this study to a specific time period (Bell et al., 2022).

The disadvantages of survey research for this study were that respondents might be unwilling to provide honest answers, non-responses might occur, close-ended questions might have a lower validity rate, and respondents might not fully apply their minds to answer questions due to boredom, which could lead to common method bias (CMB) (DeFranzo, 2023).

3.4 Data Collection Methods

Primary data were collected through a self-report data collection method. This method deployed self-administered questionnaires (SAQ) with closed-form questions (De Leeuw, 2008). The survey questions were designed in a structured rank-ordered format in which the questions and answers were presented to the respondent to make an appropriate choice or choose the desired response through a Likert scale. The study’s participants answered the questionnaires themselves upon receiving an electronic link to the survey.

SAQ was selected as the data collection method as it supports a quantitative survey by putting consumer insights into a quantifiable context using numbers. The scores generated by the Likert scale were summated for statistical analysis. This method aimed to collect data from many respondents to enable the extraction of statistically sound conclusions (Quantilope, 2023; Sadan, 2017).

The SAQ data collection method was an inexpensive approach for disseminating questionnaires and aimed to reach many respondents rapidly due to the researcher's commitment towards deadlines. An online survey assured respondents anonymity because they could answer without disclosing their identity. Another benefit of online surveys is that there is a high possibility that the participants reached are internet users and, as a result, potential online shoppers, which provides a significant advantage in testing e-commerce adoption. Furthermore, it enables frictionless data transmission from the survey application to the database without manual human intervention (Guzzo et al., 2016).

3.5 Population and Sample

This section describes the process that the researcher followed to identify the population and sample frame to distribute the electronic link of the questionnaire to the prospective respondents.

3.5.1 Population

The target population was ordinary adult citizens (18 years of age and older) in South Africa. It included people from all nationalities, considering they were temporary or primary residents in the country. The objective of the study's parameters was to reach people with internet access and previous or current use experience of B2C e-commerce platforms deployed by the FMCG industry.

People completing the survey should have had access to the internet through mobile data, Wi-Fi, or fibre connections. In addition, it is assumed that the respondents have basic digital capabilities and have previously used or tried to use a B2C e-commerce platform to purchase FMCG products online. FMCG is processed foods, pre-packaged meals, alcoholic/non-alcoholic beverages, confectionary, fresh/frozen/dry foods, medication, cosmetics, cleaning products, toiletries, and stationary (Kenton, 2021).

3.5.2 Sample procedure

Permission was requested from various departments at the University of the Witwatersrand to have access to their students' e-mail addresses to distribute the electronic questionnaire. Once the departments gave their permission, the Registrar approved the research project. Permission was also requested from an FMCG company to access their employees' e-mail addresses to distribute the questionnaire. The human resources department approved the request, and the researcher was granted access to the list of e-mail addresses.

3.5.3 Sampling method

A non-probability convenience sampling method was applied to reach 700+ respondents to complete the questionnaire. The study targeted many respondents due to the complexity of the conceptual framework and the number of hypothesis statements to be tested.

Convenience sampling was a suitable approach to this study because it reaches respondents based on their availability and accessibility, which makes the process ideal for a research project with time constraints (Holton & Burnett, 2005). This method includes a single-phase sampling procedure by utilising:

a) The researcher's personal contact list
b) A pre-selected and pre-approved group of students at the University of the Witwatersrand
c) A list of employee e-mail addresses from a local FMCG company
d) Social media platforms

The Registrar’s Office distributed the questionnaire to the University of the Witwatersrand students via an electronic e-mail link. The researcher distributed the electronic survey link to the FMCG company employees. Additionally, the electronic link was shared on community instant messaging services like WhatsApp as well as social media sites like Facebook and LinkedIn.

The initial survey distribution requested that prospective respondents redistribute the survey to their networks (acquaintances, colleagues, or relatives), initiating a secondary approach, the snowball sampling method. The term "snowball" describes how a respondent forwards the questionnaire to one or more recipients, causing the sampling process to behave like a snowball and taking on an accumulative nature in selecting respondents (dos Santos et al., 2022). The advantage of the snowball sampling method is that the original respondents reach additional respondents, connecting the researcher with potential respondents who meet similar inclusion criteria. This process improves the chances of achieving the desired sampling size (Schindler, 2019). A non-probability sampling method represents itself, and the results cannot be extrapolated back to the broader population (Cohen et al., 2002).

3.5.4 Sample frame

The sample frame is a detailed list of every component of the population from which the sample is taken (Hair et al., 2007). The SAQ was distributed to approximately N = 7,386 respondents. N = 743 responses were received, consisting of N = 624 valid responses. Valid responses are responses where participants provided informed consent to participate and then completed the survey.

The respondents were randomly reached through the distribution of an electronic survey link by applying the following methods as articulated in Table 7.

Table 7: Survey Questionnaire Reach

	Sample Frame	**Method of survey distribution**	**The approximate number of Respondents reached**
1.	All undergraduate and postgraduate students in the School of Business Sciences and Wits Business School at the University of Witwatersrand.	E-mail	N = 5,406
2.	All the administrative and academic staff at Wits Business School at the University of Witwatersrand.	E-mail	N = ± 100
3.	All the administrative and academic staff in the Faculty of Commerce, Law and Management, which forms part of the following Schools at the University of Witwatersrand: · School of Accountancy(± 64) · School of Business Sciences (± 50) · School of Economics & Finance (± 69) · Wits School of Governance(± 26)	E-mail	N = ± 210
4.	All the administrative and academic staff in the Faculty of Humanities, which forms part of the following Schools at the University of Witwatersrand: · Wits School of Arts (± 30) · Wits School of Education (± 15) · Human and Community Development(± 30) · School of Literature, Language and Media (± 15) · School of Social Sciences (± 30)	E-mail	N = ± 110

	Sample Frame	Method of survey distribution	The approximate number of Respondents reached
5.	Wits Alumni's LinkedIn and Facebook Social media pages.	Post on LinkedIn and Facebook	An undisclosed number of followers.
6.	Wits Library staff.	E-mail	N = ± 30
7.	Beverage Company.	E-mail	N = ± 1,000
8.	Direct messages to all South African contacts on the students' LinkedIn Social media page.	Direct messages through LinkedIn Messenger to the prospective respondents	N = ± 300
9.	Direct messages to South African people in the FMCG industry through a randomised search on LinkedIn Sales Navigator.	Direct messages through LinkedIn Sales Navigator to the prospective respondents	N = ± 150
10.	Direct messages to all South African contacts on the students' Facebook Social media page.	Direct messages through Facebook Messenger to the prospective respondents	N = ± 50
11.	WhatsApp messages to the students' primary telephone contacts. The primary contacts reached then redistributed the message to their contacts, establishing snowball sampling.	Direct messages through the WhatsApp messaging application to the prospective respondents	N = ± 30
12.	Various posts over three months on Facebook community groups, LinkedIn community groups and Survey Circle Community social media pages.	Posts on LinkedIn and Facebook	An undisclosed number of followers.

3.6 The Research Instrument

The survey in a questionnaire format (SAQ) was created using Qualtrics, a web-based survey tool. The survey consisted of three parts. The first part presented an overview of the research topic and requested participant consent. The second part had the demographic and behavioural pattern questions related to online shopping. These essential categorical questions employed a nominal or ordinal scale (Huiping & Shing-On, 2017; Schindler, 2019).

Part three tested the hypothesis statements of the dependent and independent variables by deploying a seven-point Likert scale. The Likert scale was used because it measures human attitude. Attitude is a preferred method of acting/reacting in a particular situation based on relatively stable organisational or societal beliefs and ideas. On a seven-point Likert scale, the larger spectrum of choices offers more independence for the participant to pick an option closer to their preferred selection (closest alternative). The scale was balanced symmetrically with the same number of options available to reflect a negative or positive attitude compared to an independent/neutral choice (Joshi et al., 2015).

Some survey questions were adopted from existing instruments, like the original UTAUT2 model (Venkatesh et al., 2012) or related studies. This approach's advantage is that the questions were previously tested and have construct validity. However, some of these questions had to be rephrased to ensure they were understandable and concise. The researcher designed the research instrument related to the AARRR model (McClure, 2007), as these questions do not exist in the literature. The research instrument is available in Appendix H.

Seven Point Likert Scale:
Strongly Disagree = 1
Disagree = 2
Somewhat disagree = 3
Neither agree or disagree = 4
Somewhat agree = 5
Agree = 6
Strongly agree = 7

Figure 7: Seven-point Likert scale (Joshi et al., 2015)

3.7 Procedure for Data Collection

3.7.1 Pre-testing and pilot questionnaire

Pre-testing was performed after preparing the Qualtrics survey and while waiting for approval from the two institutions to proceed with the research. A pilot questionnaire was distributed to a convenience sample of 10 e-commerce shoppers and statisticians with research experience in IT. The respondents in the pre-testing phase had to give feedback on whether the questionnaire instructions were brief and comprehensible. The respondents also had to consider the time they spent completing the questionnaire (Bell et al., 2022).

The pre-testing also requested the respondents to consider the questionnaire's structure and format on both the web and mobile app versions of Qualtrics. Evaluations of the questionnaire's content, question structure, and ease of understanding and completion of its statements were used to assess the face validity of the instrument. Content validity was tested in the pilot questionnaire by determining whether the questions aligned with the study’s objectives and proposed conceptual framework (Bell et al., 2022).

Feedback from the pre-testing was incorporated into the final questionnaire in Qualtrics. The questionnaire was shortened slightly to reduce the time spent completing the questionnaire. The questionnaire was now ready for distribution to the sample frame.

3.7.2 Questionnaire distribution

An electronic link was generated from the Qualtrics platform and added to an e-mail invitation to respondents. The electronic link was also copied onto new social media posts to enable online distribution. The link was further distributed via short messaging services (SMS) and instant messaging services like WhatsApp, LinkedIn and Facebook Messenger. This procedure was fast and efficient and ensured that the responses were recorded privately and confidentially.

The data collection process commenced on 1 March 2023 and ended on 31 July 2023. Due to the nature of the process, being anonymous, there was no possibility of following up on the non–responses. The researcher did not know who had received the survey, and it was impossible to send reminders to non-respondents.

3.8 Data Analysis Strategies and Interpretation Strategies

The demographic questions from the questionnaire were analysed through descriptive statistics due to their categorical nature. The Likert-scaled items were analysed with inferential statistics, and the data analysis process was approached in different phases due to the complexity of the conceptual framework:

Phase 1 – A factor analysis was conducted to reduce the measurable and observable variables into a smaller number of factors that are unobservable but have a common variance. This method was chosen due to the sample size of > 700 respondents and the volume of scales in the research instrument (Yong & Pearce, 2013).

Phase 2 – A multiple regression analysis was completed between the newly established factors (PE, EE, FC, SI, HM) and BI of the UTAUT2 model (Venkatesh et al., 2012). The aim was to determine whether a linear relationship existed between PE, EE, FC, SI and HM with BI. The relationship would also indicate whether variations in one or more factors are linked to changes in the dependent variable (Field, 2013). A multiple regression analysis was conducted to determine whether hypotheses H_1 to H_7, H_{16}, H_{17} and H_{18} should be accepted or rejected.

Phase 3 – A correlation analysis was conducted to evaluate the association between BI and the UG construct and each UG factor (acquisition, activation, retention, referral, revenue). The aim was to determine the strength and direction of the associations to validate whether H_{11} to H_{15} should be accepted or rejected (Hair et al., 2007).

Phase 4 – A moderation analysis was conducted on satisfaction as the moderator, measuring the interaction effect between BI and the UG construct factors and FC and UG construct factors. The purpose was to understand whether the interaction effect is significant to validate H_{19} and H_{20}.

Phase 5 – A moderation analysis was conducted with age, gender and experience as the moderators between the UTAUT2 factors (Venkatesh et al., 2016) PE, EE, FC, SI, HM and BI. The purpose was to understand whether the interaction effect is significant to validate H_8, H_9 and H_{10}.

3.9 Possible Limitations and Challenges of the Study

The following limitations were identified that could create possible challenges in executing the study:

i. The cross-sectional approach did not incorporate changes over time, providing limited evidence of e-commerce continuance use intention or retention over the long term.
ii. Posting electronic questionnaires on social media reached a large population of prospective respondents. There was, unfortunately, limited participation due to the questionnaires disappearing amongst the clutter on social media and the general unwillingness of people to respond to posts from an unknown person.
iii. The electronic questionnaires sent to the University of the Witwatersrand students were mostly disregarded due to many surveys being circulated to the university student population.
iv. The respondents were not equally spread across all ages, races or gender groups due to the limitations of non-probability convenience sampling.
v. The survey's response rate during April 2023 was low due to the Easter holiday season and people not responding to e-mails.

3.10 Quality Assurance

3.10.1 External validity

The degree to which the study's findings can be extrapolated outside the present research setting is known as its external validity (Bell et al., 2022). It is also the degree to which conclusions can be drawn from observations to generalise them accurately to other unobserved circumstances from another data set. The generalisability of results can be attributed to a representative sample from the population (Holton & Burnett, 2005).

A. Methods to enhance external validity

The researcher applied the following methods to ensure the external validity of the study (Leedy & Ormrod, 2015):

- ***i)*** ***Real-world setting*** – This research project was conducted authentically by collecting responses from human respondents who are known and unknown to the researcher.
- ***ii)*** ***A representative sample*** – Every possible effort was made to gather respondents representing a representative population sample.
- ***iii)*** ***Replication of results in a different context*** – The applicability of the current research results was compared with similar studies that had been historically conducted and market research statistics.

B. Threats to external validity

In this study, threats to external validity were mitigated by the following three approaches:

- ***i)*** ***"Interaction of selection and treatment"*** – a risk could have surfaced if a sample with an unequal representation of respondent characteristics compared to the population was collected. For example, predominantly female versus male respondents or potentially only a few respondents in a certain age or racial group. Fortunately, an equal number of males and females participated in the study. Results based on gender can be generalised in the study's conclusions (Leedy & Ormrod, 2015).
- ***ii)*** ***"Interaction of setting and treatment"*** – should participants in only one geographical area or outside of a particular B2C e-commerce platform's district of service be recruited to participate in the survey, a generalisation regarding their location would not be made (Creswell & Creswell, 2017). The majority of this study's participants were from Gauteng. This is consistent with Gauteng having the highest number of residents and largest population density in South Africa (StatsSA, 2023).

iii) ***"Interaction of history and treatment"*** – the survey results reflect interactions between variables within a specific time frame. Results can, therefore, not be generalised to past or future situations (Creswell & Creswell, 2017). However, the results could be compared with those from the models and theories outlined in Chapter 2.

3.10.2 Internal validity

Internal validity is to show that the data genuinely support a study's explanation for a specific occurrence, problem, or data set. The study's internal validity can be threatened by the participants' experiences or by methodological errors caused by investigative processes or operations that could negatively impact the study's assumptions and conclusions (Bell et al., 2022).

A. Types of Internal Validity

i) ***Construct Validity.*** The degree to which an instrument assesses a characteristic based on patterns of human behaviour that cannot be observed directly. When questions are asked to evaluate the underlying construct, there should be some evidence that the measurement or operation measures what it claims to measure (Leedy & Ormrod, 2015).

ii) ***Convergent Validity.*** It examines how closely two construct metrics should be related conceptually. The highly theoretical correlation between the measures of other constructs and the instrument used is known as convergent validity. Convergent validity is a type of construct validity (Hajjar, 2018).

iii) ***Discriminant Validity.*** Discriminant validity is used to determine whether measurements that should be related are indeed unconnected. Discriminant reliability is a type of construct validity. Researchers/scholars must validate convergence and discrimination to prove construct validity (Hajjar, 2018).

iv) ***Criterion Validity.*** Criterion validity assesses a construct's performance to determine whether the instrument measures what it claims to measure concerning objective criteria. To achieve criterion validity, the scores of the measurement instrument are compared to real-world observations. Criterion validity can be measured with concurrent and predictive validity (Field, 2013).

v) ***Content Validity/Face Validity.*** The extent to which a measurement instrument measures a particular characteristic based on its face value. The measurement tool should show a representative sample of the topic being tested. High content validity is present in the measurement instrument if the questions proportionally reflect the various parts of the content domain (Leedy & Ormrod, 2015).

The Pattern Matrix of the exploratory factor analysis (EFA) confirmed construct validity in Table 22 and Table 24 (Chapter 4). Criterion validity was confirmed by comparing the total variance explained of the UTAUT2 model (Venkatesh et al., 2012) with the results from similar studies, as explained in section 5.4. Content validity was tested by the pilot questionnaire, as discussed in section 3.7.1.

B. Threats to Internal Validity

The following types of threats to internal validity could have been encountered and should be mitigated if uncovered (Creswell & Creswell, 2017):

i) History – as time lapses during the study, the macro-environmental conditions of the market can change. For example, with another wave of COVID-19 infections and lockdowns, e-commerce transactions might surge unnaturally due to legislation changes limiting the trading hours of brick-and-mortar stores (BusinessTech, 2022a). In addition, the Russian–Ukrainian war has had a tremendous impact on global supply chains, food security, and the supply of Brent crude oil, which could impact online sales positively or negatively as the situation fluctuates (BusinessTech, 2022b).

ii) Selection – selecting participants and their feedback could bias the study's outcome if some participants are exceptionally clever and digitally savvy and others are less fortunate and not digitally savvy (Creswell & Creswell, 2017).

iii) Timing – the timing of the study is critical in receiving valuable information. Peak purchasing periods like Easter, Black Friday or Christmas might see more people using B2C e-commerce platforms versus out-of-season periods.

The researcher noticed a slow uptake of survey responses during the 2023 Easter period and extended the data collection process beyond April 2023.

iv) ***Study attrition*** – respondents who drop out of the study for various reasons, and their responses must be discarded from the final analysis. Their opinions, therefore, remain unknown to the researcher. A much bigger sample was recruited to make provision for the dropout rate.

To mitigate the threats mentioned above, the results of this study were triangulated with other similar academic studies and data collected through market research studies (Leedy & Ormrod, 2015).

3.10.3 Reliability

The reliability of the research instrument is the consistency with which the instrument yields a dependable result when the entity measured has not changed. Firstly, the study strived to achieve reliability through administering the instrument in a standardised approach from one person to another. Secondly, the researcher consistently applied similar criteria to evaluate judgment in the analysis phase (Leedy & Ormrod, 2015).

Thirdly, Cronbach's alpha was calculated to evaluate internal consistency reliability (also called coefficient alpha ᾰ). Cronbach's alpha measures the extent to which similar results are yielded in a single instrument (Leedy & Ormrod, 2015). Higher numbers indicate a more dependable scale for Cronbach's alpha, which spans from 0 to 1. Recording a Cronbach's alpha greater than 0.7 is considered acceptable reliability (Collier, 2020).

In addition, this analysis gauges how consistently replies are given to elements within a construct (internal consistency). Finally, it is critical to note that reliability is required but insufficient to ensure validity (Leedy & Ormrod, 2015). Using a seven-point Likert scale improved the reliability of the responses by reducing ambiguity and providing respondents with more options from which to select (Joshi et al., 2015).

3.11 Ethical Considerations

Participants in this research project were protected from any ethical issues arising and related to the following categories (Leedy & Ormrod, 2015):

i) Guarding against harm

Questions asked in this research project have not offended the participants nor discriminated against their social or ethical status and did not cause psychological suffering.

ii) *Voluntary and informed participation*

Potential respondents received electronic Research Project Information and Respondent Participation sheets. Information about the project and the nature of the research was explained in these documents. It was stipulated that participation was voluntary, and the respondents had the opportunity to make an informed choice on whether they agreed to participate in the project. A total of six respondents did not provide their consent, and they were excluded from the electronic survey immediately once consent was denied.

iii) Right to privacy

All participants were reassured that their responses were collected and kept anonymous, confidential, and non-traceable throughout the research process.

iv) Honesty in the profession

The intent of this research project was for the researcher to report the findings wholly and honestly. Under no circumstances would the reader be misled, nor would data be fabricated to influence the final result.

The ethical forms and declarations of the University of the Witwatersrand have been completed and submitted. Ethical clearance was provided under the protocol number WBS/DB443960/568. Refer to Appendix F for a copy of the certificate. As a result, the proposed study aligns with the ethical guidelines of the institution and falls into a low-risk category due to the following reasons:

i. Questions requested details about consumers' day-to-day online shopping routines.
ii. Questions requested information regarding expectations towards and reactions when using B2C e-commerce platforms.

iii. Questions requesting biographical information were kept to a minimum.
iv. Only people older than 18 years of age were surveyed.
v. Surveys were and still are anonymous.
vi. The data gathered was and is used solely for the study.

The research approach and subsequent data analysis have followed the highest standards of ethical and governance procedures to ensure that the responses to the survey cannot be modified or tracked back to the respondents. The researcher acted trustworthy throughout the data collection process and remained objective during the analysis and publication of the results.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

Chapter 4 aims to present the research project results to answer this study's main research question: ***What are the determinants that influence user growth in B2C e-commerce platforms in the South African FMCG industry*?**

The analysis was approached in five phases. Phase one consisted of an EFA of the UTAUT2 model (Venkatesh et al., 2012) and the UG construct. This resulted in newly formed factors on both constructs. In phase two, a regression analysis was performed with the UTAUT2 factors as predictors of BI. A second regression analysis was performed between BI as the independent variable and UG as the dependent variable. A correlation analysis was then performed to understand the relationships between the UG factors (AARRR) and BI as the third phase of the analysis. Three different moderation analyses were then performed to test the moderating effect of:

- satisfaction on the relationship between BI and the UG construct;
- satisfaction on the relationship between FC and the UG construct; and
- age, gender, experience, and their relationship between the UTAUT2 factors and BI.

4.1.1 Data cleaning

After the data collection phase in Qualtrics, the data were extracted into Excel, where it was cleaned, edited, and coded. The extracted dataset consisted of 743 respondents. There were 86 respondents discarded because they had missing values and were incomplete. Additionally, seven respondents were removed because one respondent was too young (17 years or younger), and six respondents did not consent to the survey. Finally, another 26 respondents chose the "I do not shop online" option, and their records had to be eliminated from the data. The final number of valid surveys was N = 624. The next step was to check the data for common method variance.

4.1.2 Response rate

The response rate was computed using the formula provided by Bell et al. (2022):

Number of usable questionnaires/ (Total sample – (uncontactable members of the sample and invalid questionnaires)) * 100

= (624/ (7,386-119)) * 100

= (624/7267) * 100

= 8,58%

The result is a 8,58% response rate for the survey. This rate is aligned with previous research by Manfreda et al. (2008), which concluded that web survey response rates vary between 6% and 15% (Manfreda et al., 2008).

4.1.3 Common Method Variance and Discretisation Error

Common method variance (CMV) is a frequent occurrence in social science studies where bias is created when the valid link between the scale items is not captured due to the systematic covariation that CMV generates. This bias could lead to elevated correlations between the constructs or inaccurate parameter estimates related to the study's reliability and convergent validity of the constructs (Rodríguez-Ardura & Meseguer-Artola, 2020).

The following preventative measures were taken upfront during the questionnaire design to prevent CMV from arising in the survey:

- A detailed statement at the beginning of the survey ensured the respondents' confidentiality and anonymity.
- The wording of the questionnaire was selected carefully to be specific, explicit and concise.

- Questions measuring the predictor and criterion constructs were mixed throughout the questionnaire.
- Different question formats were created to break the monotonous flow of the Likert-scaled items.

Harman’s single-factor test was applied to the data set to test for CMV. KMO = .823, and Bartlett’s Test of Sphericity were significant. An EFA with an unrotated factor solution yielded five factors, explaining 60% of the variance for the aggregate factors. If CMV were present in the data, the first component would explain more than 50% of the covariance between the items and the criterion constructs (Rodríguez-Ardura & Meseguer-Artola, 2020). This result rules out a high degree of CMV, but the test might not be accurate enough to rule out CMV entirely (Fuller et al., 2016).

On closer analysis of each respondent’s responses, it was noticed that CMV still presented itself in the data. This happens when there is insufficient variance in a particular respondent’s responses, which suggests that they have not applied their minds adequately to the statements. These respondents’ responses are invalid and will spuriously increase the correlations between the items due to the bias created by repeatedly selecting the “Fully Agree and Agree or Fully Disagree and Disagree” options on the scales. Therefore, these responses must be omitted from the analysis.

The standard deviation for all the responses from each respondent in the data set was calculated, followed by the mean standard deviation of the total data set. The mean standard deviation equalled 1.7. A 12% trimming methodology was then applied, which resulted in all respondents with a standard deviation of 1.5 times higher or lower than 1.7 being removed from the dataset (Field, 2013). The calculation resulted in 74 respondents from the original data set of N = 624 respondents being removed.

The remaining 550 respondents were rescaled to prevent discretisation errors. Discretisation error occurs when continuous latent variables are classified into discrete ordinal categories. This happens when a single numerical value is assigned to a category whilst several underlying values are already present and grouped in the same category. Information concerning a single response might be lost if continuous data are categorised (Stacey, 2005).

This mainly happens in psychology, marketing, business, or social sciences studies, where Likert scale items are classified as ordinal data and assigned numeric values. Since the raw data are ordinal, a challenge is faced during the data analysis phase because parametric statistical techniques can only be applied to interval-level data. To deliver the impact of a parametric statistical analysis, the ordinal data have to be rescaled to interval-level data using an algorithmic optimisation approach – the distribution fitting approach (Stacey, 2005).

The algorithm's execution maximises the goodness of fit between the model and the observed number of responses for each category of responses for each survey item. When the numerically scaled values are substituted for the ordinal values in the data set, the arithmetic means, and variances of the variables should be equal to the means and variances of normal distributions fitted to the ordinal data within the bounds of the model's goodness of fit (Stacey, 2005).

Implementing the distribution fitting approach protected the survey results from being impaired. Using this algorithmic approach, the ordinal level data were refitted to interval level data by applying the x^2 Statistic. This process not only improved the validity of the data set but protected the study from discretisation error. The data were now valid interval-level data and reliable for applying statistical procedures (Stacey, 2005). The next step was to export to Statistical Package for Social Sciences (SPSS) version 29 for analysis.

4.2 Demographic Profile of the Respondents

The following section presents the demographic data of the respondents who participated in the study. This includes data about each respondent's gender, age, ethnic group, location in South Africa, highest level of education and before-tax monthly income.

4.2.1 Respondent Consent

There were only six respondents who did not provide their consent to proceed with the survey. These respondents were removed during the data cleansing process.

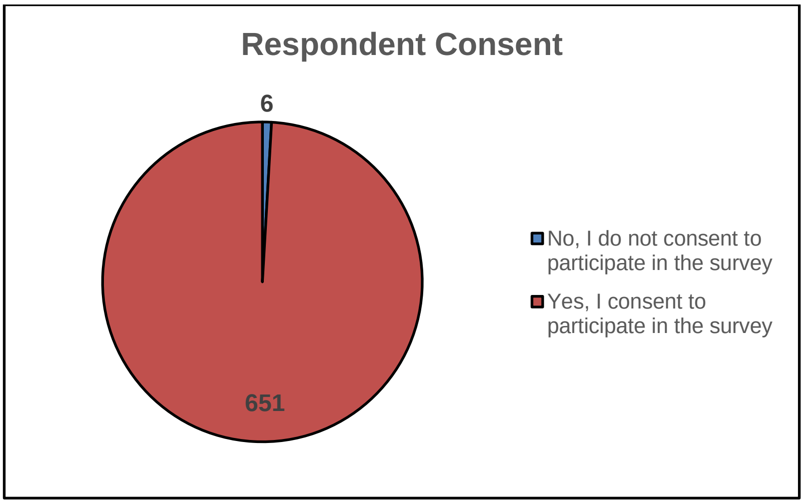


Figure 8: Respondent Consent chart

4.2.2 Gender

The respondents' gender split was more or less 50% male and 50% female. Only three respondents selected "non-binary" or "I prefer not to say". Later in the chapter, the moderating role that gender has in the relationship between the independent variables and BI will be discussed. Understanding the differences between male and female behaviours in online shopping is out of the scope of this study.

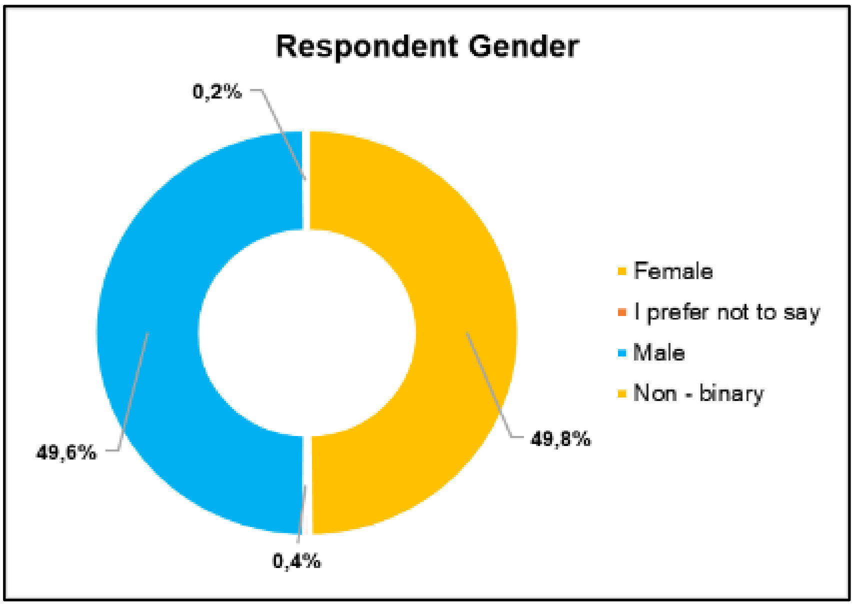


Figure 9: Respondent Gender chart

4.2.3 Age

Most respondents (35.3%) fell in the 41-to-50-year age category. (The first category of 17 years or younger was removed from the data.)

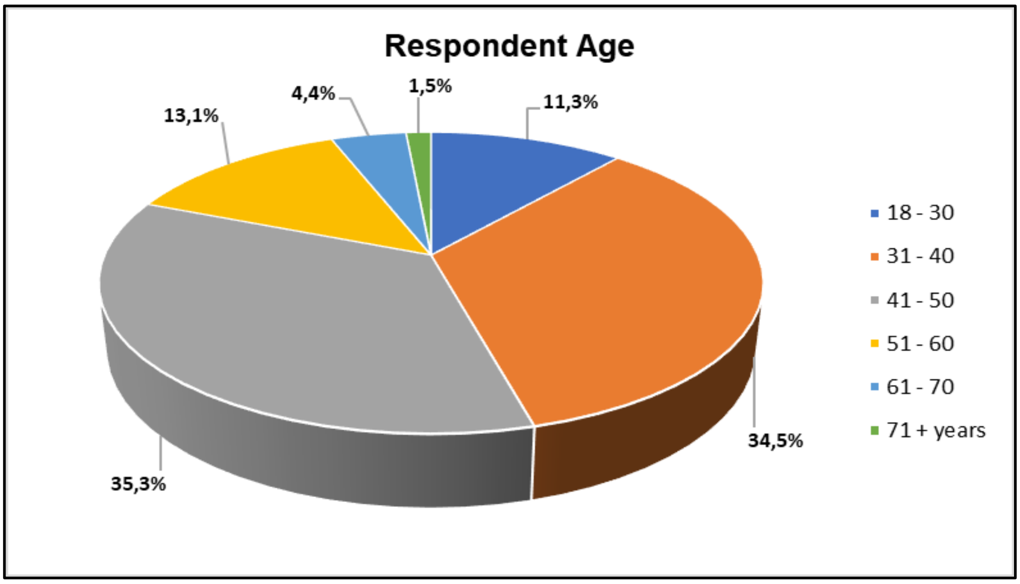


Figure 10: Respondent Age chart

Table 8: Demographic Profile of Respondents

Category	Number of Respondents	%
Gender		
Female	274	49,8%
Male	273	49,6%
I prefer not to say/non-binary	3	0,6%
Age		
18 - 30 years	62	11,3%
31 - 40 years	190	34,5%
41 - 50 years	194	35,3%
51 - 60 years	72	13,1%
61 - 70 years	24	4,4%
71 + years	8	1,5%
Ethnic Group		
African	172	31,3%
Asian & Mixed Race & Other	10	1,9%
Coloured	25	4,5%
Indian	51	9,3%
White	292	53,1%
Qualification		
Bachelor's Degree	131	23,8%
Diploma	88	16,0%
High school	8	1,5%
Matric Certificate	42	7,6%
Other	7	1,3%
Postgraduate Degree or higher	274	49,8%
Income		
< R9,999 per month	32	5,8%
R10,000 - R25,000 per month	64	11,6%
R26,000 - R50,000 per month	153	27,8%
R51,000 - R75,000 per month	125	22,7%
R76,000 + per month	176	32,0%
Location		
Eastern Cape	7	1,3%
Free State	4	0,7%
Gauteng	420	76,4%
KwaZulu-Natal	17	3,1%
Limpopo	4	0,7%
Mpumalanga	7	1,3%
North West	8	1,5%
Northern Cape	6	1,1%
Other	20	3,6%

Category	Number of Respondents	%
Western Cape	57	10,4%

4.2.4 Ethnic Group

The ethnic group most represented in the sample was White (53.1%), then African (31.3%), and Indian (9.3%) people.

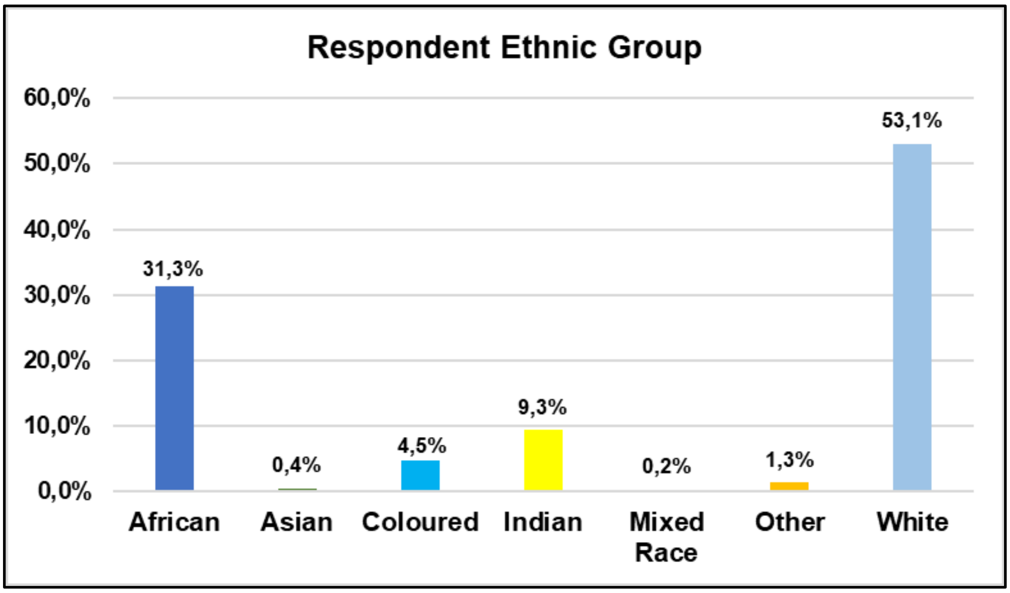


Figure 11: Respondent Ethnic Group graph

4.2.5 Location

The most popular location of residence for respondents was Gauteng (76.4%), the Western Cape (10.4%), Other (3,6%) or Kwa-Zulu Natal (3.1%).

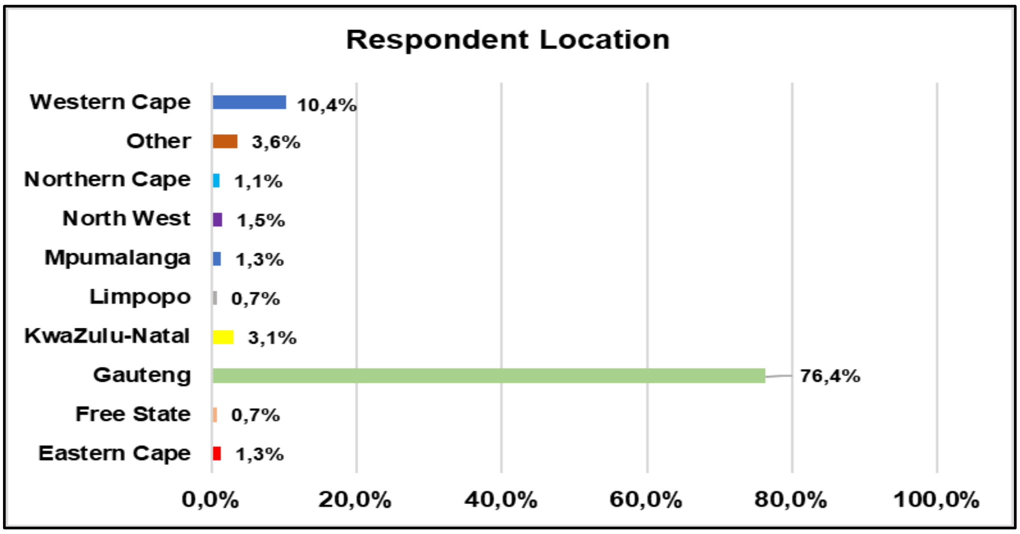


Figure 12: Respondent Location by Province in South Africa graph

4.2.6 The highest level of Education Obtained

Most respondents said they had a postgraduate degree or higher (49.8%), with 23.8% stating they have a bachelor's degree or diploma (16%).

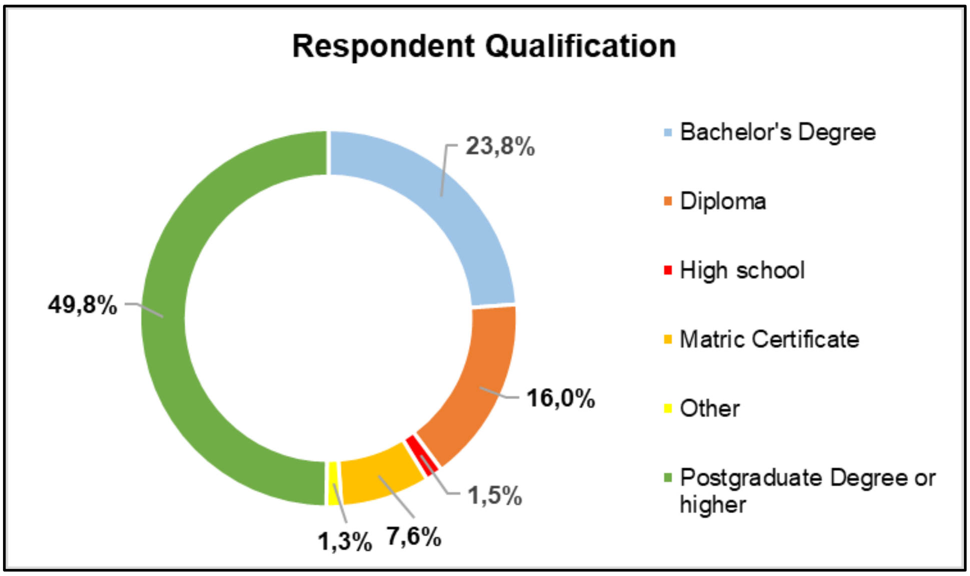


Figure 13: Respondent Qualification chart

4.2.7 Before-tax Income bracket

The largest category of the respondents said they earn more than R76,000 per month (32%). For the remainder of the sample size, 50.5% earn within the following two brackets: R51,000 to R75,000 per month (22.7%) and R26,000 to R50,000 per month (27.8%).

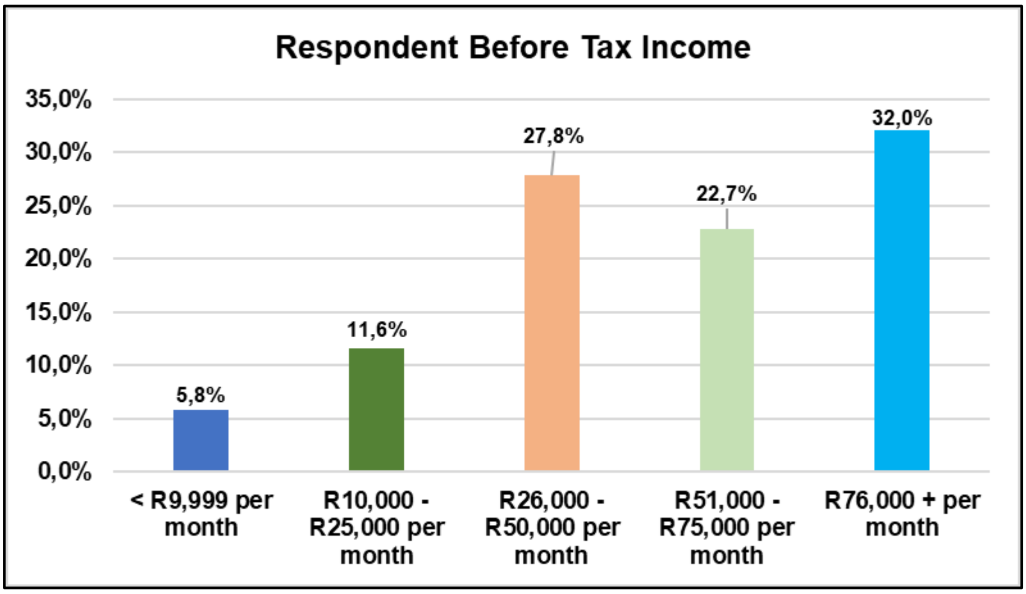


Figure 14: Respondent Income graph

4.3 Respondent's Online Buying Patterns

4.3.1 Internet usage

There were 550 respondents who all bought online at different frequencies. A total of 20% confirmed that they bought once a month, 16% confirmed that they bought every two weeks, 18% confirmed that they bought more than once a week, 15% confirmed that they bought once per week, and 27% bought seldom, occasionally or every three months. The numbers prove that at least 69% of respondents buy online once per month. The monthly statistic has increased considerably from 2013, when 42% of customers bought online once per month (Rudansky-Kloppers, 2014).

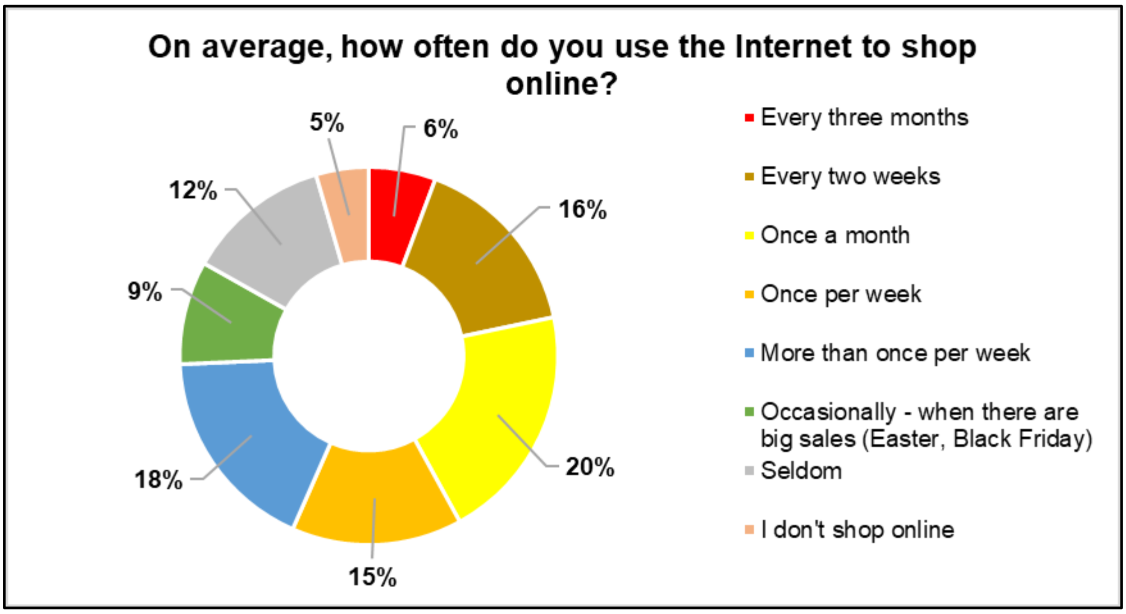


Figure 15: Respondent Purchasing Frequency chart

4.3.2 Online duration

An average of 49% of respondents stated that they spend ± 30 minutes online browsing and shopping weekly. That is 2 hours per month. In addition, 19% of respondents said they spend 45 or 60 minutes online weekly. Therefore, 87% of respondents complete online shopping in an hour or less weekly.

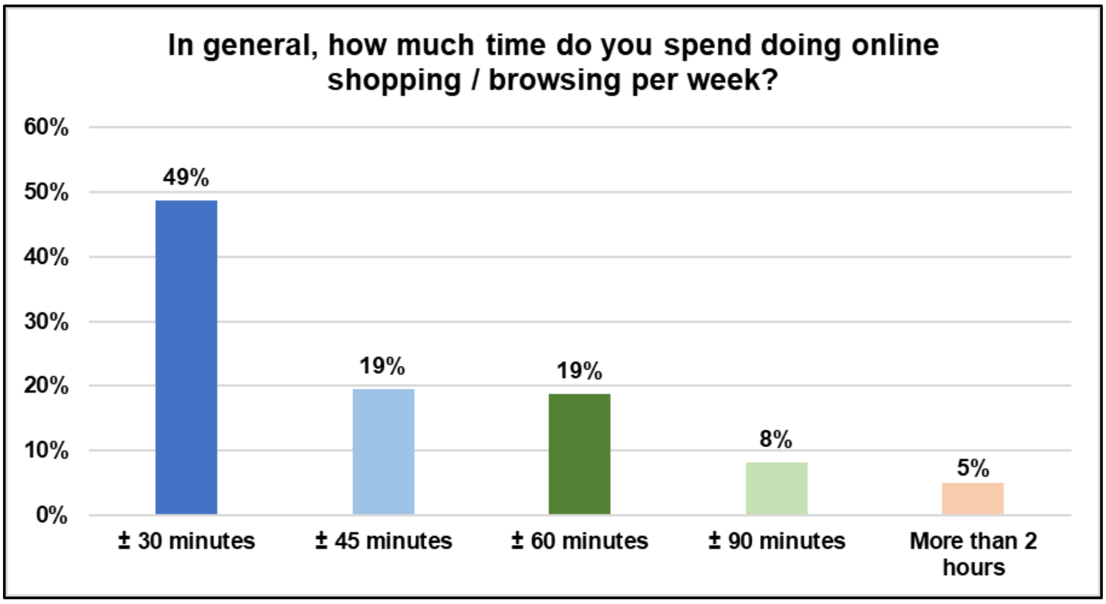


Figure 16: Online Shopping Duration graph

4.3.3 Number of online platforms utilised per month

The respondents were asked how many websites or apps they use, and 75% of respondents stated that they use between one and three websites or apps monthly to complete their online shopping. Only 22% of respondents said they use four to six websites or apps monthly to complete their online shopping.

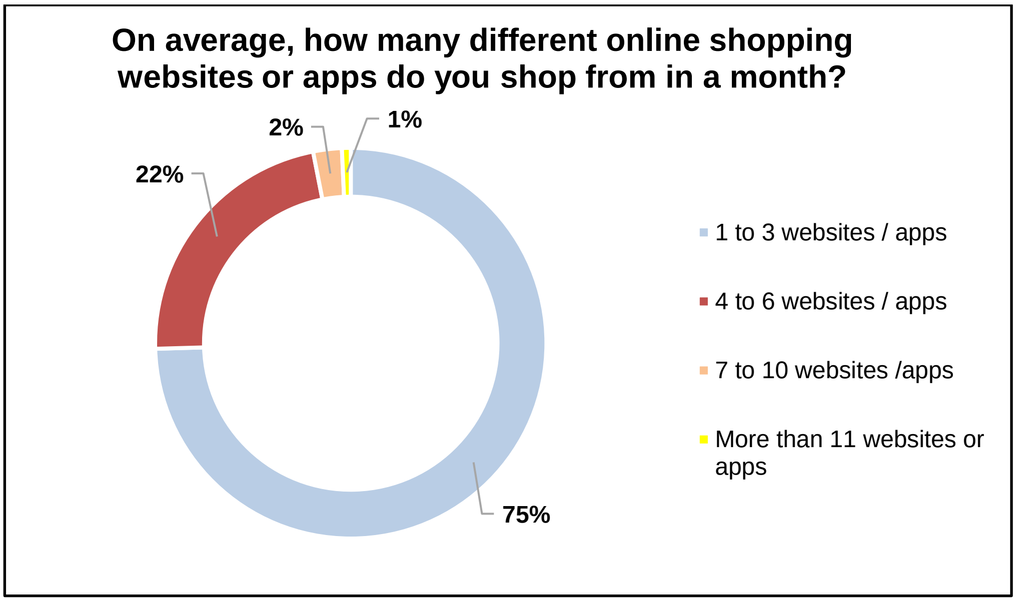


Figure 17: Number of Shopping websites/apps used per month chart

4.3.4 Online shopping experience

Online shopping experience reflects the time that has elapsed between the current time and the time the respondent started using the Internet to buy online (Venkatesh et al., 2012). Half of the respondents (50%) said that they have been buying online for one to four years, whilst 33% said that they have been buying online for five to ten years.

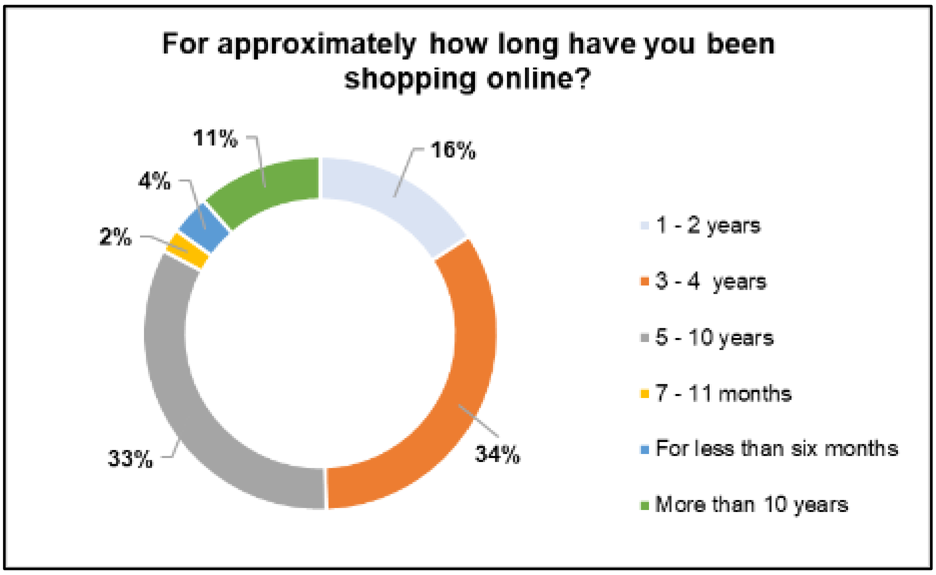


Figure 18: Online Shopping Experience chart.

4.4 Cross-tabulation of Respondents' demographic characteristics with their buying patterns

The moderators from the UTAUT2 model (Venkatesh et al., 2012), age and gender, were cross-tabulated with respondents' buying patterns to understand their interrelationships better. Shopping frequency and the number of apps used were cross-tabulated with another moderator, shopping experience, to explore the influence experience has on shopping patterns.

*Table 9: Age*Shopping Frequency Cross-tabulation*

		Age * Shopping Frequency Cross-tabulation														Total	
		Once per week		More than once per week		Every two weeks		Once a month		Every three months		Occasionally - when there are big sales (Easter, Black Friday)		Seldom			
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Age	18 - 30 years	9	10,7%	8	7,8%	10	10,9%	8	6,8%	6	18,2%	11	21,6%	10	14,1%	62	11,3%
	31 - 40 years	27	32,1%	39	38,2%	35	38,0%	46	39,3%	12	36,4%	17	33,3%	14	19,7%	190	34,5%
	41 - 50 years	34	40,5%	43	42,2%	35	38,0%	38	32,5%	8	24,2%	15	29,4%	21	29,6%	194	35,3%
	51 - 60 years	10	11,9%	10	9,8%	11	12,0%	20	17,1%	4	12,1%	4	7,8%	13	18,3%	72	13,1%
	61 - 70 years	2	2,4%	1	1,0%	1	1,1%	4	3,4%	3	9,1%	3	5,9%	10	14,1%	24	4,4%
	71 + years	2	2,4%	1	1,0%	0	0,0%	1	0,9%	0	0,0%	1	2,0%	3	4,2%	8	1,5%
Total		84	100,0%	102	100,0%	92	100,0%	117	100,0%	33	100,0%	51	100,0%	71	100,0%	550	100,0%

*Table 10: Age*Shopping Experience Cross-tabulation*

		Age * Shopping Experience Cross-tabulation												Total	
		For less than six months		7 -11 months		1 – 2 years		3 – 4 years		5 -10 years		More than 10 years			
		N	%	N	%	N	%	N	%	N	%	N	%	N	%
Age	18 - 30 years	4	20,0%	0	0,0%	16	18,4%	25	13,5%	17	9,3%	0	0,0%	62	11,3%
	31 - 40 years	5	25,0%	3	25,0%	25	28,7%	63	34,1%	73	39,9%	21	33,3%	190	34,5%
	41 - 50 years	5	25,0%	5	41,7%	27	31,0%	62	33,5%	63	34,4%	32	50,8%	194	35,3%
	51 - 60 years	6	30,0%	2	16,7%	13	14,9%	24	13,0%	19	10,4%	8	12,7%	72	13,1%
	61 - 70 years	0	0,0%	2	16,7%	4	4,6%	7	3,8%	9	4,9%	2	3,2%	24	4,4%
	71 + years	0	0,0%	0	0,0%	2	2,3%	4	2,2%	2	1,1%	0	0,0%	8	1,5%
Total		20	100,0%	12	100,0%	87	100,0%	185	100,0%	183	100,0%	63	100,0%	550	100,0%

*Table 11: Income*Shopping Frequency Cross-tabulation*

		Income * Shopping Frequency Cross-tabulation														Total	
		Once per week		More than once per week		Every two weeks		Once a month		Every three months		Occasionally - when there are big sales (Easter, Black Friday)		Seldom			
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Income	< R9,999 per month	4	4,8%	4	3,9%	3	3,3%	5	4,3%	2	6,1%	6	11,8%	8	11,3%	32	5,8%
	R10,000 - R25,000 per month	5	6,0%	9	8,8%	5	5,4%	11	9,4%	7	21,2%	11	21,6%	16	22,5%	64	11,6%
	R26,000 - R50,000 per month	12	14,3%	20	19,6%	30	32,6%	42	35,9%	7	21,2%	16	31,4%	26	36,6%	153	27,8%
	R51,000 - R75,000 per month	22	26,2%	24	23,5%	20	21,7%	32	27,4%	8	24,2%	11	21,6%	8	11,3%	125	22,7%
	R76,000 + per month	41	48,8%	45	44,1%	34	37,0%	27	23,1%	9	27,3%	7	13,7%	13	18,3%	176	32,0%
Total		84	100,0%	102	100,0%	92	100,0%	117	100,0%	33	100,0%	51	100,0%	71	100,0%	550	100,0%

*Table 12: Online time*Shopping websites/apps per week Cross-tabulation*

How much time shopping / browsing per week * Online shopping websites/apps Cross-tabulation							
		Number of websites or apps				Total	% Contribution
		1 to 3 websites / apps	4 to 6 websites / apps	7 to 10 websites / apps	More than 11 websites or apps		
Time per Week	+/- 30 minutes	239	27	1	1	268	49%
	+/- 45 minutes	72	32	3	0	107	19%
	+/- 60 minutes	63	38	1	1	103	19%
	+/- 90 minutes	29	15	1	0	45	8%
	More than 2 hours	7	11	7	2	27	5%
Total		410	123	13	4	550	100%

*Table 13: Shopping Frequency*Shopping Experience Cross-tabulation*

		Shopping Frequency * Shopping Experience Cross-tabulation						
		For less than six months	7 -11 months	1 – 2 years	3 – 4 years	5 -10 years	More than 10 years	Total
Shopping Frequency	Once per week	1	1	14	30	30	8	84
	More than once per week	2	1	6	35	39	19	102
	Every two weeks	1	0	16	24	37	14	92
	Once a month	3	3	12	46	40	13	117
	Every three months	1	1	5	11	10	5	33
	Occasionally - when there are big sales (Easter, Black Friday)	2	0	10	19	18	2	51
	Seldom	10	6	24	20	9	2	71
Total		20	12	87	185	183	63	550

a) Age and Shopping Frequency/Experience Cross-tabulation

Table 9 and Table 10 correlate respondent age with shopping experience and shopping frequency, respectively. The Chi-square test assessed the likelihood that two variables are associated (Saunders et al., 2009). The Chi-square test resulted in a significant relationship between age and shopping frequency with $x^{(30)} = 55.704$ and p = 0,003.

*Table 14: Chi-Square Test - Age*Shopping Frequency*

Chi-Square Test - Age*Shopping Frequency Cross-tabulation			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	55.704[a]	30	0,003
N of Valid Cases	550		

a. 15 cells (35,7%) have expected count less than 5. The minimum expected count is 48.

The Chi-square test also resulted in a significant relationship between age and shopping experience with $x^{(25)} = 37.988$ and p = 0,046 (Field, 2013).

*Table 15: Chi-Square Test - Age*Shopping Experience*

Chi-Square Test - Age*Shopping Experience Cross-tabulation			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	37.988[a]	25	0,046
N of Valid Cases	550		

a. 16 cells (44,4%) have expected count less than 5. The minimum expected count is 17.

For the age group 41-to-50 years, 82.7% shop online once or more per week, with 34.4% of respondents having more than five years and 33.5% between three to four years of shopping experience. The data display a correlation between the online shopping experience and frequency of shopping for respondents between 41-to-50 years old. With increased experience, these respondents have had more opportunities to reinforce routines since they have had more opportunities to interact with the internet and establish specific behavioural patterns. These behavioural patterns become habits and become automatic over time (Venkatesh et al., 2012).

Research shows that COVID-19 has compelled many people worldwide to use an online grocery service for the first time or, for those who have previously done so, to rely on it more heavily than before (Van Droogenbroeck & Van Hove, 2021). In South Africa, retailers like Pick 'n Pay, Checkers and One Day Only experienced a surge in online sales due to consumers being cautious about shopping in-store. According to a Visa survey, the coronavirus outbreak caused 64% of South African customers to make their first online grocery purchase and 53% to make their first online pharmaceutical purchase (Dludla, 2020).

These trends that emerged during the COVID-19 pandemic might explain the 33.6% of respondents in this study with 3 to 4 years of shopping experience. In general, the respondents are, therefore, quite experienced, with 78% shopping online for more than three years and only 5.8% of respondents with less than 11 months of shopping experience. Compared to respondent age, a declining trend in shopping frequency, from weekly to seldom, is visible for older consumers (above 51 years).

b) Income and Shopping Frequency Cross-tabulation

Table 11 shows that shopping frequency increases as a respondent's level of income increases. Respondents earning less than R50,000 shop monthly online, whilst respondents earning more than R50,000 per month shop more frequently online. This result is consistent with a study conducted on consumers in Gauteng, a province in South Africa, in 2014, which found that the highest percentage of online shoppers earn more than R50,000 per month (Rudansky-Kloppers, 2014). This information is valuable for retailers when crafting advertising strategies and pricing policies to target specific consumer groups.

If the data for the more frequent shoppers are clustered together (once and more than once per week), then 33.8% of shoppers shop online weekly, 16.7% shop every two weeks and 21.2% shop monthly. The relationship between income and shopping frequency is significant with the Chi-square test, $x^{(24)} = 75.209$ and p = 0,000.

*Table 16: Chi-Square Test - Income*Shopping Frequency*

Chi-Square Test - Income*Shopping Frequency Cross-tabulation			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	75.209[a]	24	0,000
N of Valid Cases	550		

a. 5 cells (14,3%) have expected count less than 5. The minimum expected count is 1,92.

c) Shopping Time and the number of Shopping apps Cross-tabulation

The data presented in Table 12 demonstrates that most respondents (43.4%) spend only 30 minutes per week online to complete their shopping by utilising 1 to 3 websites/apps. Another 24.5% of respondents spend 45 to 60 minutes on 1 to 3 websites/apps weekly to complete their online shopping. The Chi–square test for shopping time and number of websites/apps is significant with $x^{(12)}$ = 144.214 and p = 0,000.

*Table 17: Chi-Square Test – Online time*Online shopping websites/apps*

Chi-Square Test - How much time shopping/browsing per week *Online shopping websites/apps Cross-tabulation			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	144.214[a]	12	0,000
N of Valid Cases	550		

a. 9 cells (45,0%) have expected count less than 5. The minimum expected count is 0,20.

d) Shopping Frequency/Shopping Experience Cross-tabulation

Table 13 illustrates the relationship between shopping frequency and shopping experience. Almost a third of the respondents (29.2%) with more than three years of shopping experience buy once or more than once a week online. Most respondents (78.3%) have more than three years of online shopping experience, reinforcing the online shopping behaviours that emerged with COVID-19, as discussed earlier. The Chi–square test for shopping frequency and shopping experience tested significantly with $x^{(12)}$ = 95.171 and p = 0,000.

*Table 18: Chi-Square Test - Shopping Frequency*Shopping Experience*

Chi-Square Test - Shopping Frequency*Shopping Experience Cross-tabulation			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	95.171[a]	30	0,000
Likelihood Ratio	88,904	30	0,000
N of Valid Cases	550		

a. 15 cells (35,7%) have expected count less than 5. The minimum expected count is 0,72.

4.5 Factor Analysis

A factor analysis was conducted on all the variables of the UTAUT2 model (Venkatesh et al., 2012) and AARRR model (McClure, 2007) (UG construct), as well as on BI and the moderator satisfaction. The aim was to reduce the original set of items into smaller groups, called factors, whilst retaining the actual items' information and meaning.

4.5.1 Introduction to Exploratory Factor Analysis (EFA)

An EFA was conducted to understand the underlying constructs in the questionnaires better. The factors will contain items that highly correlate with each other but do not correlate strongly with items outside their group. Factor analysis seeks association by explaining the most significant common variance in a correlation matrix with the fewest number of interpretive constructs (Field, 2013).

The factors are identified by analysing the factor loadings and determining which items have high loadings on the same factors. The aim is to identify factors with "real world" meaning and not just statistical significance. In return, factor scores are computed by calculating the mean score of the factor score loadings (Beavers et al., 2013).

The factor analysis included all the independent variables in the conceptual model: PE, EE, SI, FC, PV, HM and habit from the UTAUT2 model (Venkatesh et al., 2012), as well as acquisition, activation, retention, referral and revenue from the UG construct. The dependent variable, BI, and the moderator, satisfaction, were analysed as individual factors.

a) KMO and Bartlett's Test of Sphericity

Sampling suitableness can be calculated through the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for an EFA. The KMO value ranges between 0 and 1. A value of 0 indicates that EFA would be inappropriate due to diffusion in the pattern of correlations. A value closer to 1 suggests that the pattern of correlations is relatively compressed, which should yield recognisable and reliable factors (Field, 2013).

Suppose the KMO value is equal to or more than 0.5, and the significance value (sig) of Bartlett's Test is less than 0.05; then the data are already qualified for factor analysis (Napitupulu et al., 2017).

Below are the interpretation guidelines for the KMO values (Beavers et al., 2013):

KMO Value	Meaning of Value
0.00 – 0.49	Do not factor
0.50 – 0.59	Miserable
0.60 – 0.69	Mediocre
0.70 – 0.79	Middling
0.80 – 0.89	Meritorious
0.90 – 1.00	Marvellous

The following KMO values were reported in this study:

Instrument	KMO value	Classification
UTAUT2 model*	.781	Middling
BI variable	.713	Middling
UG construct**	.737	Middling
Satisfaction	.819	Meritorious

* UTAUT2 model includes PE, EE, FC, SI, HM, PV and habit.

** UG construct includes acquisition, activation, retention, referral, and revenue.

Bartlett's Test of Sphericity is an inferential statistical approach used to evaluate the equality of variance in different populations (Arsham & Lovric, 2011). If the value derived by Bartlett's test is significant, $p < 0{,}05$, then the correlations between the variables are multivariate normal and suitable for further analysis (Hadi et al., 2016).

The following Bartlett's test values were reported in this study:

Instrument	Bartlett's Sphericity Value	Classification
UTAUT2 model*	0,000	Significant
BI variable	0,000	Significant
UG construct**	0,000	Significant
Satisfaction	0,000	Significant

* UTAUT2 model includes PE, EE, FC, SI, HM, PV and habit.

** UG construct includes acquisition, activation, retention, referral, and revenue.

The KMO measure of sampling adequacy indicates the degree of practical acceptance for each data set. At the same time, Bartlett's Test of Sphericity confirms that the items within the variables are correlated at $p < 0{,}001$, thus rendering the data suitable for factor analysis.

b) Table of Communalities

The Table of Communalities displays all the variables before (initial column) and after extraction (extraction column). Communalities are numerical indicators of how much of an item's variance the factor model can account for (Eaton et al., 2019). The initial values showed a variance = 1, which shows that the variables had no unique variance before extraction.

The values in the extraction column reflect each variable's common or shared variance, the communality, with the other variables in the table after extraction. Communalities with a cut-off value of 0.25 to 0.4 have been proposed as acceptable, whereas communalities of 0.7 or higher are considered excellent (Eaton et al., 2019). It is essential to review the communalities for each variable, as it will impact factor extraction. Please refer to Appendix A for the tables – Tables A1 to A4.

c) Factor Extraction

Three tests were performed to decide how many factors should be extracted:

- ***The Gutman-Kaiser Criterion***. Eigenvalues associated with each factor indicate the amount of variation and significant importance of each factor. Factors with eigenvalues > 1 after extraction should be retained (Hadi et al., 2016). Eigenvalues are extracted for each construct and displayed in Table 19, Table 21, Table 23 and Table 25.

- ***Cattell's Scree plot***. The scree test is a graphic method that involves a) displaying the eigenvalues (y-axis) against the components (x-axis) and b) examining the shape of the resulting curve to identify the point at which the curve changes drastically (Ledesma et al., 2015). Generally, factors above the "elbow" in the scree plot should be maintained (Hadi et al., 2016). Factors at the break of the “elbow” should not be kept (Taherdoost et al., 2022). Please refer to Figure 19, Figure 20, Figure 21 and Figure 22.

- ***Parallel Analysis* (PA).** The PA method was developed in 1965 by Horne. The researcher can ascertain the variables' significance, variable loadings, and analytical statistics with PA. The theory is that sampling variability will produce random values > 1 despite no significant variables or if all eigenvalues in the correlation matrix = 1 (Franklin et al., 1995). A parallel analysis uses random data simulation to identify several factors. The Monte Carlo Simulation Technique calculates the estimated eigenvalues by generating a random simulative (artificial) data set in addition to the actual (real) data set. These results are compared with the eigenvalues from the Gutman Kaiser-Criterion and Catell’s scree plot (Ledesma et al., 2015). Please refer to Appendix A for the Parallel Analysis in Tables A5 to A8.

d) Factor Rotation

Factor rotation is applied to change the pattern of the unrotated factors to present a sequence of loadings in an easily understandable format (Ledesma et al., 2015). An oblique rotation was applied to the data set since there was a correlation between the extracted factors. The convergent validity was evaluated by reviewing the higher factor loadings of converged items, represented by the pattern matrix, as the pattern loading is the regression coefficient of the items on each factor. To interpret the data, the factors were labelled based on a common theme emerging from the pattern loadings: the converged items for each factor. The Pattern Matrix confirmed construct validity (Hadi et al., 2016). Please refer to Table 20, Table 22, Table 24 and Table 26.

The loadings in the pattern matrix were evaluated for their feasibility for factor extraction. The values can be categorised as follows (Williams et al., 2010):

Pattern Matrix Value	Classification of Values
± 0.30	minimal
± 0.40	important
± 0.50	meaningful

The minimum acceptable factor coefficient would be values with a magnitude of .32 (explaining 10% of the variance). When naming factors, the ideal value to interpret the shared characteristics of the higher coefficients would be .40 or more, representing 16% of the variance (Reio & Shuck, 2015). Complex variables which load on more than one factor should be removed if the cross-loading is .40 or lower (Beavers et al., 2013).

After the initial factor extraction of the data for the UTAUT2 model (Venkatesh et al., 2012) and the UG construct, the following rotations were applied:

- ***UTAUT2 model*** (Venkatesh et al., 2012): A Principal Component Analysis method was applied to reduce the large number of variables in smaller components while keeping the data’s original dimensions (Beavers et al., 2013). An oblique rotation (direct oblimin) was applied since the variables were related whilst suppressing values below 0.33 (Reio & Shuck, 2015). See results in Table 22.
- ***UG construct***: A Generalised Least Squares method was applied with an oblique rotation (direct oblimin). This method was chosen since it posits that the item responses are a function of an underlying construct and only considers the common variance (Beavers et al., 2013). Values below 0.40 were suppressed to eliminate cross-loadings (Reio & Shuck, 2015). See results in Table 24.

e) Internal consistency reliability and construct validity

The ability of an instrument to measure consistently is referred to as its reliability. Internal reliability, which relates to the test's interrelatedness, is the extent to which each item in the test measures the same idea or construct. The complete consistency of a given metric is its reliability. When a measurement produces the same results consistently, it is said to have high reliability (Hair et al., 2019).

Cronbach's alpha demonstrates internal consistency. It refers to the scale's total number of variables and the strength of their intercorrelations. It measures the percentage of variability shared among factors (the covariance among factors) and ranges from zero to one (Hajjar, 2018).

In addition, the reliability coefficient also reveals the amount of measurement error in a test. The value of Cronbach's alpha is affected by the number of items tested and the interrelatedness and amplitude of the items (Tavakol & Dennick, 2011).

Different academic views on the acceptable Cronbach alpha value are available in the literature. Field (2013) states that 0.8 is good, but 0.7 is sufficient for ability tests, and a value lower than 0.7 indicates an unreliable scale. Tavakol and Dennick (2011) support values between 0.7 and 0.95 but recommend a maximum value of 0.9 (Tavakol & Dennick, 2011). Bland and Altman (1997) recommend values between 0.7 and 0.8 when comparing groups but propose values with a minimum of at least 0.9 for clinical studies (Bland & Altman, 1997). Hair et al. (2019) categorise the values as follows:

Cronbach alpha Value	**Reliability Assessment**
≥ 0.95	Too high
0.90 – 0.95	High
0.80 to < 0.90	Excellent
0.70 to < 0.80	Good
0.60 to < 0.70	Acceptable for Exploratory Research
< 0.60	Poor

For multi-item scales, a coefficient of *inter-item correlations*, the correlation between each item and the total of all other pertinent items is presented by the Cronbach alpha . The recommended range for the average inter-item correlation is 0.15 – 0.5 (Clark & Watson, 1995); however, the values could be higher, indicating a stronger correlation (Hajjar, 2018):

Inter - Item correlation:	Strength of the correlation
0.10 – 0.29	Weak correlation
0.30 – 0.49	Medium correlation
0.50 – 1.00	Strong correlation

Item-total and inter-item correlations are also applied in exploratory research (Hajjar, 2018). Item-total correlations should be at least .30 (Cristobal et al., 2007). Construct validity is satisfied if the item-total correlation score is more than 0.50 and the inter-item correlation score is higher than 0.30 (Hajjar, 2018).

f) Validity

Key elements of construct validity are provided by the EFA, which offers evidence based on both internal structure and test content. This evidence from factor analysis can be analysed to determine what the instrument measures, whether it is the intended abstract idea (a factor, dimension, or construct) or something else (Tavakol & Wetzel, 2020).

g) Cumulative Variance Extracted

An acceptable percentage for the cumulative variance depends on the area of research. At least 40% of the total variance from the original variance should be explained by the factors that were extracted. Generally, values between 50% and 60% are acceptable in the humanities (Reio & Shuck, 2015; Taherdoost et al., 2022).

4.5.2 Results of the Exploratory Factor Analysis: Behavioural Intention

The table of communalities for BI was reviewed and is available in Appendix A (Table A1), and all the variables have values > 0.7, which was considered excellent (Eaton et al., 2019). The researcher, therefore, proceeded to complete a factor extraction and rotation.

Table 19: Total Variance Explained - Behavioural Intention

Total Variance Explained - Behavioural Intention

Component	Initial Eigenvalues			*Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,306	76,858	76,858	2,306	76,858	76,858
2	0,428	14,253	91,111			
3	0,267	8,889	100,000			

**Extraction Method: Principal Component Analysis*

In Table 19, based on the Gutman-Kaiser Criterion, only one factor was retained since its eigenvalue > 1. This factor explained 76.858% of the variability in the data. The parallel analysis in Appendix A, Table A5 and Figure 19, the scree plot, confirmed the retention of only one factor. The results of the scree plot and the parallel analysis are not conclusive since they explain only 76.85% of the variance in the data.

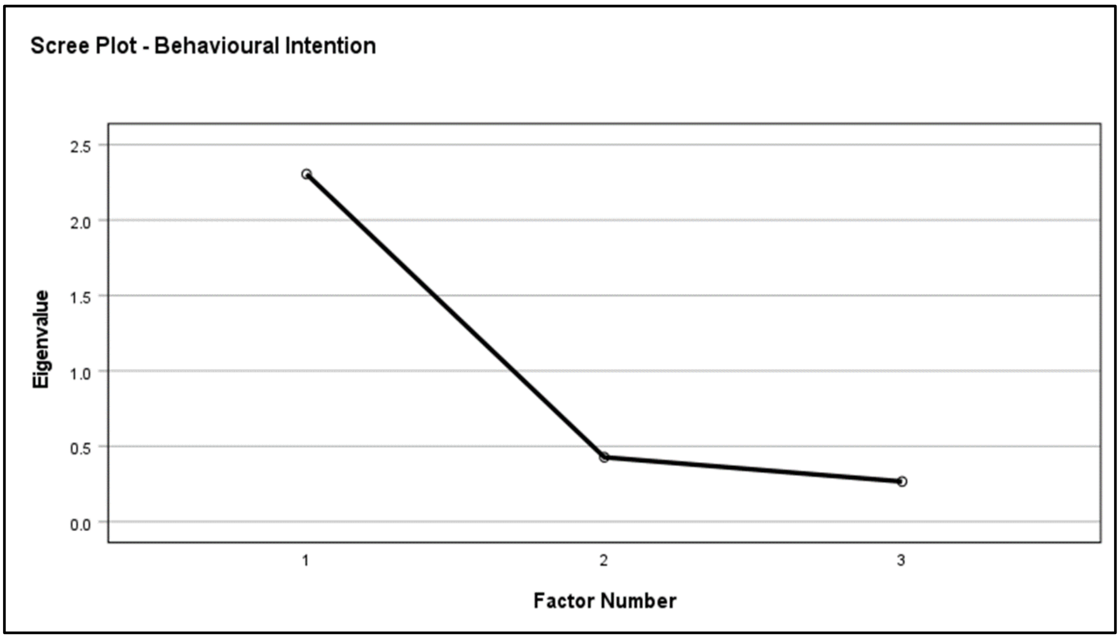


Figure 19: Scree Plot Behavioural Intention

Table 20: Factor Matrix - Behavioural Intention

Factor Matrix - Behavioural Intention[a]

	*Factor
	1
A9.1 BI_Become a regular user	0,718
A9.2 BI_Increase your basket size	0,880
A9.3 BI_Place more online orders	0,828

**Extraction Method: Principal Axis Factoring.*

a. 1 factors extracted. 10 iterations required.

Table 20 displays meaningful factor loadings (Williams et al., 2010). Table 28 confirmed the instrument's internal consistency reliability with α = .848.

4.5.3 Results of the Exploratory Factor Analysis: UTAUT2 Model

The table of communalities for the UTAUT2 model was reviewed and is available in Appendix A (Table A2). All the variables had values > 0.4, which are considered acceptable cut-off values (Eaton et al., 2019). The researcher, therefore, proceeded to complete a factor extraction and rotation.

Table 21: Total Variance - UTAUT2 model (Venkatesh et al., 2012)

Total Variance Explained - UTAUT2 model								
Factor	**Factor name**	**Initial Eigenvalues**			***Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings[a]**
		Total	**% of Variance**	**Cumula-tive %**	**Total**	**% of Variance**	**Cumula -tive %**	**Total**
1	PE	4,631	24,372	24,372	4,631	24,372	24,372	3,159
2	HM	2,075	10,921	35,293	2,075	10,921	35,293	1,990
3	SI	1,856	9,769	45,061	1,856	9,769	45,061	2,279
4	EE	1,606	8,451	53,512	1,606	8,451	53,512	2,854
5	FC	1,155	6,079	59,591	1,155	6,079	59,591	2,888
6	PV	1,051	5,532	65,123	1,051	5,532	65,123	2,368
7		0,824	4,339	69,461				
8		0,764	4,023	73,484				

9		0,732	3,855	77,339				
10		0,664	3,494	80,832				
11		0,623	3,278	84,110				
12		0,537	2,828	86,939				
13		0,460	2,420	89,359				
14		0,448	2,358	91,717				
15		0,420	2,212	93,928				
16		0,346	1,821	95,750				
17		0,296	1,558	97,308				
18		0,262	1,376	98,684				
19		0,250	1,316	100,000				

**Extraction Method: Principal Component Analysis*

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

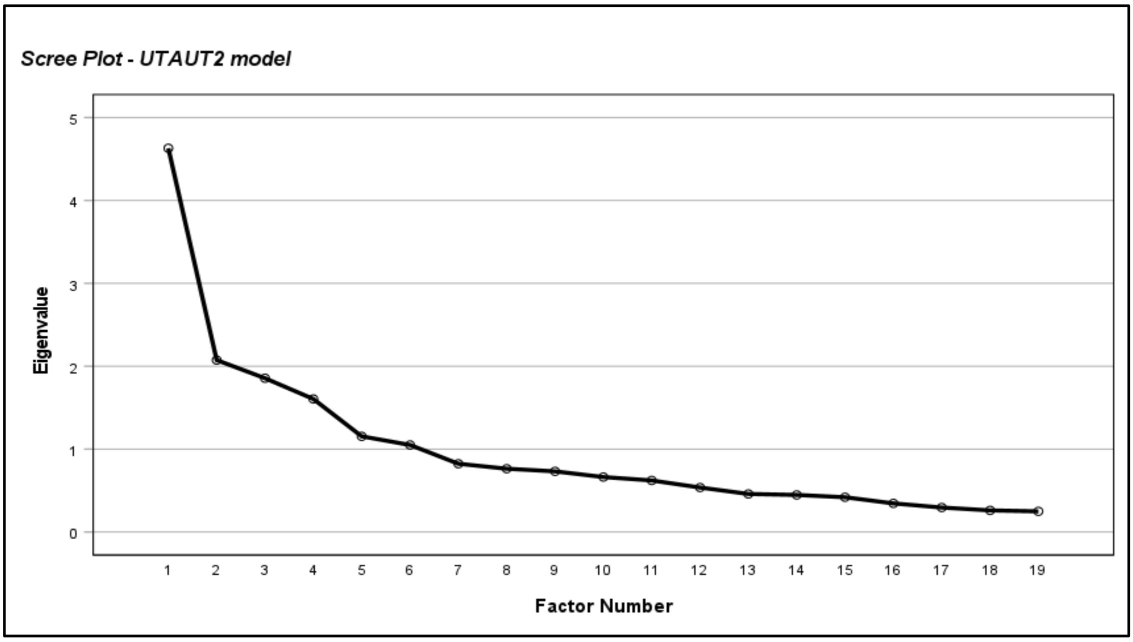


Figure 20: Scree Plot UTAUT2 model (Venkatesh et al., 2012)

Figure 20 indicates that factors one to six should be retained since all these factors had eigenvalues > 1. In Appendix A Table A6, the parallel analysis shows that there are nine factors with eigenvalues > 1. Compared to Table 21, which had six factors with eigenvalues > 1 and explains 65.123% of the variability in the data. Although the data explained a convincing 65.123% of the variability, there was still 34.877% that remained unexplained.

The Cronbach Alpha scores verified the measures' reliability with values of PE = .759, EE = .813, SI = .756 and FC = .732. PV had an α = .560, which is unacceptable for proceeding with the EFA. Item A7.1 Habit_Become a habit was removed to enable a valid Cronbach alpha of α=.812 on the HM factor. Habit did not emerge as a valid factor.

Table 22: Pattern Matrix - UTAUT2 model (Venkatesh et al., 2012)

Pattern Matrix[a] - UTAUT2 model

	*Component					
	PE	**HM**	**SI**	**EE**	**FC**	**PV**
A1.1 PE_Website app useful	0,730					
A1.2 PE_Frees up time	0,843					
A1.3 PE_Shopping tasks quicker	0,847					
A2.1 EE_Learning to use is easy				0,855		
A2.2 EE_Quick and responsive				0,871		
A2.3 EE_Product info and pricing				0,803		
A3.1 SI_People influence my decision			0,879			
A3.2 SI_People who are important			0,626			
A3.3 SI_Status symbol			0,863			
A4.1 FC_Query resolution process					0,329	
A4.2 FC_Replacement Refund					0,864	
A4.3 FC_Flexible delivery pickup					0,874	
A5.1 PV_Wifi to place order						0,735
A5.2 PV_Pay a small delivery fee						0,546
A5.3 PV_Free delivery of my order					0,544	
A6.1 HM_Browsing is enjoyable		0,845				
A6.2 HM_Exciting to order		0,841				
A7.1 Habit_Become a habit		0,595				
A7.2 Habit_Become a routine						0,789

**Extraction Method: Principal Component Analysis.*

Rotation Method: Oblimin with Kaiser Normalization[a].

a. Rotation converged in 12 iterations.

4.5.4 Results of the Exploratory Factor Analysis: UG Construct

The table of communalities in Appendix A Table A3 was analysed, and all the variables had values > 0.4 except for A13.3 Reten_Order accuracy with a value of 0.395. This value is still acceptable since it falls within the 0.25 – 0.40 range (Eaton et al., 2019). The researcher, therefore, proceeded to complete a factor extraction and rotation.

Based on the Gutman-Kaiser Criterion in Table 23, six factors had eigenvalues > 1 and explained 49.8% of the variance in the data. The parallel analysis in Appendix A Table A7 had seven factors with eigenvalues > 1. The scree plot in Figure 21 displayed six factors with eigenvalues > 1. Table 23, the parallel analysis and the scree plot explained only 49.8% of the variance in the data. There was, therefore, 50.2% that remained unexplained.

Table 23: Total Variance Explained – User Growth construct

Total Variance Explained - User Growth construct

Factor	Factor Name	Initial Eigenvalues			*Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	Retention	3,889	25,925	25,925	2,799	18,660	18,660	2,353
2	Revenue	1,588	10,588	36,513	1,108	7,389	26,049	2,050
3	Acquisition	1,371	9,138	45,651	1,133	7,551	33,600	1,704
4	Refer	1,300	8,667	54,318	1,288	8,589	42,189	1,710
5	Activation	1,057	7,044	61,362	1,143	7,623	49,813	1,998
6		1,008	6,723	68,085				
7		0,877	5,847	73,933				
8		0,810	5,401	79,334				
9		0,735	4,899	84,233				
10		0,575	3,830	88,063				
11		0,488	3,256	91,319				
12		0,456	3,038	94,357				
13		0,344	2,293	96,650				
14		0,299	1,990	98,640				
15		0,204	1,360	100,000				

**Extraction Method: Generalized Least Squares.*

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

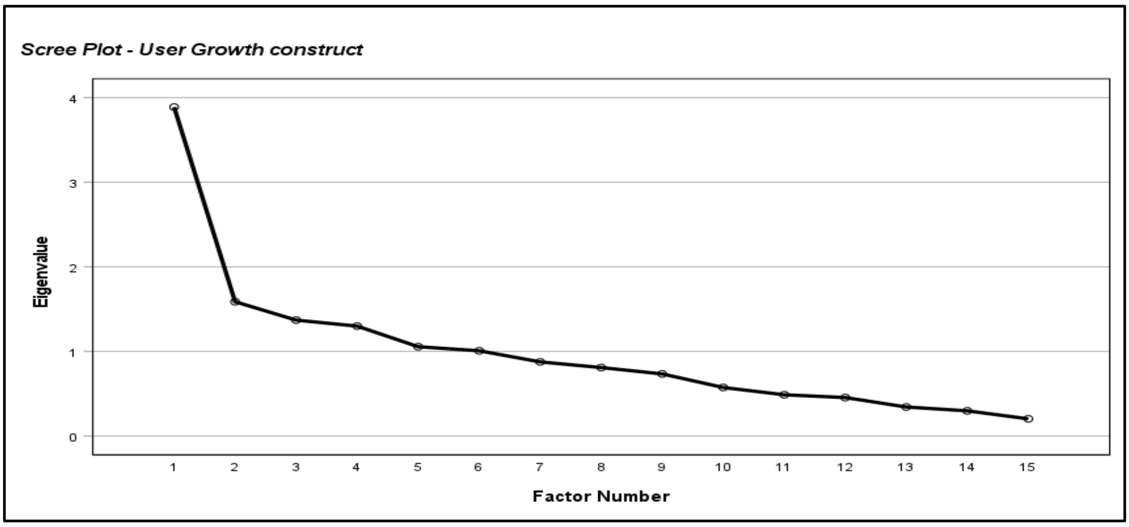


Figure 21: Scree Plot User Growth construct

Table 24: Pattern Matrix - User Growth construct

Pattern Matrix[a] - User Growth construct

	*Factor				
	1	**2**	**3**	**4**	**5**
	Retention	**Revenue**	**Acquisition**	**Referral**	**Activation**
A13.2 Reten_Delivery selected timeslot	1,029				
A13.1 Reten_Indicators stock availability	0,527				
A13.3 Reten_Order accuracy					
A15.3 Revenue_Cashbacks		-1,017			
A15.2 Revenue_Free 30day return order service		-0,722			
A10.2 Acquisition_Info about benefits			0,973		
A10.3 Acquisition_Visited and browsed			0,437		
A10.1 Acquisition_Retailers advertise					
A15.1 Revenue_Loyalty points				0,768	
A14.3 Refer_The payment process is safe and secure				0,765	
A14.2 Refer_Online product range					
A14.1 Refer_Complete shopping tasks quickly					
A12.3 Activation_Simplicity order placement					0,749
A12.2 Activation_Ease of navigation					0,716
A12.1 Activation_Ease of registration					0,552

Extraction Method: Generalized Least Squares. Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 11 iterations.

Internal consistency reliability of the measures was confirmed with Cronbach Alpha values for all the factors: acquisition = .671, activation = .703, retention = .759, referral = .816 and revenue = .869. Although acquisition had an alpha value lower than the acceptable 0.7, it had an inter-item value of 0.505, which supports the scale's reliability (Clark & Watson, 1995). According to Cohen et al. (2002), Cronbach Alpha values < 0.7 but > 0.6 can be accepted if the inter-item correlation > 0.5. Items A13.3, A10.1, A14.1 and A14.2 had no factor loadings in the EFA. Items A13.2 and A15.3 had factor loadings > 1, which showed that the factors are highly correlated and can exceed +1 or -1 (Zhang et al., 2019).

4.5.5 Results of the Exploratory Factor Analysis: Satisfaction

The table of communalities for satisfaction was analysed and is available in Appendix A Table A4, and all the variables had values > 0.6, which is higher than the 0.25 – 0.40 cut-off recommendation (Eaton et al., 2019). Internal consistency reliability was confirmed with α = .854. The factor extraction and rotation, therefore, proceeded.

Table 25: Total Variance – Satisfaction variable

Total Variance Explained – Satisfaction variable

Component	Initial Eigenvalues			*Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,795	69,866	69,866	2,795	69,866	69,866
2	0,479	11,967	81,833			
3	0,387	9,682	91,515			
4	0,339	8,485	100,000			

**Extraction method: Principal Component Analysis*

Table 25 had only one factor with an eigenvalue > 1. This factor explained 69.8% of the data's variability, leaving 30.2% unexplained. The parallel analysis produced two factors with eigenvalues > 1. (Appendix A Table A8). The scree plot in Figure 22 indicated that one factor should be retained since this factor had an eigenvalue > 1.

Table 26: Factor Matrix – Satisfaction variable

Factor Matrix[a] – Satisfaction variable

	***Factor**
	1
A8.1 Sat_The quality of the products	0,746
A8.2 Sat_Order accuracy	0,826
A8.3 Sat_The level of customer service	0,753
A8.4 Sat_Overall happiness	0,773

**Extraction Method: Generalized Least Squares.*

a. 1 factors extracted. 4 iterations required.

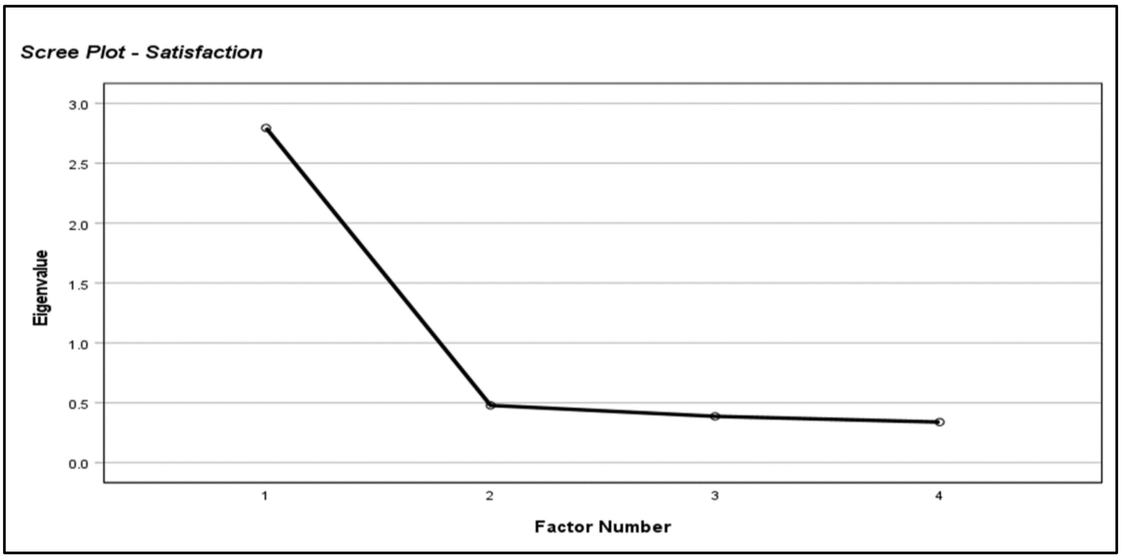


Figure 22: Scree Plot Satisfaction variable

4.5.6 Test for Multicollinearity

A Factor or Component Correlation Matrix reviews possible multicollinearity in the data. Computed correlations should be lower than 0.8 (Field, 2013). It is evident from Tables A9 and A10 in Appendix A that there was no multicollinearity between the factors.

Table 27: Summary of Validity and Reliability Metrics: UTAUT2 model (Venkatesh et al., 2012)

		Item - Total Statistics UTAUT2 Variables	Number of Items	Scale Mean if Item Deleted	Scale Variance if Item deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach Alpha if Item deleted	Factor Number	Cronbach Alpha	Average Inter – item r	Accepted / Rejected
Effort Expectancy	A2.1	Learning to use my preferred retailers' e-commerce website/app is easy	3	-0.801	1.902	0.587	0.353	0.822	4	.813	0.593	Accepted
	A2.2	My preferred retailers' e-commerce website/app is quick and responsive when searching and adding products to my basket		-0.523	1.752	0.733	0.554	0.671	4			
	A2.3	My preferred website/app's online product information & pricing supports me to evaluate and compare prices between products prior to buying online		-0.479	1.832	0.676	0.503	0.731	4			
Perforamnce Expectancy	A1.1	I find the e-commerce website/app of my preferred retailer useful (handy/ helpful/ effective)	3	-0.820	2.277	0.567	0.335	0.706	1	.759	0.521	Accepted
	A1.2	Shopping for my groceries, self-care or other products online frees up time to achieve things that are important to me		-0.882	2.061	0.642	0.414	0.621	1			
	A1.3	Online shopping helps me accomplish my shopping tasks quicker		-0.437	1.760	0.581	0.345	0.705	1			
Social Influence	A3.1	People who influence my decision-making think that I should shop for my products online by using an e-commerce website/app	3	0.517	2.617	0.633	0.443	0.618	3	.756	0.507	Accepted
	A3.2	People (friends/ family/ co-workers) who are important to me think that I should be ordering my products online		1.005	3.017	0.481	0.232	0.787	3			
	A3.3	Using an e-commerce website/app is a status symbol in my social networks (Facebook, Instagram, Twitter, LinkedIn)		0.430	2.511	0.650	0.457	0.597	3			
Facilitating Conditions	A4.1	My usage of an e-commerce website/app is dependent on the availability of a query resolution process via online messaging/ telephone /email customer support							rejected			
	A4.2	It is important that my preferred e-commerce website/app facilitates valid replacement or refund requests of my order	3	-0.269	2.317	0.625	0.506	0.589	5	.742	0.500	Accepted
	A4.3	I order on my preferred e-commerce website/app since it provides me with flexible delivery / pick up options		-0.289	2.344	0.674	0.529	0.540	5			
	A5.3	I prefer to buy from e-commerce websites / apps that offers free delivery of my order		-0.092	2.538	0.428	0.188	0.827	5			

		Item - Total Statistics UTAUT2 Variables (continued)	Number of Items	Scale Mean if Item Deleted	Scale Variance if Item deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach Alpha if Item deleted	Factor Number	Cronbach Alpha	Average Inter – item r	Accepted / Rejected
Price Value	A5.1	Using a secure internet connection/WIFI to place my online order (with free delivery) is more economical than the return travelling cost and time to shop instore	3	0.202	1.805	0.429	0.184	0.363	6	.560	-0.4193	Rejected
	A5.2	I will rather pay a small delivery fee, than increasing my order value to enable me to qualify for free delivery of my order		-0.213	2.102	0.336	0.122	0.509	6			
	A7.2	Placing my online orders for food, beverages, self-care products, books etc. has become a routine for me		-0.828	1.893	0.348	0.130	0.495	6			
Hedonic Motivation	A6.1	Browsing through an e-commerce website/app is enjoyable	2	0.885	0.572	0.684	0.468	0.422	2	.812	.684	Accepted
	A6.2	I find it exciting to order my products through an e-commerce website/app		0.867	0.608	0.684	0.468	0.440	2			
	A7.1	Ordering on my preferred e-commerce website / app has become a habit for me							rejected			

Table 28: Summary of Validity and Reliability Metrics: Behavioural Intention and Satisfaction

		Item - Total Statistics Behavioural Intention	Number of Items	Scale Mean if Item Deleted	Scale Variance if Item deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach Alpha if Item deleted	Factor	Cronbach Alpha	Average Inter – item r	Accepted / Rejected
Behavioural Intention	A9.1	In future, will you become a regular user of your preferred retailers' website/app	3	.2041	3.334	.659	.437	.843	7	.848	.652	Accepted
	A9.2	In future, will you increase your basket size and the variety of products that you order online?		-.2547	3.159	.764	.594	.745	7			
	A9.3	In future, will you Place more online orders as you become more comfortable with the online shopping process?		.0377	3.055	.731	.562	.775	7			
		Satisfaction										
Satisfaction	A8.1	A satisfactory experience with my preferred e-commerce website/app has been impacted by The quality of the products offered online	4	-1.4496	4.493	.672	.466	.828	1	.854	.598	Accepted
	A8.2	A satisfactory experience with my preferred e-commerce website/app has been impacted by order accuracy - the retailer deliver what I have ordered		-1.1820	3.881	.737	.549	.797	1			
	A8.3	A satisfactory experience with my preferred e-commerce website/app has been impacted by the level of customer service received		-1.4049	3.929	.686	.473	.820	1			
	A8.4	A satisfactory experience with my preferred e-commerce website/app has been impacted by my overall happiness with the online shopping experience		-1.3122	3.915	.703	.496	.812	1			

Table 29: Summary of Validity and Reliability Metrics: User Growth construct

		Item - Total Statistics User Growth Variables	Number of Items	Scale Mean if Item Deleted	Scale Variance if Item deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach Alpha if Item deleted	Factor Number	Cronbach Alpha	Average Inter – item r	Accepted / Rejected
Acquisition	A10.1	I am aware of e-commerce websites or apps because Retailers advertise them on TV, radio and in newspapers		-.4686	1.975	.165	.043	.671	rejected			
	A10.2	I am aware of e-commerce websites or apps because I have gathered enough information about their benefits - timesaving, cost-saving, available	2	-.2205	2.066	.445	.283	.140	3	.671	.505	Accepted
	A10.3	I am aware of e-commerce websites or apps because I have visited some websites and apps and have browsed through the available products		-.7184	2.308	.329	.256	.327	3			
Activation	A12.1	My adoption of a website or app is determined by Ease of the online registration.	3	-1.3056	2.512	.465	.218	.677	5	.703	.440	Accepted
	A12.2	My adoption of a website or app is determined by ease of online navigation - search and selecting of products		-1.2266	2.251	.561	.320	.559	5			
	A12.3	My adoption of a website or app is determined by simplicity of order placement		-.7008	2.227	.535	.298	.592	5			
Retention	A13.1	My decision to reuse a website/app is impacted by Indicators that shows stock availability as I compile my basket	2	-.0248	1.528	.490	.377	.455	1	.759	.613	Accepted
	A13.2	My decision to reuse a website/app is impacted by Order delivery that takes place in my selected time slot		-.0273	1.384	.551	.403	.359	1			
	A13.3	My decision to reuse a website/app is impacted by Order accuracy (products & quantities) are delivered as placed		-.4582	1.374	.297	.095	.759	rejected			
Referral	A14.1	I will refer my preferred e-commerce website/app if It enables me to complete my shopping tasks quickly	No Factor loading									
	A14.2	I will refer my preferred e-commerce website/app if I am happy with the online product range at different price points	No Factor loading									
	A14.3	I will refer my preferred e-commerce website/app if The payment process is safe and secure	2	.2650	.576	.689	.474	n.a	4	.816	.689	Accepted
	A15.1	I choose to use a website or app with the possibility of receiving the following benefits loyalty points on all online purchases		.1282	.584	.689	.474	n.a	4			
Revenue	A15.2	I choose to use a website or app with the possibility of receiving the following benefits the availability of a free 30-day return order service	2	.6979	1.855	.676	.607	.109	2	.869	.769	Accepted
	A15.3	I choose to use a website or app with the possibility of receiving the following benefits the potential cash backs that I can receive through my insurance/med aid/gym/mobile operator		.5107	1.920	.567	.597	.285	2			

4.5.7 Conclusion: Exploratory Factor Analysis for all Constructs

Construct validity was validated through the factor analysis for each construct, confirming that the instrument measures what it should do. Each factor with a higher initial eigenvalue than the random eigenvalue should be retained (Hayton et al., 2004). Based on the comparison of the data between the Gutman-Kaiser criteria, the parallel analyses and scree plots, the following factors were proposed:

- For the UTAUT2 model (Venkatesh et al., 2012) factors 1 to 5 should be retained.
- For the BI variable, factor 1 should be retained.
- Factors 1 to 5 should be retained for the UG construct according to their eigenvalues; Acquisition (α = .671) had a low alpha but was retained due to the eigenvalue > 1.
- For the satisfaction variable, factor 1 should be retained.

Table 30: Eigenvalues Comparison

UTAUT2 model	Factors	Initial eigenvalues	Random eigenvalues	% of Variance Explained	% Cumulative Variance Explained
1	Performance Expectancy	4.631	1.3274	24,37	24,37
2	Hedonic Motivation	2.075	1.2753	10,92	35,29
3	Social Influence	1.856	1.2262	9,76	45,06
4	Effort Expectancy	1.606	1.1886	8,45	53,51
5	Facilitating Conditions	1.155	1.1543	6,07	59,59
6	Price Value	1.051	1.1142	5,53	65,12
7		.824	1.0798		rejected
Satisfaction	**Factors**	**Initial eigenvalues**	**Random eigenvalues**	**% of Variance Explained**	**% Cumulative Variance Explained**
1	Satisfaction	2.795	1.096	69.86%	69.86%
Behavioural Intention	**Factors**	**Initial eigenvalues**	**Random eigenvalues**	**% of Variance Explained**	**% Cumulative Variance Explained**
1	Behavioural Intention	2.306	1.067	76.85%	76.85%
User Growth construct	**Factors**	**Initial eigenvalues**	**Random eigenvalues**	**% of Variance Explained**	**% Cumulative Variance Explained**
1	Retention	3.889	1.297	18,66	18,66
2	Revenue	1.588	1.2264	7,38	26,05
3	Acquisition	1.371	1.1771	7,55	33,60
4	Refer	1.300	1.1361	8,58	42,19
5	Activation	1.057	1.0970	7,62	49,81
6		1.008	1.0619		rejected

4.6 Multiple Regression Analysis

The statistical method of fitting a linear model to data so that the independent variables can predict the dependent variable is known as regression analysis. (Field, 2013). Regression concentrates on separating the variance in the dependent variable into explained and unexplained components. The intent is to determine whether the independent variables explain significant variance in the dependent variable (Bell et al., 2022). The following assumptions of multiple regression need to be tested before proceeding with the analysis:

a) Independent errors: Durbin-Watson Test

This test tests for serial correlations between errors, especially where residuals are adjoining. If the test statistic is less than 1.5 and greater than 2.5, there is possibly an autocorrelation problem. However, autocorrelation is unlikely if the value is between 1.5 and 2.5 (Zach, 2021).

b) Homoscedasticity

The assumption is that the residuals of the dependent variable should have the same variance at each variable level (homoscedasticity); however, when the variances are uneven, they display heteroscedasticity. Homoscedasticity is determined by plotting the standardised residuals against the standardised predicted values, as depicted in Figure 23. The dots should be dispersed randomly and exhibit no apparent patterns, such as funnelling. If there are any outliers, they should be easily identifiable and should then be removed from the data (Field, 2013).

The standardised residuals and Mahalanobis distance metrics can be extracted in SPSS through residual statistics. Respondent numbers 198, 333 and 408 were identified as outliers (values < - 3 or bigger > + 3) in the regression analysis between UTAUT2 and BI. The outliers were excluded from the regression analysis. The Standardised residuals were then plotted on a histogram and are visible in Figure 24; they range from - 3 to + 3.

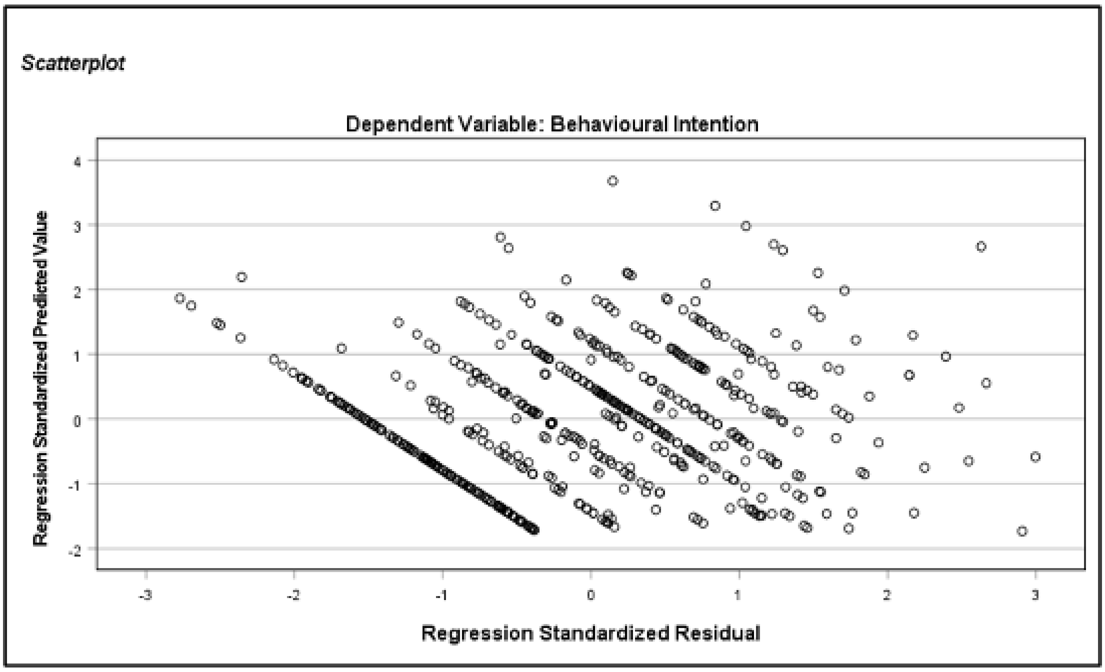


Figure 23: Scatterplot: Regression Standardised Residual: BI

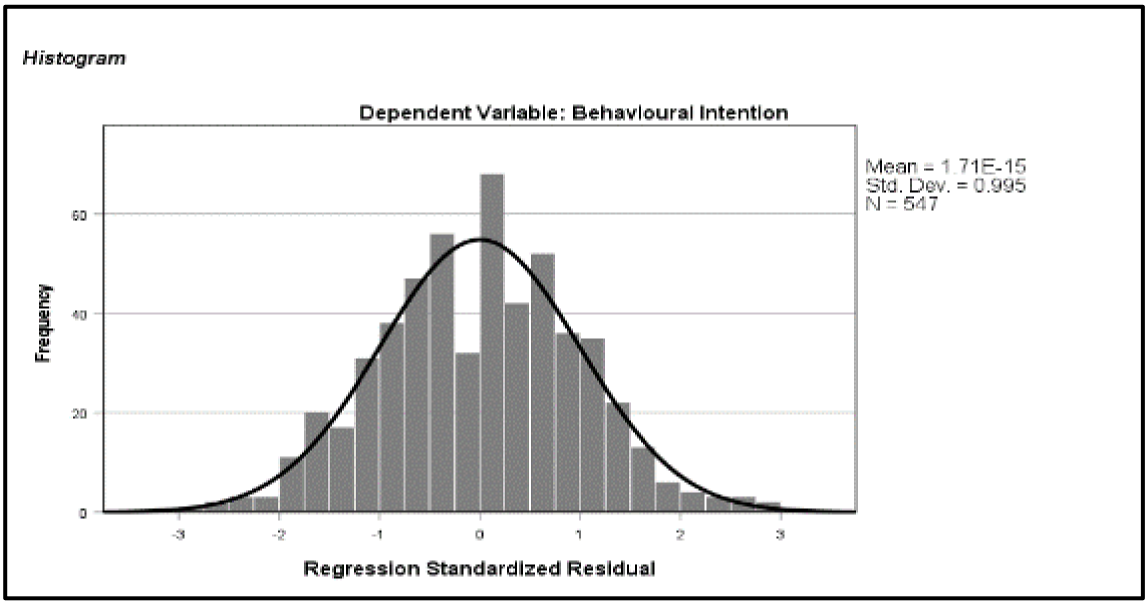


Figure 24: Histogram: Regression Standardised Residuals: BI

The tests for Homoscedasticity for the other two regression models, BI and UG, and FC and UG can be found in Appendix A (Figure A1, Figure A2, Figure A3 and Figure A4).

c) Multicollinearity

Multicollinearity is measured by analysing the Variance Inflation Factor (VIF) and Tolerance values. When correlation exists among independent variables, the standard error of independent coefficients will increase, consequently inflating the variance of the independent variables' coefficients. The VIF is an indicator of how much the variance is inflated. The following guidelines are provided for the interpretation of the VIF values (Daoud, 2017):

VIF Value:	**Level of correlation:**
VIF = 1	variables are not correlated
VIF > 1 < 5	variables are moderately correlated
VIF > 5	variables are highly correlated

Multicollinearity can be found by assessing the Tolerance value for each independent variable. Tolerance is known as the degree of variation in one independent variable that the other independent variables cannot explain. Collinearity is indicated by tolerance values smaller than 0.10 (Daoud, 2017).

d) Multiple coefficients of Determination (R^2)

The multiple coefficients of determination (R-squared value) are the primary indicators of how well the data fits the regression model. This measure assesses whether the amount of variance explained by the independent variables about the dependent variable is greater than the amount of variance which would have occurred by coincidence (Bell et al., 2022). The interpretation of R^2 is the measure of total influence by the independent variables explained by the dependent variable (Singh, 2023). The recommended effect sizes for R-squared are (Steyn & Ellis, 2003):

Size of R^2:	Conclusions on R^2:
Smaller than 0.13	Non-significant
0.13 – 0.25	Significant
Larger than 0.25	Practically important

e) The F–test and ANOVA

Analysis of Variance (ANOVA) analyses variance by comparing means or the distribution of data values within and between data sets. The ANOVA test displays the significance of the model or the relationship in question. If the test is significant, the study can perform the linear regression.

The F-test determines the ratio between the dependent variable's explained and unexplained variance (or error variance) as determined by a regression equation (Bell et al., 2022). Variances measure the dispersion of the data points around the mean. When the individual data points deviate farther from the mean, the variances are higher (StatisticsHowTo, 2023).

The F-ratio or F-statistic represents these variances. A significant F-ratio with a probability of less than 0.05 indicates that there is little chance that any difference between the groups could have happened by chance alone. This is considered statistically significant (Saunders et al., 2009).

This F-test tests the significance of the overall effect size of the model. If the model is good, the improvement in prediction from using the model should be significant, and the difference between the observed data and the model will be minor. The higher the value of the F-statistic, the more variance in the dependent variable is explained by the independent variable (Hair et al., 2019).

f) Regression Coefficients

The Unstandardized Coefficients Beta display the values for the regression equation in predicting the dependent variable from the independent variable. The Standardized Coefficients Beta shows the values obtained when all the values (from both dependent and independent variables) in the model are standardised to measure on the same scale before regression (Mertens et al., 2017). The T-statistic is calculated on the ratio of explained variance against error. It has a probability distribution that differs according to the degrees of freedom for each test (Field, 2013).

g) The p-value

A statistical measure called the p-value is employed to verify a hypothesis by validating it against an observed data set. The chance of obtaining the observed results on the premise that the null hypothesis is true is measured by the p-value. A p-value of 0,05 or lower is generally considered statistically significant. The lower the p-value, the greater the statistical significance in the observed data set or notable variance being tested (Beers, 2023).

4.6.1 Results: Regression Analysis UTAUT2 Model (Venkatesh et al., 2012) and BI

The relationship between the UTAUT2 model (Venkatesh et al., 2012) and BI is significant with $p < 0{,}001$, as displayed in Table 31. The $R^2 = 0{,}298$ in Table 32 indicates that the value is important and that the independent variables account for 29.8% of the variance in BI.

Table 31: ANOVA - UTAUT2 model (Venkatesh et al., 2012) and BI

ANOVA - UTAUT2 model and BI[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	120,845	4	30,211	57,731	<,001[b]
	Residual	285,206	545	0,523		
	Total	406,051	549			

a. Dependent Variable: Behavioural_Intention.

b. Predictors: (Constant), Facilitating_Conditions, Social_Influence, Effort_Expectancy, Performance_expectancy.

Table 32: Model Summary - UTAUT2 model (Venkatesh et al., 2012) and BI

Model Summary[b] - UTAUT2 model and BI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			Durbin-Watson
					df1	df2	Sig. F Change	
1	.546[a]	0,298	0,292	0,72340	4	545	0,000	1,892

a. Predictors: (Constant), Facilitating_Conditions, Social_Influence, Effort_Expectancy, Performance_expectancy.

b. Dependent Variable: Behavioural_Intention.

The values displayed in Table 33 show that the relationship between PE and BI, and FC and BI are significant with $p < 0,000$. The VIF and Tolerance Values are within the acceptable ranges and the data displays no multicollinearity (Mertens et al., 2017). The Durbin-Watson test delivered a value of 1.892 which displays no autocorrelation in the data (Zach, 2021).

Table 33: Coefficients - UTAUT2 model (Venkatesh et al., 2012) and BI

Coefficients[a] - UTAUT2 model and BI

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0,023	0,067		0,348	0,728		
	PE	0,194	0,053	0,156	3,673	0,000	0,711	1,407
	EE	-0,036	0,050	-0,028	-0,720	0,472	0,865	1,156
	SI	0,056	0,040	0,052	1,398	0,163	0,906	1,104
	FC	0,622	0,057	0,454	10,949	0,000	0,741	1,349
	HM	0,057	0,050	0,042	1,136	0,256	0,942	1,062

a. Dependent Variable: Behavioural Intention

Table 33 also shows that for every unit of change in PE there is a 15.6% positive increase in BI and for every one unit change in FC there is a 45.4% positive increase in BI. The stronger relationship between FC and BI aligns with the result of a study on Preservice Teachers' Acceptance of Learning Management Software (LMS) (Raman & Don, 2013).

4.6.2 Results: Regression Analysis BI and UG Construct

Table 34: ANOVA - BI and UG construct

ANOVA - BI and UG[a] construct

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24,792	1	24,792	199,003	<,001[b]
	Residual	67,898	545	0,125		
	Total	92,690	546			

a. Dependent Variable: UG

b. Predictors: (Constant), BI

Table 34 shows that the relationship between BI and the UG construct is significant $p < 0{,}001$. BI explains 26.7% ($R^2 = 0{,}267$) of the variance in UG (Table 35). The effect size of R^2 is of importance. This result aligns with a study on the acceptance of LMS software, which found that BI explains 29.5% ($R^2 = 0{,}295$) of the variance in LMS use (Raman & Don, 2013). The Durbin-Watson value of 1,928 is > 1,5 and < 2,5, which displays no autocorrelation in the data (Zach, 2021).

Table 35: Model Summary - BI and UG construct

Model Summary[b] - BI and UG construct

Model	R	R Square	Sig. F Change	Durbin-Watson
1	.517[a]	0,267	0,000	1,928

a. Predictors: (Constant), BI.

b. Dependent Variable: UG

Table 36 shows a 51.7% positive change in UG for every unit change in BI (Cohen et al., 2002). The data displays no multicollinearity, and the VIF and Tolerance values are within range (Mertens et al., 2017).

Table 36: Coefficients - BI and UG construct

Coefficients[a] - BI and UG construct

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-0,015	0,015		-0,990	0,323		
	BI	0,253	0,018	0,517	14,107	0,000	1,000	1,000

a. Dependent Variable: UG

4.6.3 Results: Regression Analysis Facilitating Conditions and UG Construct

Table 37: ANOVA - FC and UG construct

ANOVA - FC and UG[a] construct

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49,382	1	49,382	404,636	<,001[b]
	Residual	66,390	544	0,122		
	Total	115,771	545			

a. Dependent Variable: User Growth

b. Predictors: (Constant), Facilitating Conditions

The relationship between the FC factor and the UG construct is significant, $p < 0,001$ (Table 37). FC explained 42.7% ($R^2 = 0.427$) of the UG construct's variability and is important in demonstrating the FC and UG relationship (Table 38).

Table 38: Model Summary - FC and UG construct

Model Summary[b] - FC and UG construct

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics			Durbin-Watson
					df1	df2	Sig. F Change	
1	.653[a]	0,427	0,425	0,34934	1	544	0,000	1,861

a. Predictors: (Constant), Facilitating Conditions.

b. Dependent Variable: User Growth.

The data shows no multicollinearity with the VIF and Tolerance values within range (Mertens et al., 2017). The Durbin-Watson test delivered a value of 1,861 and demonstrated no autocorrelation in the data (Saunders et al., 2009). Table 39 shows a positive 65.3% change in UG for every one unit change in FC.

Table 39: Coefficients - FC and UG construct

Coefficients[a] - FC and UG construct

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-0,082	0,015		-5,425	0,000		
	Facilitating_Conditions	0,492	0,024	0,653	20,116	0,000	1,000	1,000

a. Dependent Variable: User Growth.

4.7 Correlation Analysis

Pearson's r – The Pearson product-moment correlation coefficient is represented by r for sample statistics. This number measures the direction and strength of the linear relationship between two continuous variables. When there is a perfect positive relationship between variables r = 1, and if r = -1, there is a negative relationship, r = 0 indicates no relationship (Bell et al., 2022). The following guidelines are provided by Haldun Akoglu (2018) to determine the effect sizes of Pearson's r (Akoglu, 2018):

Correlation Coefficient		Effect Size
+1	-1	Perfect
+0,9	-0,9	Strong
+0,8	-0,8	Strong
+0,7	-0,7	Strong
+0,6	-0,6	Moderate
+0,5	-0,5	Moderate
+0,4	-0,4	Moderate
+0,3	-0,3	Weak
+0,2	-0,2	Weak
+0,1	-0,1	Weak
0	0	Zero

4.7.1 Results: BI and UG Factors Correlation Analysis

Table 40: Correlations – BI and UG construct

		Acquisition	Activation	Retention	Referral	Revenue	BI
BI	Pearson Correlation	.308**	.226**	.318**	.403**	.509**	--
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	
	N	550	550	550	550	550	550

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

The relationship between BI and the UG Construct factors is significant, with p < 0,000 for all the factors (Table 40). Pearson's moment correlation coefficient is squared for each dependent variable to explain the % variance in each dependent variable that is predicted by the independent variable, BI.

Table 41: Multiple coefficients of determination for UG factors

	Acquisition	Activation	Retention	Referral	Revenue
Significance p < 0,001	0,000	0,000	0,000	0,000	0,000
Pearson's r Behavioural Intention	.308	.226	.318	.403	.509
Effect Size	Weak	Weak	Weak	Moderate	Moderate
R - squared	**9.4%**	**5.1%**	**10.1%**	**16.2%**	**25.9%**

The multiple coefficients of determination (R^2) in Table 41 indicate that BI accounted for the following percentages of variability in each factor: 9.4% in acquisition, 5.1% in activation, 10.1% in retention, 16.2% in referral and 25.9% in revenue. There were weak correlations between acquisition and BI, activation and BI, and retention and BI. Revenue and refer showed moderate correlations with BI.

4.7.2 Results: Habit and UG Factors Correlation Analysis

The relationship between habit and the UG construct could not be tested due to habit not emerging as a valid factor in the EFA.

4.8 Moderation Analysis

A moderating variable is a variable that influences the manner (e.g. magnitude and/or direction) in which an antecedent is affecting an outcome. A moderated regression model explaining whether a moderator modifies the intensity or/and direction of the connection between an antecedent (independent variable) and an outcome can be used to evaluate a basic moderation effect (Memon et al., 2019).

A moderation analysis was conducted to determine whether satisfaction moderated the relationship between BI and each of the UG factors. A second moderation analysis was performed between the UTAUT2 factors and BI to determine the moderation effects of age, gender, and experience. The significant relationships are illustrated in graphs in Figures 25 to 28.

4.8.1 Results: Satisfaction as the moderator between BI and the UG variables

A. Acquisition

The regression coefficient for the interaction between BI and satisfaction is positive and statistically significant $b^3 = 0.1028$, $t\ (1{,}546) = 2.2849$, $p = 0{,}0227$. The relationship between BI and acquisition is moderated by satisfaction and is significant, $F(1{,}546) = 14{,}3905$, $p < 0{,}0227$. Satisfaction's moderation effect accounts for 7.33% of the variance in acquisition (Appendix A, Table A17). Figure 25 shows that the effect between BI and acquisition becomes stronger with increased levels of satisfaction.

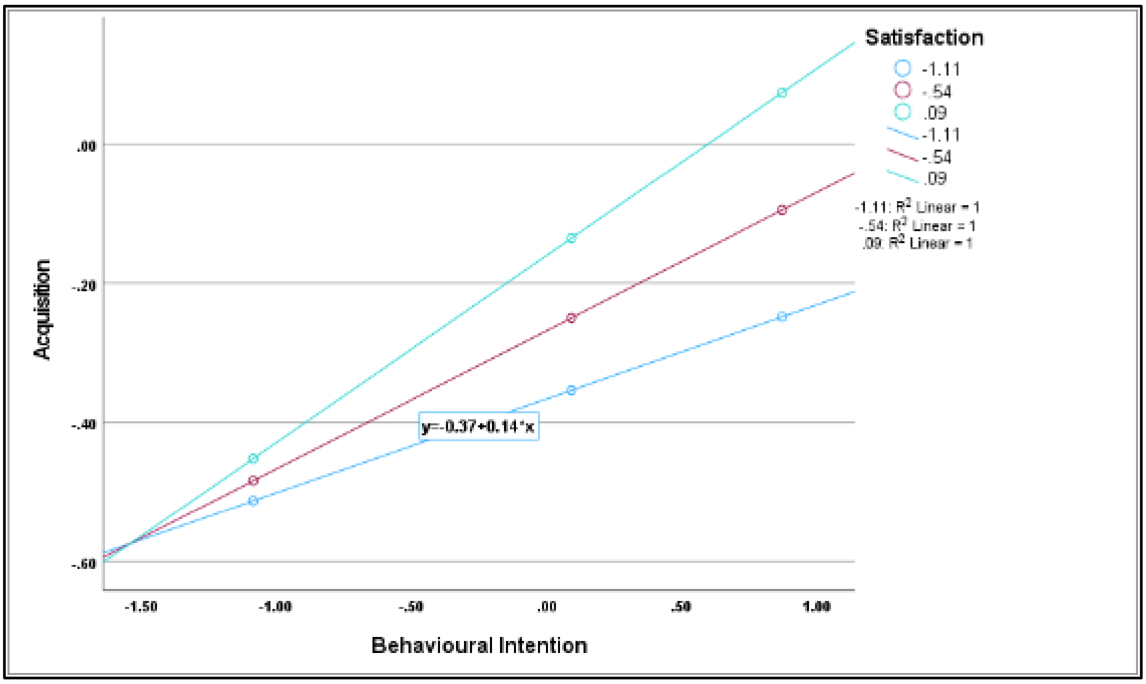


Figure 25: Moderation graph: BI - satisfaction - acquisition

B. Activation

- The regression coefficient for the interaction of satisfaction between BI and activation is statistically non-significant, p = 0,4345.

C. Retention

- The regression coefficient for the interaction of satisfaction between BI and retention is statistically non-significant, p = 0,9340.

D. Revenue

- The regression coefficient for the interaction of satisfaction between BI and revenue is statistically non-significant, p = 0,9453.

E. Refer

- The regression coefficient for the interaction of satisfaction between BI and referral is positive and statistically significant b^3 = 0.1678, t (1,546) = 3.2956, p = 0,0010. The relationship between BI and referral is moderated by satisfaction and is significant, F (1,546) = 12,9351, p < 0,0010. Satisfaction's moderation effect accounts for 6.64% of the variance in referral (see Appendix A, Table A18). Figure 26 shows that the effect between BI and referral remains unchanged if satisfaction levels are constant. However, if satisfaction levels increase the effect between BI and referral becomes stronger.

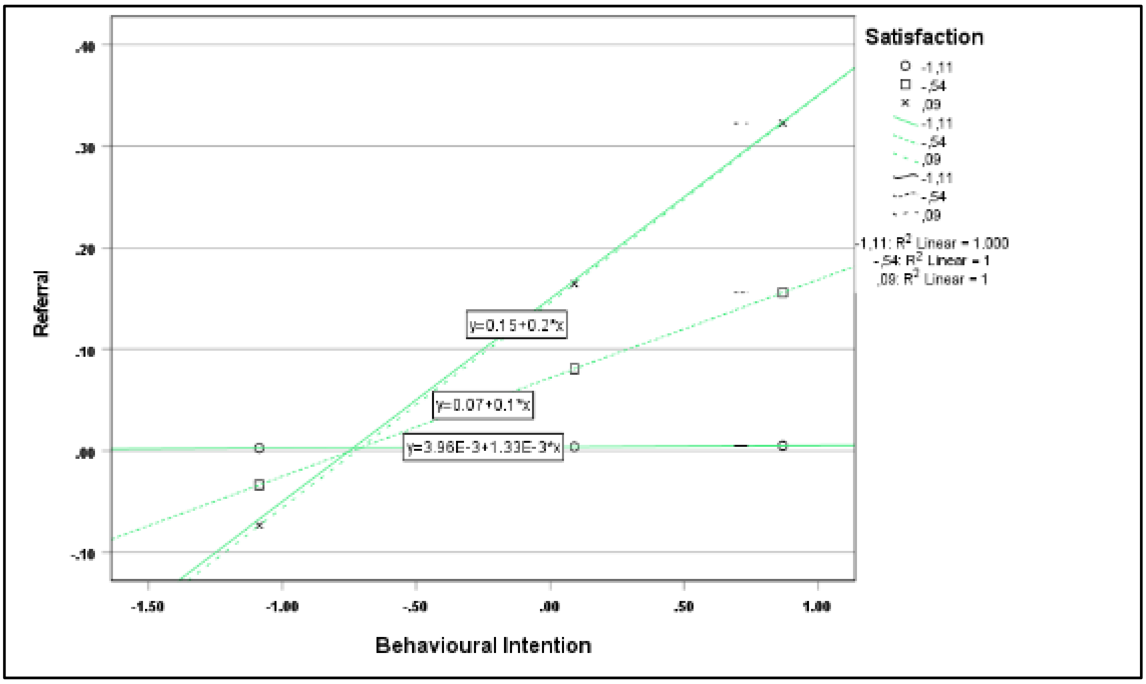


Figure 26: Moderation graph: BI - satisfaction - referral

4.8.2 Results: Satisfaction as the moderator between BI and the UG construct

The moderation coefficient for the interaction effect of satisfaction between BI and the UG construct is positive and statistically significant b^3 = 0.0513, *t* (1,546) = 2,1782, *p* = 0,0298. Satisfaction moderates the relationship between BI and UG and is significant, F (1,546) = 111,7559, p < 0,0000. Satisfaction's moderation effect accounts for 38.04% of the variance in UG see Appendix A, Table A18. The effect between BI and UG becomes stronger as levels of satisfaction increases which is visible in Figure 27.

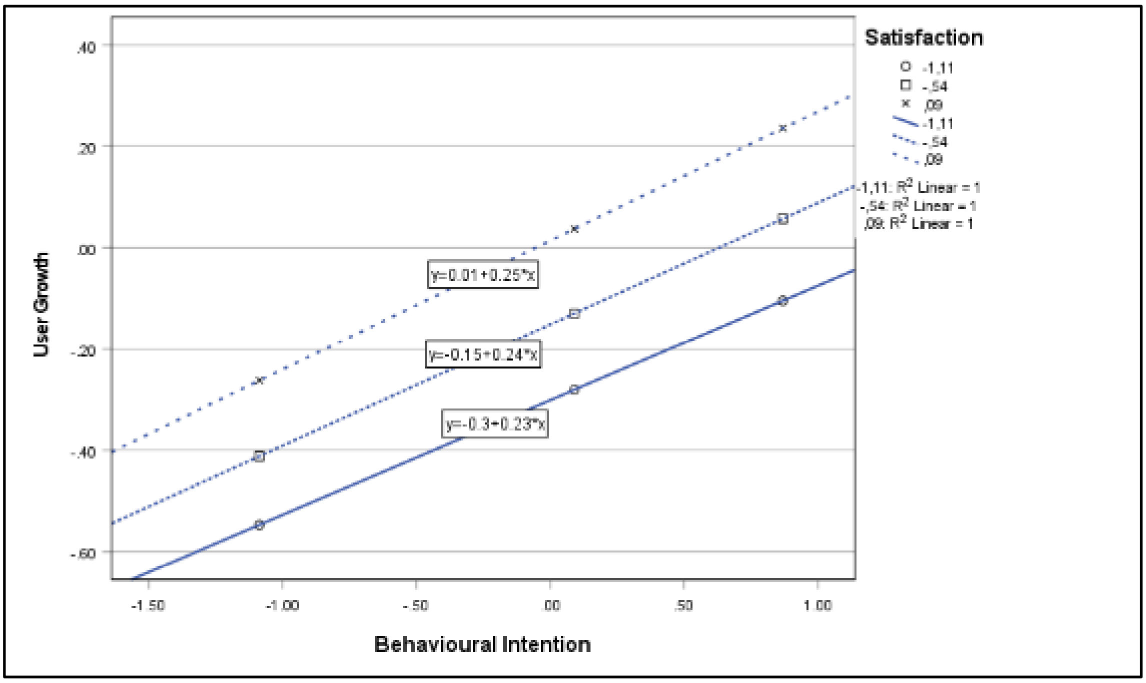


Figure 27: Moderation graph: BI - satisfaction – UG construct

4.8.3 Results: Satisfaction as the moderator between FC and the UG construct

Figure 28 displays the moderation coefficient for the interaction effect of satisfaction between FC and the UG Construct which is positive and statistically significant b^3 = 0.0633, t (1,546) = 2,2414, p = 0,0254. Satisfaction moderates the relationship between FC and UG and is significant, F (1,546) = 1348536, p < 0,0000. Satisfaction's moderation effect accounts for 42.56% of the variance in UG. (Appendix A, Table A22).

The moderating effect of satisfaction on UG becomes stronger with increased levels of FC which can be seen in Figure 28. The better customer service and support services a retailer offers, the higher their customers' satisfaction which will result in UG in B2C e-commerce platforms.

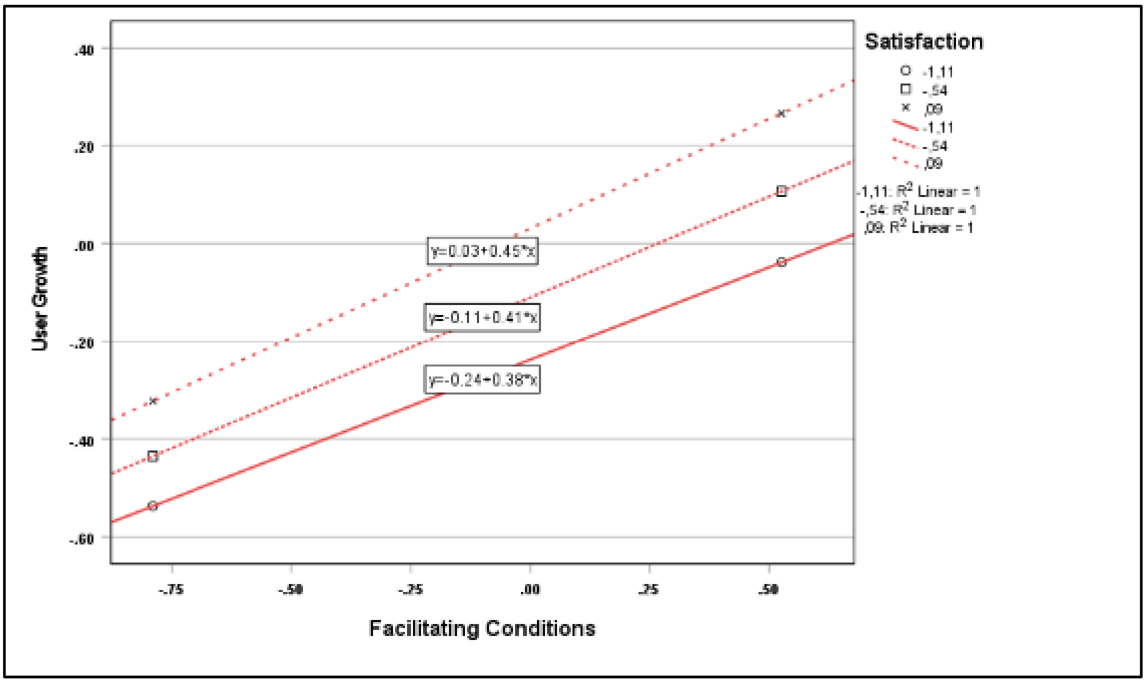


Figure 28: Moderation graph: FC – satisfaction – UG construct

4.8.4 Results: Age, gender and experience as moderators between the UTAUT2 factors (Venkatesh et al., 2012) and BI

A. Age

- None of the regression coefficients tested significant, as seen in Appendix A Table A19. Therefore, the assumption can be made that age does not moderate the relationship between PE, p = 0,2436, EE, p = 0,8611, SI, p = 0,3991, FC, p = 0,8333 and BI.

B. Gender

- None of the regression coefficients tested significant, as seen in Appendix A Table A20. Therefore, the assumption can be made that gender does not moderate the relationship between PE, p = 0,3429, EE, p = 0,9122, SI, p = 0,1467, FC, p = 0,7018 and BI.

C. Experience

- None of the regression coefficients tested significant, as seen in Appendix A Table A21. Therefore, the assumption can be made that experience does not moderate the relationship between EE, p = 0,6635, SI, p = 0,8159, FC, p = 0,2615 and BI.

4.9 Summary of the results

After the data cleansing was completed, the data were adjusted to remove respondents where CMV was identified. The data were then rescaled to prevent discretisation error. The researcher was left with 550 valid responses from respondents to analyse.

The demographic profile of the respondents displays an equal number of male (50%) and female (50%) respondents. Most of the respondents (69.8%) fall into the age group 30-to-50 years old and belong to either the White (53.1%) or African (31.3%) ethnic groups.

The sample contained predominantly respondents who reside in Gauteng, South Africa (76.4%), who are well educated, with 49.8% having a postgraduate degree or higher. Most respondents (54.7%) earn more than R51,000 per month individually, which is well above the South African national average household threshold income of R50,582 in 2022 (Cowling, 2023b).

The cross-tabulations delivered several significant relationships. The respondents are familiar with e-commerce shopping, with 69% buying after spending approximately 120 minutes online monthly. Most respondents (67%) have been buying online for three to ten years, and one can conclude that most people are familiar with the process and experienced in online shopping.

The factor analysis produced five factors for the UTAUT2 model (Venkatesh et al., 2012), five factors for the UG construct and a BI and satisfaction factor. The multiple regression analysis produced a significant relationship between PE and BI, and FC and BI. BI and UG, as well as FC and UG, also tested significantly and had sizable coefficients of determination. A strong and positive correlation, with modest impact sizes for revenue and referral, was found by the correlation study between BI and the UG construct.

Satisfaction moderates the relationship between BI and the UG construct, particularly in the acquisition and referral phases. Satisfaction also moderates the relationship between FC and UG. Age, gender and experience did not moderate the relationship between BI and the UTAUT2 factors (Venkatesh et al., 2012).

It is evident from the results that PE and FC influence BI to buy on a B2C e-commerce platform. BI influences UG in B2C e-commerce platforms whilst being moderated by satisfaction, and the relationship strengthens with increased intensity from the activation to the referral phases.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

Chapter 4 presented the research study's results using descriptive statistics, an exploratory factor, a regression, correlation, and moderation analyses. Chapter 5 focuses on the interpretation and subsequent discussion of the results. Due to the study's exploratory nature, the focus will be on understanding the insights delivered by this study compared to the literature on the relevant constructs.

Figure 29 displays the revised conceptual framework with the five valid factors from the UTAUT2 model (Venkatesh et al., 2012) and the five valid factors from the UG construct. Both the significant and insignificant relationships are displayed between the independent and outcome variables and their respective moderators. The moderating effect of satisfaction between BI and UG, and FC and UG is also demonstrated.

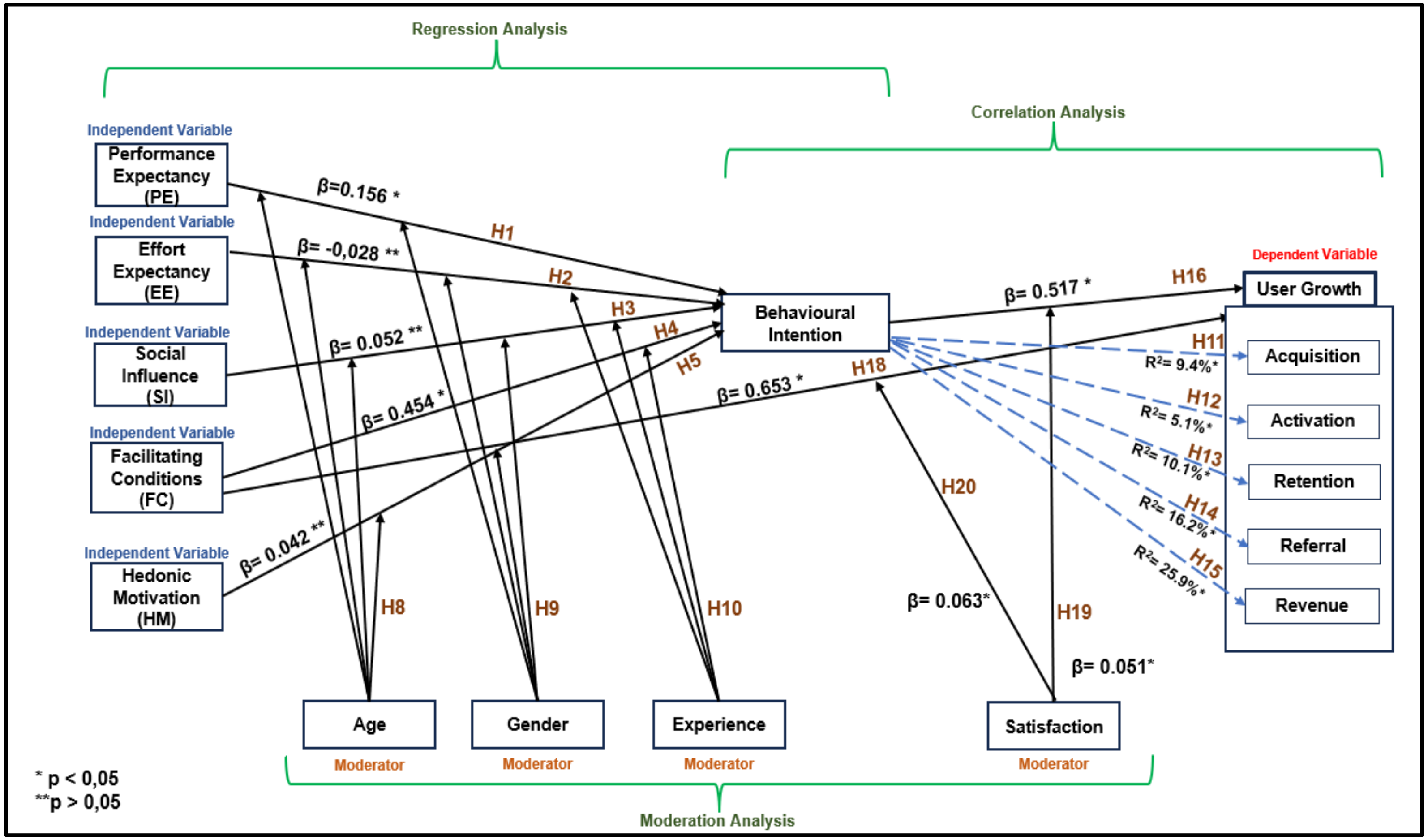
The first section of Chapter 5 reviews age, gender and experience (H_8, H_9, H_{10}) as moderators of the UTAUT2 model (Venkatesh et al., 2012). The second section reviews hypothesis statements one to seven regarding the relationship between the independent variables (factors) and BI as the dependent variable. The focus then shifts to the UG construct to analyse the association between BI and the UG factors (H_{11} to H_{18}). Lastly, the moderating effect of satisfaction between BI and the UG construct (H_{19}), and FC and the UG construct (H_{20}) is discussed.

5.2 Summary of Findings

Table 42 summarises the statistical results according to the data in Chapter 4. Eleven of the 20 hypothesis statements are accepted. The discussion in Chapter 5 focuses on the accepted hypothesis statements, with some comments on the rejected hypothesis statements and their implication for the study.

Table 42: Summary of Statistical Results

Hypothesis Statement	Accepted/ Rejected
H1: PE influences customers’ BI to use B2C e-commerce platforms	Accepted
H2: EE influences customers’ BI to use B2C e-commerce platforms	Rejected
H3: SI influences customers’ BI to use B2C e-commerce platforms	Rejected
H4: FC influence customers’ BI to use B2C e-commerce platforms	Accepted
H5: HM influences customers' BI to use B2C e-commerce platforms	Rejected
H6: Habit influences customers' BI to use B2C e-commerce platforms	Rejected
H7: PV influences customers' BI to use B2C e-commerce platforms	Rejected
H8: Age will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms	Rejected
H9: Gender will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms	Rejected
H10: Experience will moderate the effect of EE, SI and FC on customers’ BI to use B2C e-commerce platforms	Rejected
H11: Customers’ BI influences acquisition in becoming aware of B2C e-commerce platforms	Accepted
H12: Customers’ BI influences activation in the adoption of B2C e-commerce platforms	Accepted
H13: Customers’ BI influences retention in reusing B2C e-commerce platforms	Accepted
H14: Customers’ BI influences the referral to B2C e-commerce platforms	Accepted
H15: Customers’ BI is influenced by the revenue received (benefits) from reusing B2C e-commerce platforms	Accepted
H16: Customers’ BI influences user growth in B2C e-commerce platforms	Accepted
H17: Customers’ habits affect user growth in B2C e-commerce platforms	Rejected
H18: FC affects user growth in B2C e-commerce platforms	Accepted
H19: Customers’ BI to use B2C e-commerce platforms is moderated by satisfaction	Accepted
H20: The effect of FC on UG in B2C e-commerce platforms is moderated by satisfaction.	Accepted



Direct effect		**Direct effect: Measured Indicator Variable**	

Figure 29: Revised Conceptual Framework

5.3 Demographic profile of respondents

The following section will discuss the three UTAUT2 (Venkatesh et al., 2012) moderators, age, gender, and experience, which were tested as moderators between the UTAUT2 factors and BI.

5.3.1 Respondents age and gender

H_8: Age will moderate the effect of PE, EE, SI and FC on BI to use B2C e-commerce platforms – rejected.

H_9: Gender will moderate the effect of PE, EE, SI and FC on BI to use B2C e-commerce platforms – rejected.

In the original UTAUT2 model (Venkatesh et al., 2012), PE, EE, SI, FC, HM and habit are all moderated by different combinations of age and gender. In this study, age and gender tested insignificant, and it can be concluded that they did not moderate the relationship between BI and PE, BI and EE, BI and SI, and BI and FC. The non-moderating impacts of gender when individuals are genuine users with prior computer and internet knowledge demonstrate how gender discrepancies tend to vanish under discretionary settings and with greater expertise (Venkatesh et al., 2003).

The results of this study are consistent with a study in Spain that found that gender did not moderate the intention to use internet banking applications (Arenas Gaitán et al., 2015). Research on mobile apps for restaurants (Palau-Saumell et al., 2019) found that neither age nor gender moderated the intention to use or actual usage of the application. A study on mobile banking in Ghana found that the users' age does not affect intention to use, actual use, and sustained usage (Crabbe et al., 2009). This conflicts with M-payment services, which are more likely to be adopted by younger consumers than older consumers (Park et al., 2019). Age and gender will, therefore, not form part of any further discussions of this study.

5.3.2 Respondent experience

H_{10}: Experience will moderate the effect of EE, SI and FC on BI to use B2C e-commerce platforms - rejected.

Behavioural intention and use behaviour are influenced by one's technological experience and are demonstrated by the fact that novice and seasoned consumers approach electronic purchases differently. Asset specificity (the product under consideration) and uncertainty impact on inexperienced customers' decision-making processes, but only uncertainty does so for experienced consumers. The more experience the consumer has, the more the buyer becomes accustomed to the procedure (Liang & Huang, 1998).

Moderation effects of experience between FC and BI, and FC and use behaviour were significant for people with more than three years of experience in a study on the acceptance of mobile apps for restaurants (Palau-Saumell et al., 2019). However, although most respondents (> 70%) in this study have more than three years of online experience, experience had an insignificant moderating effect between FC and BI. It can, therefore, be summarised that most of the respondents (78%) in this study have sufficient experience (3+ years) to use e-commerce platforms since the results did not detect any shortages in expertise.

It can be concluded that experience did not moderate the relationship between EE, SI, and FC with BI. This result is consistent with "Use of Shopee E-commerce", where age, gender and experience did not moderate behavioural intention or use behaviour of the Shopee platform (Maulidina et al., 2020).

5.4 UTAUT2 model: Discussion of Results

An EFA was performed on the variables of the UTAUT2 model, and five factors emerged from the evaluation. After that, a regression analysis was performed between the UTAUT2 factors and BI (Venkatesh et al., 2012). The results have shown a significant relationship between PE and BI, and FC and BI. The UTAUT2 model (Venkatesh et al., 2012) applied in this study is statistically significant with $p < 0{,}001$. $R^2 = 0.298$ and indicates that 29.8% of the variance in BI to use an e-commerce platform is explained by the independent variables/factors (PE, EE, FC, HM, SI).

This result is consistent with a similar study conducted in two supermarket groups in Belgium, which reported $R^2 = 0.29$, demonstrating a variance of 29% in BI for potential adopters of e-grocery shopping (Van Droogenbroeck & Van Hove, 2021). The results are also supported by a study on the Elderly and Internet Banking, which concluded with a 38.6% variance in intention to use internet banking (Arenas Gaitán et al., 2015).

With all interaction items, the original UTAUT2 model (Venkatesh et al., 2012) explains 74% of the total variance in BI. However, if the interaction items are omitted, only 44% of the total variance in BI is explained (Venkatesh et al., 2012). The results of this study show that the data explain 65.123% of the total variance in BI. This result aligns with an Indian study on student's acceptance of e-commerce applications, which demonstrated that 63.3% of the total variance in BI could be explained by the data (Candra et al., 2023)

First Research Objective

To gain an improved understanding of the determinants that influence customers' behavioural intention to buy on B2C e-commerce platforms in the FMCG industry in South Africa.

Research Question 1

Which determinants influence a customer's behavioural Intention to use B2C e-commerce platforms in South Africa?

5.4.1 Hypothesis 1

H_1: PE influences customers' BI to use B2C e-commerce platforms - ***accepted.***

The regression coefficient of PE ($\beta = 0.156$; $p < 0{,}000$) correlates the second highest with BI after FC. This result illustrates that respondents find using an e-commerce platform useful, and it assists them in saving time and completing their shopping tasks quickly. These results are consistent with another South African study conducted in 2013, which showed that convenience, time-saving, and delivery options motivate online shopping (Rudansky-Kloppers, 2014).

PE explains 24.37% of the variance in the data, and for every positive unit change in PE there is a 15.6% change in BI. Consumers will start and continue to use technologies only if they are useful (Venkatesh et al., 2003). When technology is utilitarian, the user prioritises usefulness over ease of use, which explains why PE (PU) (β= 0.156) emerged as a stronger antecedent of BI than EE (β = -0,028) in this study. This result confirms the theoretical principles of UTAUT (Venkatesh et al., 2003) which reported that if a platform is really useful, consumers will accept it despite it not being easy to use (Ferreira Barbosa et al., 2022).

PE was identified as a strong indicator of BI in the following studies: E-grocery shopping (Human et al., 2020; Van Droogenbroeck & Van Hove, 2021), M-payment use intention (Tang et al., 2021), Adoption of Navigation apps by Travellers (Castanha et al., 2023), Mobile Banking (Samartha et al., 2022; Saxena et al., 2022), the Use of Fitness Centre apps (Ferreira Barbosa et al., 2022), Online shopping in Tanzania (Hungilo & Setyohadi, 2020), the use of Fintech payment solutions (Puspitaningsih & Jati, 2023).

5.4.2 Hypothesis 2

H_2: EE influences customers' BI to use B2C e-commerce platforms - ***rejected.***

EE explains only 8.45% of the variance in the data, with a low negative regression coefficient with BI (β = -0,028; p = 0,472). These results show that EE does not significantly influence BI to use a platform. Therefore, following the acceptance of H_1, a platform's usefulness in achieving a desired outcome is more important to respondents than a platform's ease of use or complexity. PE > EE.

The effect of EE declines over time as the customer becomes more accustomed to the platform's functionality. Table 13 displays the significant relationship between shopping experience and shopping frequency, reinforcing that the initial ease of use and complexity challenges have subsided for respondents with more than three years of online shopping experience (78%) (Venkatesh & Bala, 2008).

Previous studies where EE did not have a significant influence on BI: Factors influencing the use of Shopee (Maulidina et al., 2020), How long tail and trust affect online shopping behaviour (Singh & Matsui, 2017) and Understanding online banking adoption in a developing country (Khan et al., 2017).

5.4.3 Hypothesis 3

H_3: SI influences customers' BI to use B2C e-commerce platforms - *rejected.*

SI (β = 0,052; p = 0,163) explains 9.76% of the variance in the data. The relationship between SI and BI is insignificant, and respondents are not influenced by friends, family members or peers when they consider using or are using an e-commerce platform. They also do not recognise that their image is enhanced by using an e-commerce platform.

This finding is contradictory to other studies where SI has a significant influence on BI to use or to continue using a platform. For example, a study on the Use Intention of O2O e-commerce found that subjective norms and social structure significantly affected willingness to use (Zhu et al., 2022). An Indonesian study on the platform Shopee found that SI positively impacted behavioural intention to use Shopee (Setiyani et al., 2023). However, in a Malaysian study, SI did not affect user's M-payment usage (Tang et al., 2021), nor did SI impact the Adoption of Navigation apps by Travellers (Castanha et al., 2023) or the adoption of Mobile Banking (Saxena et al., 2022).

The impact of SI on the intention to use or actual use of technology could vary by country due to the individualistic or collectivist culture of the consumers. Collectivism is the preference for a close-knit social structure in which individuals put their trust in others to watch out for them and place their own interests below those of the group. On the other hand, individualism is the preference for a loosely structured social structure in which people are supposed to care for themselves and pursue their own interests (Pal et al., 2019). Collective mental programming differentiates members of one group or category from others, which is known as culture (Lee et al., 2007). South Africa tends to have a more collectivist than individualistic culture (Eaton & Louw, 2000). Still, due to the many cultures with which people identify in the country, there is a high level of diversity, and at the country level, it is difficult to classify the whole population as either individualistic or collectivist.

Another reason why SI did not test significantly in this study might be due to the respondents being in the living standards measure (LSM) 8 to 10 category (Ntloedibe & Ngqinani, 2020). They are more individualistic and more financially empowered with higher monthly incomes. These respondents were included at random due to the convenience sampling process.

5.4.4 Hypothesis 4

H_4: FC influence customers' BI to use B2C e-commerce platforms - ***accepted.***

The regression analysis delivered a coefficient of β = 0,454 and a significant relationship ($p < 0,000$) between FC and BI. FC, however, only accounts for 6.07% of the total variance in the data. The significant relationship between FC and BI demonstrates some fluctuation because every unit change in FC causes a 45.4% positive change in BI. Therefore, in this study, FC has the most significant impact on BI and reinforces the vital role of customer support and services in B2C e-commerce.

The availability of organisational support in the event of any system failures or technological difficulties gives a person a psychological sense of relief. In the context of e-commerce, FC relates to customer service and support being available during and after the online shopping process. FC also consists of sustainable services (access to electricity and Wi-Fi) readily available to conduct e-commerce activities supported by a regulatory environment. These conditions are currently under pressure in South Africa, and e-commerce is subjected to a high cost of use (Liew et al., 2014).

The factor analysis found that FC, PE and EE account for 38% of the variance in BI. This result contradicts the theoretical principles of UTAUT, which defined that if PE and EE are present in the model, FC becomes insignificant in relationship to BI (Venkatesh et al., 2003).

This result corresponds with a Malaysian study on Facebook adoption, where FC significantly impacted adoption (Liew et al., 2014) and Fitness Centre apps, where FC had a notable effect (Ferreira Barbosa et al., 2022). FC is not always dominant and has proved to have no impact on studies like the Adoption of Navigation apps and Internet Banking by the Elderly (Arenas Gaitán et al., 2015; Castanha et al., 2023) and the Behavioural Intentions of E-commerce Shopee Users (Setiyani et al., 2023).

5.4.5 Hypothesis 5

H_5: HM influences customers' BI to use B2C e-commerce platforms – ***rejected.***

HM explained 10.9% of the variance in the data, with a low regression coefficient of $\beta = 0{,}042$; $p = 0{,}256$. A possible explanation for HM being insignificant in this study is the respondents' level of experience, which plays down the effect of HM on technology use (Venkatesh et al., 2012).

The low correlation between HM and BI but the higher correlation between PE and BI indicates that HM in this study relates to utilitarian benefits provided by the platforms rather than hedonic benefits. Utilitarian benefits include flexible navigation and search options, convenience and detailed product information, all supporting task-orientated actions to perform online “work” in contrast to hedonic benefits that are playful and fun (Bridges & Florsheim, 2008).

People who use platforms for utilitarian benefits to complete their shopping tasks are also likely to spend less time online than those who use the internet for hedonic reasons like browsing. Half of the respondents (49%) in this study stated that they spend approximately 30 minutes online weekly to complete their shopping tasks. One can, therefore, conclude that e-commerce platforms in this study are used to satisfy utilitarian goals.

The results of this study align with findings on the Adoption of Navigation apps (Castanha et al., 2023), the Intentions of e-commerce Shopee users (Setiyani et al., 2023) and mobile shopping in older adults (Huang, 2023). However, Van Droogenbroek and Van Hove. (2021) found that a significant relationship between BI and HM is due to consumers who enjoy e-grocery shopping and are likelier to use the channel (Van Droogenbroeck & Van Hove, 2021). HM impacted positively on BI in previous studies, e.g. Mobile apps for Restaurants (Palau-Saumell et al., 2019) and E-grocery shopping in Mauritius (Human et al., 2020).

5.4.6 Hypothesis 6

H_6: Habit influences customers' BI to use B2C e-commerce platforms - ***rejected.***

Habit like PV did not emerge as a valid factor in the EFA. Respondents (62%) do not have a routine for purchasing their FMCG products online regularly. More than half (53%) of respondents also agreed that they have not yet established an online ordering habit.

The presence of habit functions in combination with the moderator experience. The respondents in this study have experience, with 78% stating that they have been shopping online for more than three years; however, with only 15% that shop online weekly, they lack habit. According to Limayem et al. 2007, habit is established through a minimum weekly repetition in a stable environment. A stable environment encourages habit formation by requiring a little of a person’s attention to respond to certain situations. Once the habit is formed, behaviour is automatic without conscious awareness. However, experienced users base their decisions to continue using technology on either usefulness (PE) or image perceptions (SI). In this study, PE was the dominant determinant (Limayem et al., 2007).

This result is consistent with the intention to use and actual usage of an LMS where habit also tested insignificantly (Ain et al., 2016). Habit also did not significantly impact the acceptance of online shopping in a study in Tanzania (Hungilo & Setyohadi, 2020). The result is, however, contradictory with similar studies utilising the UTAUT2 model (Venkatesh et al., 2012) which found that habit had a significant impact on the adoption of Navigation apps (Castanha et al., 2023), E-grocery apps (Human et al., 2020; Setiyani et al., 2023), Fitness Centre Apps (Ferreira Barbosa et al., 2022) and Internet Banking (Arenas Gaitán et al., 2015).

5.4.7 Hypothesis 7

H_7: PV influences customers' BI to use B2C e-commerce platforms - *rejected.*

PV explains 5.53% of the total variance in the data. Although e-commerce platforms are freely accessible, the consumer must bear the costs of a) obtaining an e-commerce application (downloading) and b) transacting on the application (accessibility to an internet connection).

With the PV not emerging as a factor in the EFA, the result shows that the respondents are not bothered by costs incurred, like data bundles, Wi-Fi connection, or delivery fees, when buying online in South Africa. This is surprising as South Africa has some of the highest data bundle fees in the world, the second highest in Africa after Namibia, and higher than the United Kingdom and Germany (Illidge, 2022). However, in analysing the respondent's socio-economic status, it is apparent that most of them fall into the LSM 8 to 10 groups and are financially empowered to afford the higher data bundle and internet connection costs (Ntloedibe & Ngqinani, 2020).

Most respondents (71%) also indicated that they prefer to order from organisations that provide free delivery, but 40% of respondents do not mind paying for the delivery themselves. This result is consistent with other studies like the Use of the Shopee e-commerce platform (Maulidina et al., 2020) that found the relationship between PV and BI insignificant in individual technology adoption contexts. However, it contradicts a Tanzanian study on the Acceptance of online shopping, where PV was found to have a significant impact (Hungilo & Setyohadi, 2020).

5.5 AARRR Construct: Discussion of Results

Second Research Objective

To investigate how customers' behavioural intentions influence user growth in B2C e-commerce platforms in the South African FMCG industry.

Research Question 2

To what extent do customers' behavioural intentions influence user growth in B2C e-commerce platforms in South Africa?

All the variables in the UG construct (acquisition, activation, retention, revenue, and referral) (McClure, 2007) emerged as valid factors in the EFA, and the relationship between BI and UG tested significant $\beta = 0.517$; $p = 0{,}000$. It is critical to understand to what extent the individual variables in the UG construct contribute to the model's significance.

The increased effect of BI on each UG variable as the customer transitions from the pre-purchase to the purchase and post-purchase phases is visible in the R^2 value. The value increases from 5.1% during activation to 10.1% during retention, 16.2% during referral and 25.9% in the revenue stage. This result proves that BI is growing stronger as the relationship between the retailer and the customer strengthens.

5.5.1 Hypothesis 11

H_{11}: Customers' BI influences acquisition in becoming aware of B2C e-commerce platforms - *accepted.*

Acquisition explains 7.5% of the total variance in UG. BI is responsible for $R^2 = 0.094$ (9.4%) of the variability in acquisition, and there is a weak but significant ($p < 0{,}000$) correlation between BI and acquisition with $r = .308$ ($R^2 = 9.4\%$).

Acquisition has a solid connection to browsing a platform since it measures page visits, click-throughs and bounce rates (McClure, 2007). Most respondents agreed that they had visited some websites and applications and browsed through the available products. The weak correlation between BI and acquisition could be attributed to awareness and brand loyalty. The consumers have just become aware of the platform and have not yet adopted it; they are also not loyal to the brand yet; therefore, the BI to use a platform at this point is reasonably low (Lai, 2022). Since satisfaction moderates BI and acquisition at this point, the retailer could undoubtedly lose some trialists of the platform if they are unsatisfied with their experience.

Retailers can improve awareness by defining the consumer target market they want to attract to use their platform. Secondly, identify the appropriate channels (web, social media, TV, radio, events) to attract consumers. Thirdly, design targeted marketing activities by channel to reach the target market and draw them to the platform to browse and review the products. Lastly, improve the look and feel of the landing page by ensuring it is interactive, informative and reactive for an optimal consumer experience (Zhang, 2021).

5.5.2 Hypothesis 12

H_{12}: Customers' BI influences activation in the adoption of B2C e-commerce platforms - *accepted.*

Once a customer is aware of a platform, the retailer (seller) foresees them converting to using the platform by registering and placing an order. Activation accounts for 7.6% of the total variance in the UG construct. The correlation between BI and activation is $r = .266$ ($R^2 = 5.1\%$; $p < 0{,}000$), signifying a weak but significant correlation, which could be attributed to the fact that the customer is still transitioning from the acquisition stage to considering the adoption of the platform and has not yet converted to using the platform. The user must still become activated by registering to use the platform or signing up for a newsletter.

The respondents in this study agreed that successful activation depends on a satisfactory online experience that includes easy online registration and navigation and seamless order placements. Once the user is “activated”, the retailer can attach a name to their digital identity and tailor marketing activities to a specific person. Before that, the user remains anonymous in the acquisition stage and is of little value to the retailer until the conversion occurs. Activation depends on successful acquisition efforts, as described in section 5.5.1 above (McClure, 2007).

5.5.3 Hypothesis 13

H_{13}: Customers’ BI influences retention in reusing B2C e-commerce platforms - *accepted.*

User retention rate can be defined as the percentage of users who continue to use the application after a fixed amount of time, divided by the total number of new users within a given data period. It is also when an existing product user returns after a period to purchase another product from the same retailer (Zhang, 2021).

Retention is the essential factor in the AARRR model, and it is demonstrated by accounting for 18.6% of the total variance in the UG construct. Retention is the most important element in achieving UG (Zhang, 2021). The significant relationship with BI ($p < 0{,}000$) also became slightly stronger in moving from activation ($R^2 = 0.226$) 5.1% to retention ($R^2 = 0.318$) 10.1%, demonstrating the customer's increased willingness to convert to using the platform. The dominance of retention can be attributed to a) the significant relationship between time spent online shopping and the number of apps/websites utilised and b) the significant relationship between shopping frequency and shopping experience (length of usage) that indicates the intensity of consumption and a higher intention to reuse applications (Venkatesh & Davis, 2000). Refer to section 4.3.4.

Building a successful business requires existing customers to return to the platform to buy products. Registered customers must, therefore, adopt a platform and continuously return to use the platform (Kumar & Ayodeji, 2021). Retailers should maintain interaction with users by building a steady relationship with them since it is more cost-effective than recruiting new users. Customer lifetime value

(CLV) > Customer Acquisition costs (CAC). CLV is the entire net income a business might anticipate from a customer during their lifetime (Rosset et al., 2002). Research by Frederick Reichheld showed that profits could increase by 25% to 95% by increasing customer retention by 5% (Gallo, 2014).

Retailers can perform several activities to monitor and drive retention (Lai, 2022):

a) Measurement of churn rate

Customer churn rate is a metric that gauges the proportion of customers who part ways with a business during a specific time frame (Gallo, 2014). Retailers should frequently determine their customer churn rate to ensure that they keep abreast of changes (customers quitting or dropping off the platform) and can implement measures sooner rather than later to slow down churn. Retailers must act fast, with more interaction and higher discounts, to recover lost customers.

b) Lengthen customer life cycle duration when reaching retention.

Increase the frequency of use to decrease user churn and promote long-term user retention.

c) Apply the Recency Frequency Monetary (RFM) model to customer purchase data.

This model explains that three datasets should be evaluated at this point (Lai, 2022):

a) Recency – most recent purchase data.
b) Frequency – frequency of purchases.
c) Monetary – value of purchases.

Combining the RFM data with the customer's online buying frequencies could bring valuable insights to enable the retailer to set up strategies to drive UG. For example, some customers might have a low buying frequency but high value, extend coupons to them to attract them back to the platform to purchase again. Others might have a high purchase frequency but with small basket sizes. Approach them to increase their basket size with value bundle offerings (3-for-2 promotions) (Lai, 2022). Please refer to section 6.4 for further recommendations.

5.5.4 Hypothesis 14

H_{14}: Customers' BI influences the referral to B2C e-commerce platforms - *accepted*.

"User referrals" is a strategy for gaining new users by leveraging the social impact of current users (Zhang, 2021). Most respondents answered each of the three questions in the referral construct positively. Referral accounts for 8.5% of the total variance in the UG construct. A moderate effect size is present with r =.403, R^2 = 0.162; p < 0,000, reflecting that BI causes 16.2% of the variability in referral.

The long-term sustainability of a platform relies on the continuous growth of user numbers. Retailers must implement referral strategies that incentivise the referrer and referee to ensure that existing satisfied customers refer their friends, family, and peers to the platform. Acquaintance referrals are often more believable than advertisements, and powerful referral strategies could lead to exponential UG (Zhang, 2021).

The interaction effect between BI and referral with satisfaction as a moderator is significant (p = 0,001). This result clarifies that customers will only refer to a platform if they are satisfied with the customer service and the products delivered.

5.5.5 Hypothesis 15

H_{15}: Customers' BI is influenced by the revenue received (benefits) from reusing B2C e-commerce platforms - ***accepted.***

The initial AARRR model calculates a platform's revenue depending on the number of people who utilise it (McClure, 2007). Due to the different approach of this study, revenue is measured from a customer's perspective and how they can extract value from the relationship (Prahalad & Ramaswamy, 2004).

Revenue accounts for 7.3% of the variance in UG. The moderate interaction effect is represented by r =.509, R^2 = 0.259; p < 0,000, reflecting that BI causes 25.9% of the variability in revenue. The higher R^2 value than in previous stages confirms the importance of the customer's intent to become co-creators of value and recipients of value offerings during the purchase process. The value offerings can be presented in various forms through gamification in loyalty programmes, ecological elements, such as sustainability training or particular activities aimed at lessening the environmental impact, and social elements, like tailored messages and offerings or personal invitations to special events (Dreher & Ströbel, 2023).

The strong emergence of revenue indicates that the prospective benefits a customer would receive from using a platform are a deciding matter in selecting a platform. Retailers must understand that customers use a platform to achieve a particular outcome (i.e., complete grocery shopping), and strategies should be designed with incentives that reward consumers for not only using but also the repeated usage of a platform.

It can, therefore, be concluded that BI to use a particular platform is more compelling if the revenue received by the customer is significant compared to similar platforms. The emergence of this trend strongly relates to co-creation value (CV), where the organisation and the consumer partner through platforms to create value (Zhu et al., 2022).

5.5.6 Hypothesis 16

H_{16}: Customers' BI influences UG on B2C e-commerce platforms - *accepted.*

BI emerged as a single factor after factor extraction, accounting for 76.8% of the total variance in the data. The relationship between BI and UG is significant, $p < 0,001$. BI and UG have a moderate correlation ($r = 0.517$) and $R^2 = 0.267$. BI is responsible for 26.7% of positive change in UG. This result reconfirms that UG is synonymous with “Use Behaviour” from the original UTAUT2 model (Venkatesh et al., 2012).

This result compares very well with the original UTAUT2 model, of which the direct effect model explains 35% of use behaviour (Venkatesh et al., 2012). The results are also comparable with a Malaysian study, which reported ($R^2 = 0.295$)

29.5% of the variance in the intention to use an LMS system (Raman & Don, 2013). An Indonesian study on the Intentions to Use the Shopee platform recorded that FC, Habit and BI explain 41.3% of use behaviour on the platform (Maulidina et al., 2020).

System use can be categorised by its duration, intensity and frequency of use (Venkatesh et al., 2003). This study has shown the significance between online shopping experience and shopping frequency ($p < 0,000$). However, although 78% of respondents have more than three years of shopping experience, most respondents (68%) spend less than 45 minutes per week online and only 15% shop weekly. UG is, therefore, negatively influenced due to the low frequency and intensity of use.

Users with more shopping experience (> 3 years in this study) have a stronger intensity to buy, which is confirmed by the strong emergence of BI. This finding aligns with a survey of the Greek online market (Giannakos et al., 2011) and consumers' repurchase intent on B2C e-commerce platforms (Cody-Allen & Kishore, 2006). With the absence of habit in this study, BI emerges as the strongest antecedent of use (Maulidina et al., 2020).

5.5.7 Hypothesis 17

H_{17}: Customers' habit affects UG in B2C e-commerce platforms - *rejected.*

Habit did not emerge as a factor during the EFA, and this hypothesis statement is rejected. This result aligns with the adoption of online banking in a developing country where habit also did not test significantly (Khan et al., 2017).

5.5.8 Hypothesis 18

H_{18}: FC affects UG in B2C e-commerce platforms - *accepted.*

The relationship between FC and UG is significant ($p < 0,001$). The regression coefficient is $\beta = 0.653$, showing a 65.3% positive change in UG for every unit change in FC. The $R^2 = 0.427$, which explains 42.7% of the variability in UG. The linear positive relationship between FC and UG shows that UG would be directly impacted if customer service and support levels decline or increase.

This result is directly comparable with research on the factors of consumers' purchase behaviour of the Pinduoduo e-commerce platform. This study recorded a regression coefficient of $\beta = 0.595$ and $R^2 = 0.389$, which explains 38.9% of the variability between FC and the purchase behaviours on the Pindoudou e-commerce platform (Zhang & Yang, 2019). This result reinforces that when consumers have access to customer support and services, it plays a significant role in their platform usage (Venkatesh et al., 2012).

The impact of FC on actual use is significant in research on Mobile apps for Restaurants (Palau-Saumell et al., 2019), the Acceptance of an LMS (Raman & Don, 2013) and Online Banking adoption (Khan et al., 2017). However, it is insignificant in the Adoption of Internet Banking by the Elderly (Arenas Gaitán et al., 2015).

5.6 Satisfaction Construct: Discussion of Results

Third Research Objective

To understand the effect of customer satisfaction on user growth in B2C e-commerce platforms in the South African FMCG industry.

Research Question 3

To what extent does satisfaction affect behavioural intention to use B2C e-commerce platforms in South Africa?

Satisfaction can be described as the process when a person compares a product's actual performance or results to the anticipated performance or results; they may feel satisfied or disappointed. Satisfaction is experienced as a result of the upfront expectations about a product or service that have been met (Ratih et al., 2021). To build lasting relationships with customers, customer satisfaction is crucial. Research indicates that satisfied customers exhibit favourable purchasing intentions, including repeat purchases, positive word-of-mouth, and long-term loyalty (Rudansky-Kloppers, 2014).

5.6.1 Hypotheses 19 and 20

H_{19}: Customers' BI to use B2C e-commerce platforms is moderated by satisfaction – ***accepted.***

H_{20}: The effect of FC on UG in B2C e-commerce platforms is moderated by satisfaction - ***accepted.***

Satisfaction was extracted as a single factor and explained 69.8% of the variance in the data. Satisfaction was tested as a moderating variable between BI and the UG construct, BI and each UG variable, and FC and UG construct. Satisfaction moderates the relationship between BI and UG with $\beta = 0{,}0624$, $t\ (1{,}546) = 2{,}5649$, $p < 0{,}000$ and accounts for 38.71% of the variance in UG, meaning that a satisfied customer has a 38.71% chance of increasing usage of a platform, i.e. becoming a regular user of an e-commerce platform.

The relationship between FC and UG is also moderated by satisfaction $\beta = 0{,}0633$, $t\ (1{,}546) = 2{,}2414$, $p < 0{,}000$, and satisfaction accounts for 42.56% of the variability in UG. Due to this high level of variability, a customer who is satisfied with the service levels of a retailer has a 42.56% chance of becoming a regular user (displaying UG on a platform); however, a dissatisfied customer has a 42.56% chance of terminating its relationship with the retailer. Retailers must ensure that they keep customers satisfied by maintaining customer service reliability and continuously improving products and after-sales services to enhance customer loyalty and market share growth (Zhang & Yang, 2019).

Satisfaction also moderates the relationship between BI and acquisition $\beta = 0{,}1028$, $t\ (1{,}546) = 2{,}2849$, $p < 0{,}000$. Firstly, this result confirms the importance of the initial point of customer interaction, the web design. A visually appealing and well-informational website draws users in and sparks positive satisfaction (Cody-Allen & Kishore, 2006). Secondly, newly acquired customers are likely to provide feedback on their satisfactory/dissatisfactory experiences, and retailers should ensure that they are happy with the platform to facilitate positive feedback (Van Wangenheim & Bayón, 2007).

The relationship between BI and referral is also moderated by satisfaction $\beta = 0{,}1678$, $t\ (1{,}546) = 3{,}2956$, $p < 0{,}000$. Referral in this context closely relates to Word-of-Mouth (WOM) advertising (Stokes, 2018), which has a positive relationship with satisfaction and shows that when satisfaction is high, customers are more likely to tell others about how happy or relieved they are about their recent purchases (Van Wangenheim & Bayón, 2007).

Other factors also affect satisfaction, like information quality and system quality of online retail websites that encourage repurchase decisions (Kumar & Ayodeji, 2021). Information quality is linked to PE, and system quality is related to EE. With PE being a significant predictor of BI in this study and EE being insignificant, it is evident that the respondents' satisfaction is influenced by the website/app's accurate, timely and well-organised information rather than the physical structure or usability of the system (Cody-Allen & Kishore, 2006).

The satisfaction gained from previous online shopping experiences positively influences repurchase intention. It is reconfirmed in this study that satisfaction moderates the relationship between BI and UG for the respondents who had three years or more experience (Giannakos et al., 2011). Managers must pay close attention to all the elements that impact customer satisfaction, which is crucial to customer retention. From the results that were discussed, it is evident that BI to use an application has a positive relationship with satisfaction (Ferreira Barbosa et al., 2022).

5.7 Conclusion

Chapter 5 presented the results by hypothesis statement and provided an in-depth review of each finding. The results show that FC and PE have a significant influence on BI. However, EE, HM and SI do not significantly influence BI to use an e-commerce platform. The fact that PV and habit did not emerge as factors brings interesting insights to the study. Habit is a major antecedent of BI to use and actual use of an e-commerce platform. In the absence of habit, consumers have not yet established routines to regularly purchase online, which will impact continuance intention over the long term. The omittance of PV shows that consumers are not price sensitive to the costs of using a platform.

Satisfaction influences the intention to shop and actual online shopping, especially in a platform's acquisition and referral phases. Consumers’ intention to purchase is influenced by the accurate and complete information on a website/app, and they would only refer to the platform if they are satisfied with their experience. Satisfaction also moderates the relationship between FC and UG, which highlights that UG could fluctuate depending on the customers’ level of satisfaction.

Retention is the strongest predictor of UG and is responsible for 18.6% of the variability in the model. The correlation between BI and UG strengthens with the transition from retention to referral to revenue. The relationship between BI and UG peaks in the revenue phase, displaying that a consumer’s intention to use a website or application is the strongest when they receive something in return for their effort, demonstrating the principles of co-creation value between retailers and consumers (Prahalad & Ramaswamy, 2004).

UG in B2C e-commerce platforms can be achieved when customers are satisfied with a retailer's products and services, which strengthens the customers’ behavioural intention to make first-time and subsequent purchases from the retailer’s platform. As time lapses, the behavioural intention becomes stronger, and the customers become retained on the platform, after which they will refer to the platform and receive rewards for continuously purchasing. Should the retailers' service and support decline, the customers' behavioural intentions will weaken, and so will their usage of the platform/purchases from the platform.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter presents the conclusions by research question following the analyses and discussions from the previous chapter. A final summary concludes the outcome of the research project, followed by recommendations for practice and an outline of the managerial implications of the study. In closing, the study's contributions are discussed, and suggestions for future research are provided.

6.2 Summary of Results

The study set out to address the main research problem: to investigate the factors that drive behavioural intention that results in system use and generate UG in B2C e-commerce platforms in the FMCG industry in South Africa.

A quantitative research approach was followed through a survey research method by applying a non-probability convenience sampling process. The researcher collected N = 743 respondents, of which 624 were valid respondents. After a data cleansing and rescaling process, there were 550 respondents left to proceed with the analysis. The analyses included a factor, regression, correlation and mediation analysis.

The study results have shown that PE and FC significantly influence the BI to use an e-commerce platform. In return, BI significantly influences UG, and the significance was found throughout all UG factors. The relationship between BI and UG strengthens as the customer transitions from activation to retention to referral and the revenue phases of the UG construct.

Satisfaction was found to have a significant moderating effect between BI and UG, as well as between FC and UG. The BI to use a platform strengthens if a customer is satisfied with the platform. It is evident that customers who are satisfied with the customer service and support of a retailer will increase their usage of a platform, leading to UG in B2C e-commerce platforms. However, if insufficient customer service and support are provided, the customers will be dissatisfied, and UG will decline.

EE, SI, HM and PV had an insignificant effect on BI. This result demonstrates that the customers have experience using platforms for utilitarian purposes, and the PU of a platform is more important than the PEOU of a platform. The opinions of others do not influence customers as they have already entered the adoption phase of using platforms, and they are also not bothered by the costs involved in using a platform. Habit did not emerge as a valid factor and demonstrates that customers do not consider ordering their products on B2C e-commerce platforms as a necessity (Hwang & Mulyana, 2022). Gender, age and experience did not moderate the relationship between the UTAUT2 factors (Venkatesh et al., 2012) and BI.

6.3 Conclusions

The study's research objectives were:

i) To gain an improved understanding of the determinants that influence customers' behavioural intention to buy on B2C e-commerce platforms in the FMCG industry in South Africa.

   Status: Achieved

ii) To investigate how customers' behavioural intentions influence user growth in B2C e-commerce platforms in the South African FMCG industry.

   Status: Achieved

iii) To understand the effect of customer satisfaction on user growth in B2C e-commerce platforms in the South African FMCG industry.

   Status: Achieved

The three research objectives are associated with each other and significantly influence UG in B2C e-commerce platforms in the FMCG industry in South Africa. FC and PE are the determinants influencing the intention to use a platform. The usefulness of a platform and the presence of customer support determine the strength of the intention to consider using the platform. The determinants of UG are acquisition, activation, retention, referral and revenue, and BI has a significant impact on these factors in the following manner:

a) BI influences acquisition by becoming aware of a platform as advertised on TV and through the dissemination of advertising campaigns on web links. The customer then starts browsing the platform and considers its benefits.
a) Activation is triggered by establishing a sense of identity between the retailer and the customer, with the customer evaluating the ease of online browsing and registration. The customer intends to become a platform user by submitting personal information to the platform.
b) Retention is accomplished through the intention to adopt a platform. The customer places an order with the expectation that the order will be delivered with the correct quantities and in his preferred timeslot, which stimulates more purchases and increases the repurchase rate and retention of the platform.
c) Referral to the platform by existing customers takes place when a satisfactory experience with the platform influences their intention to share a testimony of their encounter with the platform. A successful referral program leads to explosive UG. Viral spread can be attributed to the products being offered at low prices and the ability of existing users to invite new users, giving them access to free cashouts and goods.
d) Revenue realisation occurs if customer expectations are met while not compromising customer experience. The intention to purchase will strengthen if the retailer has successfully co-created value on the platform through rewards and loyalty incentives.

With PE testing significantly and EE insignificantly, the respondents are still in the adoption phase of the platforms (Kim et al., 2005). One can assume that they have entered the retention phase due to the insignificance of SI, which causes perceptions and views of others to have a minor impact on the retention phase of a platform. In this phase, the customer has gained experience using the platform and would, to a lesser extent, listen to others and their perceptions of using the platform (Venkatesh & Davis, 2000).

Therefore, the assumption can be made that the initial non-users of platforms in this study have responded to triggers and transitioned from the non-adopter to the adopter stage of platforms (Van Droogenbroeck & Van Hove, 2021). However, since habit does not play a big role in the adoption phase of technology (Limayem et al., 2007), it is evident that respondents in this study have experience with online shopping but have not formed habits to use the platforms regularly. This might be because online shopping has not yet become a necessity in their daily lives due to the high availability and easy accessibility of FMCG retail outlets in South Africa. With over 81,000 FMCG retail outlets in townships and major metropolitan areas in South Africa, customers have a broad range of retailers to shop from in-store (Schwabe, 2023).

Habits are established by repeating the same actions over and over again until they are ingrained in the human brain’s circuitry (Gaines, 2021). Buying groceries is a routine and habitual activity due to the frequency of the action, and by establishing habits through routines, weekly order placement should become automatic (Limayem et al., 2007). With 71% of respondents buying monthly and 15% buying weekly from B2C e-commerce platforms in the FMCG industry, the frequency and intensity of the respondents’ buying patterns are insufficient to establish habits. This finding will have implications for retailers over the long term since intention strengthens over time as habits are formed (Limayem et al., 2007).

The importance of customer satisfaction resurfaced in this research, and retailers should always be cognisant that a consumer's level of satisfaction is determined by comparing their post-purchase experience with their purchasing experience and their perceived expectations (Kim et al., 2009). Customer satisfaction will influence the intention to become a frequent platform user by evaluating how the purchase process was executed and the level of customer service and support received.

In conclusion, UG or system use is the most dependent variable in the IS literature (Limayem et al., 2007) and is achieved by retaining satisfied customers on IS. IS success is a direct result of system use. "IS continuance behaviour" or retention describes a stage of usage where IS use goes beyond conscious behaviour and integrates into daily routine activities. IS continuance behaviour is strengthened by satisfaction, reinforcing the intention to continue using a system/technology (Limayem et al., 2007).

6.3.1 Research Question 1

Which determinants influence a customer's behavioural Intention to use B2C e-commerce platforms in South Africa?

FC and PE are the two most dominant determinants influencing customers' behavioural intentions to use B2C e-commerce platforms in South Africa. Customers are more concerned about a platform's usefulness than its ease of use. This result is demonstrated with PE testing significantly and EE insignificantly, and it is evident that customers use their preferred platforms for practical purposes, like completing shopping tasks, rather than hedonic purposes like browsing. This result aligns with the literature review and reinforces the research by Koufaris (2002) that an e-commerce platform is adopted for its valuable activities rather than its effortlessness. It also supports earlier research that found that PU is a more dominant driver than PEUO and plays a vital role in system use intention (Venkatesh & Davis, 2000).

The absence of habit emerging as a significant factor in this study shows that the usage of B2C e-commerce platforms by the respondents in this study is still in an early introductory phase of adoption in the customer life cycle, and not enough time has elapsed to establish habits (Limayem & Hirt, 2003). The result is reinforced by PE and FC emerging as significant factors ahead of EE, reconfirming that customers are in the adoption phase of platforms and FC is predictive of intention (Venkatesh et al., 2012).

The fact that the respondents have not established habits yet is not necessarily negative because they are more susceptible to information and trying out alternative platforms without habits. Therefore, retailers must continue to improve their platforms and the rewards programmes offered at this point in the life cycle to ensure that the customers remain satisfied. Rewards stimulate habit formation (Gaines, 2021), and respondents in this study might not have formed habits due to insufficient rewards being offered for their loyalty and online purchases.

Once habits are established, customers will pay less attention to alternative platforms, and online retail sales and retention will increase on their preferred platforms (Khalifa & Liu, 2007). Retention can be achieved through repeated purchases, and if the customer is satisfied, habit is established automatically. Prior experience is a key facilitator of habit formation, and good experiences when performing specific actions are essential for developing habits since they make people more likely to repeat the same thing (Limayem et al., 2007).

The significant relationship between shopping frequency and shopping experience also influences the BI to use B2C e-commerce platforms (Venkatesh et al., 2003). This result works in concert with the positive relationship between BI and UG since having satisfied customers will create an environment where users will continue to use platforms (Cheung et al., 2015). The principles of the ECT model (Bhattacherjee, 2001) will serve here since IS continuance is determined by satisfaction and the perceived usefulness (PE) of a platform (Cheung et al., 2015).

6.3.2 Research Question 2

To what extent do customers' behavioural intentions influence user growth in B2C e-commerce platforms in South Africa?

BI significantly influences UG through all UG factors (acquisition, activation, retention, referral and revenue), and the relationship intensifies as the customer transitions through the phases of the customer journey. For every unit change in BI, there is a 51.7% positive change in UG. The opposite is also true; should BI weaken, then the strength of the association with the UG construct will decline.

BI influences acquisition through awareness and consideration of the activities that trigger a customer's attention or actions that a customer would perform in exploring a platform. Activation is the first step in converting to use a platform. BI is slightly less during this stage because the consumer must submit personal information to become activated. However, the intention to adopt the platform is successful once the customer has completed their first “happy visit” on the platform (McClure, 2007).

BI strengthens as the customer uses the platform, and with continued use, the customer becomes retained on the platform. If the customer is satisfied with the platform's usability and services, they will intend to refer to the platform. BI heightens in the revenue phase (presence of the strongest correlation $R^2 = 0.259$) since the value exchange and extraction between the retailer and customer reaches a pinnacle. If the customer is satisfied with value co-creation, he will return to the platform to continue using and receiving benefits from the platform. The full AARRR model, from user acquisition to user referral, represents a closed loop of the whole customer life cycle (Zhang, 2021).

Retention accounting for most of the variance in the data confirms that retention is the strongest predictor of UG. Retention or IS continuation relies on the user's happiness with the application. At this point, user satisfaction with an IS tends to increase their intention to use the system. The more useful an application is, the better it meets user expectations, leaving users more satisfied (Limayem et al., 2007).

6.3.3 Research Question 3

To what extent does satisfaction affect behavioural intention to use B2C e-commerce platforms in South Africa?

Satisfaction affects the BI to use an e-commerce platform by moderating the relationship between BI and UG, BI and acquisition, BI and referral, and FC and UG. The definition of satisfaction in the context of e-commerce is an affective state that reflects the consumer's emotional response to the entire transactional experience with a platform (Mofokeng, 2021). BI will likely decline/increase with varying satisfaction levels throughout the purchase process. If satisfaction strengthens, it will lead to UG in B2C e-commerce platforms. If satisfaction weakens, fewer consumers will acquire a platform, and existing users will extend fewer referrals to the platform. The dissatisfaction in the post-purchase phase could harm the continuance intention of B2C e-commerce platforms (Bhattacherjee, 2001).

In the pre-purchase (acquisition) phase, 85% of respondents confirmed they had visited and browsed websites and reviewed the products. Platforms that significantly and favourably offer superior products and quality information that is accurate, relevant and complete affect customer satisfaction and loyalty whilst promoting repurchase intention (Miao et al., 2022).

In the post-purchase phase, the customer judges and evaluates all the combined experiences with a retailer concerning their products, processes and after-sales services to determine whether their expectations are met. Expectations are formed based on past buying experiences, friends' and peers' advice and competitor information. Expectations are also developed based on total customer value, which is the difference between the total customer cost vs the value delivered. If the customer is satisfied that his expectations have been met and that customer value has materialised, they will refer to a platform. It is essential to understand customer value as it is a driver of satisfaction (Chi Lin, 2003) and an antecedent of repurchase intention (Miao et al., 2022).

Customer value presented itself through revenue in the UG construct. Since the benefits a customer obtains from a platform could fluctuate, this fluctuation could leave customers satisfied/dissatisfied depending on whether their expectations were met. Customer satisfaction must increase if customers are viewed as active players in co-creating value. As customers’ participation rises, their motivation and commitment to the co-creation process increases. They can recognise a higher quality of service because of their participation. This element has a direct impact on satisfaction. A customised product or service to meet the customer's needs will result in higher customer satisfaction (Vega-Vazquez et al., 2013).

BI also influences UG in other vital areas dependent on customers' satisfaction with the customer experience. The customer experience is the customers' internal and subjective reaction to their direct or indirect interactions with a retailer (Ratih et al., 2021). The other areas include product variety, information quality, perceived security and user experience in the acquisition and activation phases. Promotions, pricing, flexible order fulfilment, and timely delivery options of the exact order (order accuracy) are in the retention phase. Service quality, brand image, and trust are important in the revenue or referral phases (Rudansky-Kloppers, 2014).

There is a growing consensus that in both traditional and e-retailing, customer satisfaction is not only a critical performance outcome and a driving force behind customers' ongoing behaviour but also a significant predictor of customer loyalty and the key to the longevity and success of an e-retailer (Mofokeng, 2021).

6.4 Recommendations for Practice

Retailers can track their customers along the customer life cycle by adopting a data-driven orientation combined with big data analytics from digital platforms like Amplitude, Google Analytics or Sendgrid (Bargoni et al., 2024). To ensure that BI is strengthened, the retailer should use data-driven insights to design targeted marketing activities for each phase of the purchase life cycle (McClure, 2007; Qianling & Lan, 2016; WoshipM, 2018):

A. Acquisition

The retailer should generate leads from open-interface social networking sites to lead prospective customers to their home pages. Traffic could also be driven to a retailer’s platform by using opinion leaders to recommend the retailer’s platform and influence trail on the platform. Ensure that search engine optimisation (SEO) (McGaw, 2015) is optimised so that the platform name appears in searches on the most popular search engines.

The acquisition of a platform can also be spurred on by implementing short-term tactical promotions, like limited-time product offers or free delivery on all purchases. Or increase exposure to the website/application through cooperative advertising with major brands. During the acquisition phase, ensure that the website copy is improved by including YouTube videos.

B. Activation

The availability of user data plays an essential role during the activation phase, and browsing history should be used to identify searched products or pages to enable the retailer to send the user a promotion on some of these items. Also, ensure that the channel (e.g. Facebook, Instagram, X) through which the users became "activated" is recorded, then reuse that channel to attract similar users.

To build engagement on the platform, implement pop-up chatbots or flash messages to guide the user through the activation process to promote registration. Then, incentivise users to register on the platform with a promotional code or a free product. After the user is registered, use the user's details, like age and occupation, gathered through the registration process to design a targeted strategy for their persona.

C. Retention

Identify which customers have quit the platform and their last point of interaction. Contact them again through email or a messaging service, reminding them of the previous product they viewed on the platform. If the customers don't respond to this prompt, determine the "loss interval" of customers, i.e. the period in which the losers have not interacted with the platform – a day, a week or a month. Design targeted strategies to trigger engagement with each group of customers. Finally, adopt a customer recall mechanism by sending the customers reminders to return to the platform.

D. Referral

Provide loyal customers with referral codes to share with friends to register on the platform. Reward the loyal customer with a discount voucher once their referrals register. This method attracts new customers and rewards existing customers' brand loyalty. Next, implement the K-coefficient as a regular metric.

K = *the number of invitations each customer sends to friends* X *the conversion rate of people who receive invitations to invite new users* (WoshipM, 2018).

If K > 1, the customer base will continue to increase; if K < 1, the customer base will gradually stop growing.

Lastly, add a “review” section on the platform with positive statements from influencers promoting selected products. Give the influencers promotional codes to use in their posts, and track how many referrals buy through submitting the promotional codes.

E. Revenue

Introduce a loyalty points system and reward customers with points as they buy. Once the loyalty system is successful, introduce tiering to reward different levels of retention (1 x week buyer, 1 x month buyer, etc.). Run promotions by applying pricing strategies according to the tiering of the customer groups or apply for discount pricing promotions with VIP user-only access. Continue personalising the relationship between the retailer and the buyer (customer). Recognise key life events with the customer, i.e. birthdays. Celebrate with the customer by extending a unique voucher.

Convenient conditions also have a beneficial impact on users' intention to use a product continuously. Numerous studies have revealed that consumers' intentions to purchase are highly influenced by perceived benefits like cost or time-saving returns from platforms (Zhu et al., 2022).

Customers must be kept satisfied with the customer experience and benefits received as satisfaction will either directly or indirectly have a favourable impact on their intention to make repeat purchases in the future (Kumar & Ayodeji, 2021). Continuously improving customer experience is crucial to raising the likelihood that customers will purchase again, become retained on a platform and drive UG on platforms. Establishing and preserving a loyal base of long-term customers depends on customer happiness (Yan et al., 2022).

6.5 Managerial Implications

The study's results have delivered essential considerations for managers who are managing B2C e-commerce platforms or are planning to design and build platforms as part of digital transformation strategies in their businesses:

i) People use platforms to fulfil a specific need or solve a particular problem, enabling them to achieve their goals, do their jobs, or complete their shopping tasks. Therefore, platforms should be designed to be useful and possess the required capabilities to enable their users to achieve their desired outcomes (Thompson et al., 1991; Venkatesh et al., 2003).

ii) Platforms should instil a new process providing advantages for users, e.g. time-saving, cost-saving or increased effectiveness that is beyond and above historical processes they have been utilising (Moore & Benbasat, 1991).

iii) Users of platforms must find the platforms instrumental in reaching their goals or fulfilling their needs to such an extent that they cannot use any other method to achieve the same result (Davis et al., 1992).

iv) Ensure platform users know that customer support services are available by displaying contact information on the retailers' websites or apps (Thompson et al., 1991). The mere fact that the user knows that customer support is available drives BI to use the platform (Venkatesh et al., 2003).

v) The customer support services available to provide website or app support must be sufficient and adequate to resolve customer queries satisfactorily. Satisfactory customer service will drive UG on platforms, but unsatisfactory services will decrease UG (Moore & Benbasat, 1991).

vi) Empower the user by providing self-service website or application troubleshooting functionalities like frequently asked questions (FAQ), password reset, chatbots or live chat. These elements will give the users the sense that they have perceived behavioural control over their activities on the system and the required resources to use the system (Ajzen, 1991).

vii) UG on platforms is influenced by the usefulness and customer services provided to ensure customer satisfaction during the end-to-end online journey.

viii) The BI to become retained on a platform strengthens as the user transitions through the activation, retention, referral and revenue phases. Retailers should deploy the correct strategies during each phase of the online journey to facilitate platform UG (refer to section 6.4).

ix) Successful platforms manage to co-create value between the customer and the retailer by creating unique customer value through personalised technology, loyalty programmes, gamification and rewards. Retailers must design and build new infrastructure and governance capabilities from the inception of their platforms to involve the customer from the start in this interactive value chain and personalised dialogues (Prahalad & Ramaswamy, 2004).

6.6 Contributions of the Study

This study focused on B2C e-commerce platforms in the FMCG industry in South Africa. It contributed to the consumer use theory by firstly employing all the UTAUT2 variables (Venkatesh et al., 2012) and secondly substituting the outcome (endogenous) variable “Use behaviour” for “UG”. Thirdly, it expanded the endogenous variable's theoretical mechanisms by adding the AARRR model (McClure, 2007), the UG construct.

This research is unique since “use behaviour” has never been substituted by “UG”, and the results have shown that UG can be achieved through customer satisfaction and the intensifying relationship of BI and UG as the customer transitions through the phases of the UG construct. This study is the first in South Africa, especially due to its focus on the FMCG industry, and it contributes meaningfully to IS literature and digital commerce management practices.

The dissertation’s results have notable implications for practice, as managers can use them to guide them in designing, implementing, and managing B2C e-commerce platforms in the FMCG industry or other CPG industries. Please refer to sections 6.4 and 6.5 for more information.

6.7 Limitations of the Study

The first limitation concerns the generalisability of the findings due to using a non-probability convenience sampling method in this study. This method provided an exploratory basis for a confirmatory study at another point that would give more generalisable findings (Leedy & Ormrod, 2015).

The second limitation is the availability of literature on the AARRR model (McClure, 2007) or UG construct. This matter made the study revolutionary and unique, but the study remains exploratory, with limited previous research to compare the results.

Lastly, the study took a cross-sectional approach, producing results for a certain snapshot in time. Results may differ with a longitudinal approach as it might report how variables change over time. This could deliver interesting insights into customers' purchase behaviours on B2C e-commerce platforms over the long term.

6.8 Suggestions for further research

This study can be repeated using a probability sampling procedure combined with a longitudinal approach to guarantee that the sample represents the population. This confirmatory study should yield generalisable findings that can be applied to other contexts.

The UG construct requires further research to understand better its relationship with use behaviour in the IS literature. Prospective researchers might want to test the model with only BI, which will reduce the scales in the questionnaire and deliver a higher response rate.

The concept of habit formation and how habits are established in relation to e-commerce use also requires further research. Habit formation should be researched in the e-grocery and FMCG e-commerce context to understand better consumers' shopping behaviours between online and offline channels. South Africa has plenty of shopping malls in every city and town, providing easy access to major retailers. Consumers, therefore, do not need to order online because the retailers are so easily accessible. It will be interesting to research what factors trigger the consumer to switch from in-store buying to online ordering in South Africa.

REFERENCES

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive Absorption and Beliefs about Information Technology Usage. *MIS Quarterly*, *24*(4), 665-694.

Agarwal, R., & Prasad, J. (1997). The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies. *Decision Sciences*, *28*(3), 557-582.

Ain, N., Kaur, K., & Waheed, M. (2016). The Influence of Learning Value on Learning Management System Use: An Extension of UTAUT2. *Information Development*, *32*(5), 1306-1321.

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Akoglu, H. (2018). User's Guide to Correlation Coefficients. *Turkish Journal of Emergency Medicine*, *18*(3), 91-93.

Al-Suqri, M. N., & Al-Kharusi, R. M. (2015). Ajzen and Fishbein's Theory of Reasoned Action (TRA) (1980). In *Information Seeking Behavior and Technology Adoption: Theories and Trends* (pp. 188-204). IGI Global.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining Factors Influencing Jordanian Customers' Intentions and Adoption of Internet Banking: Extending UTAUT2 with Risk. *Journal of Retailing and Consumer Services*, *40*, 125-138.

An, L., Han, Y., & Tong, L. (2016). Study on the Factors of Online Shopping Intention for Fresh Agricultural Products based on UTAUT2. The 2nd Information technology and mechatronics engineering conference (ITOEC 2016),

Apuke, O. D. (2017). Quantitive Research Methods a Synopsis Approach. *Kuwait Chapter of the Arabian Journal of Business and Management Review*, *6*(11), 40-47. https://doi.org/https://doi.org/10.12816/0040336

Arain, A. A., Hussain, Z., Rizvi, W. H., & Vighio, M. S. (2019). Extending UTAUT2 toward Acceptance of Mobile Learning in the context of Higher Education. *Universal Access in the Information Society*, *18*(3), 659-673. https://doi.org/10.1007/s10209-019-00685-8

Arenas Gaitán, J., Peral Peral, B., & Ramón Jerónimo, M. (2015). Elderly and Internet Banking: An Application of UTAUT2. *Journal of Internet Banking and Commerce*, *20*(1), 1 - 23.

Armstrong, B., & Lee, G. J. (2021). *Digital Business* (Vol. 2). Silke Route Press.

Arsham, H., & Lovric, M. (2011). Bartlett's Test. *International Encyclopedia of Statistical Science*, *2*, 20-23.

Artana, I., Fattah, H., Putra, I., Sariani, N., Nadir, M., Asnawati, A., & Rismawati, R. (2022). Repurchase Intention Behavior in B2C E-commerce. *International Journal of Data and Network Science*, *6*(1), 147-154.

Bargoni, A., Santoro, G., Petruzzelli, A. M., & Ferraris, A. (2024). Growth Hacking: A Critical Review to Clarify its Meaning and Guide its Practical Application. *Technological Forecasting and Social Change*, *200*, 123111. https://doi.org/10.1016/j.techfore.2023.123111

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical Considerations for Using Exploratory Factor Analysis in Educational Research. *Practical Assessment, Research, and Evaluation*, *18*(1), 6. https://doi.org/https://doi.org/10.7275/qv2q-rk76

Beers, B. (2023). *P-Value: What It Is, How to Calculate It, and Why It Matters*. Investopedia. https://www.investopedia.com/terms/p/p-value.asp#:~:text=A%20p%2Dvalue%20is%20a,significance%20of%20the%20observed%20difference.

Bell, E., Bryman, A., & Harley, B. (2022). *Business Research Methods*. Oxford University Press.

Bellman, S., Potter, R. F., Treleaven-Hassard, S., Robinson, J. A., & Varan, D. (2011). The Effectiveness of Branded Mobile Phone Apps. *Journal of Interactive Marketing*, *25*(4), 191-200. https://doi.org/10.1016/j.intmar.2011.06.001

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*(3), 351-370.

Bland, J. M., & Altman, D. G. (1997). Statistics Notes: Cronbach's Alpha. *British Medical Journal*, *314*(7080), 572.

Bohnsack, R., & Liesner, M. M. (2019). What the Hack? A Growth Hacking Taxonomy and Practical Applications for Firms. *Business Horizons*, *62*(6), 799-818. https://doi.org/10.1016/j.bushor.2019.09.001

BRICS. (2023). *Framework for Ensuring Consumer Protection in E-commerce*. B. S. A. 2023. https://brics2023.gov.za/other-documents/

Bridges, E., & Florsheim, R. (2008). Hedonic and Utilitarian Shopping Goals: The Online Experience. *Journal of Business Research*, *61*(4), 309-314. https://doi.org/10.1016/j.jbusres.2007.06.017

Brown, S. A., & Venkatesh, V. (2005). Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly*, *29*(3), 399-426.

Budree, A. (2023). *E-Commerce in South Africa* (A. Budree, Ed. 4 ed.) [Handbook]. Juta.

BusinessTech. (2022a). *Covid fifth wave has peaked in Gauteng: expert*. *Businesstech*. https://businesstech.co.za/news/trending/587880/covid-fifth-wave-has-peaked-in-gauteng-expert/

BusinessTech. (2022b). *South Africa 'won't be spared' from the Russia-Ukraine war: Ramaphosa*. *BusinessTech*. https://businesstech.co.za/news/government/568890/south-africa-wont-be-spared-from-the-russia-ukraine-war-ramaphosa/

Businesswire. (2023). *South Africa FMCG (Fast Moving Consumer Goods) Market Trends Report 2023: Challenges, Competition, Outlook, Cross-Border Trade, Value Chain*. Businesswire. https://www.businesswire.com/news/home/20230525005646/en/South-Africa-FMCG-Fast-Moving-Consumer-Goods-Market-Trends-Report-2023-Challenges-Competition-Outlook-Cross-Border-Trade-Value-Chain---ResearchAndMarkets.com

Candra, D. G. A., Nuruzzaman, M. T., Sugiantoro, B., & Pratiwi, M. (2023). Analysis of Factors Affecting the Students' Acceptance Level of E-Commerce Applications in Yogyakarta Using Modified UTAUT 2. *IJID (International Journal on Informatics for Development)*, *12*(1), 326-337.

Castanha, J., Gurav, P., & Subhash, K. (2023). A Study on Behaviour Intention towards Adoption of Navigation Apps by Travellers: The UTAUT2 Perspective. *International Journal of Hospitality and Tourism Systems*, *16 Issue*(1).

Çelik, H. E., & Yilmaz, V. (2011). Extending The Technology Acceptance Model for Adoption of E-Shopping by consumers in Turkey. *Journal of Electronic Commerce Research*, *12*(2), 152-164. https://www.proquest.com/scholarly-journals/extending-technology-acceptance-model-adoption-e/docview/872187200/se-2?accountid=15083

Chang, A. (2012). UTAUT and UTAUT 2: A Review and Agenda for Future Research. *The Winners*, *13*(2), 106-114.

Chang, C.-M., Liu, L.-W., Huang, H.-C., & Hsieh, H.-H. (2019). Factors Influencing Online Hotel Booking: Extending UTAUT2 with age, gender, and experience as Moderators. *Information*, *10*(9), 281.

Chen, L., Rashidin, M. S., Song, F., Wang, Y., Javed, S., & Wang, J. (2021). Determinants of Consumer's Purchase Intention on Fresh E-commerce Platform: Perspective of UTAUT model. *SAGE Open*, *11*(2), 1-17. https://doi.org/ 10.1177/21582440211027875

Cheung, C. M., Zheng, X., & Lee, M. K. (2015). How the Conscious and Automatic Information Processing Modes Influence Consumers'

Continuance Decision in an E-commerce Website. *Pacific Asia Journal of the Association for Information Systems*, *7*(2), 25-40.

Chevalier, S. (2022). *Retail e-commerce sales worldwide from 2014 to 2026*. Statista. https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

Chi Lin, C. (2003). A Critical Appraisal of Customer Satisfaction and E-commerce. *Managerial Auditing Journal*, *18*(3), 202-212. https://doi.org/10.1108/02686900310469952

Chooprayoon, V., & Fung, C. C. (2010). TECTAM: An Approach to Study Technology Acceptance Model (TAM) in gaining knowledge on the Adoption and Use of e-commerce/e-business Technology among small and medium enterprises in Thailand. *InTech*, 31-38. https://doi.org/10.5772/8907

Clark, L. A., & Watson, D. (1995). Constructing Validity: Basic Issues in Objective Scale Development. *Psychological Assessment*, *7*(3), 309 -319. https://doi.org/1996-93318-001

Cody-Allen, E., & Kishore, R. (2006). An Extension of the UTAUT model with e-Quality, Trust, and Satisfaction Constructs. Proceedings of the 2006 ACM SIGMIS CPR conference on computer personnel research: Forty four years of computer personnel research: achievements, challenges & the future,

Cohen, L., Manion, L., & Morrison, K. (2002). *Research Methods in Education* (6 ed.). Routledge.

Collier, J. E. (2020). *Applied Structural Equation Modeling using AMOS: Basic to Advanced Techniques*. Routledge.

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social Cognitive Theory and Individual reactions to Computing Technology: A longitudinal study. *MIS Quarterly*, *23*(2), 145-158. https://doi.org/10.2307/249749 (SIM International and the Management Information Systems Research Center (MISRC))

Compeau, D. R., & Higgins, C. A. (1995). Application of Social Cognitive Theory to Training for Computer Skills. *Information Systems Research*, *6*(2), 118-143. https://doi.org/10.1287/isre.6.2.118

Copolla, D. (2022). *B2C E-Commerce*. Statista. https://www.statista.com/markets/413/topic/457/b2c-e-commerce/

Cowling, N. (2023a). *E-commerce in South Africa - Statistics & Facts*. Statista. https://www.statista.com/topics/11038/e-commerce-in-south-africa/#topicOverview

Cowling, N. (2023b). *Household disposable income in South Africa 2004-2021*. Statista. https://www.statista.com/statistics/874035/household-disposable-income-in-south-africa/#:~:text=Household%20disposable%20income%20in%20South%20Africa%202004%2D2021&text=In%202022%2C%20South%20African%20households,disposable%20income%20was%2050%2C343%20rand.

Crabbe, M., Standing, C., Standing, S., & Karjaluoto, H. (2009). An Adoption Model for Mobile Banking in Ghana. *International Journal of Mobile Communications*, *7*(5), 515-543.

Creswell, J. W., & Creswell, J. D. (2017). *Research Design: Qualitative, Quantitative, and Mixed Methods approaches* (5 ed.). Sage Publications. (Sage Publications)

Cristobal, E., Flavian, C., & Guinaliu, M. (2007). Perceived E-service Quality (PeSQ) Measurement Validation and Effects on Consumer Satisfaction and Web site Loyalty. *Managing Service Quality: An International Journal*, *17*(3), 317-340. https://doi.org/10.1108/09604520710744326

Daoud, J. I. (2017). Multicollinearity and Regression Analysis. *Journal of Physics: Conference Series 949 (2017).*

Davis, F. D. (1987). *User Acceptance of Information Systems: The Technology Acceptance Model (TAM)* [Research]. University of Michigan.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008 (Management Information Systems Research Center, University of Minnesota)

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982-1003. (University of Michigan)

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology*, *22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945

De Leeuw, E. (2008). Self-administered Questionnaires and Standardized Interviews. *Handbook of Social Research Methods*, 313-327. (Open Archives Initiative)

DeFranzo, S. E. (2023). *Advantages and Disadvantages of Surveys*. SnapSurveys. https://www.snapsurveys.com/blog/advantages-disadvantages-surveys/

Deloitte. (2020). *Digital Commerce Consumer Report*. Deloitte. https://www2.deloitte.com/za/en/pages/strategy-operations/articles/digital-commerceoffering.html?ds_rl=1292866&gclid=Cj0KCQjw7MGJBhD-ARIsAMZ0eetcL8mBDWOGpVSOGv_txdXDhSew6oFoUbe7CU8T-fAmkmNTSAMWivoaAsowEALw_wcB&gclsrc=aw.ds

Dludla, N. (2020). *South African e-commerce is a COVID-fired market of risk and reward*. Reuters. https://www.reuters.com/article/us-health-coronavirus-safrica-ecommerce-idUSKCN24G1A6

Doherty, N. F., & Ellis-Chadwick, F. E. (2006). New Perspectives in Internet Retailing: A Review and Strategic Critique of the Field. *International Journal of Retail & Distribution Management*.

dos Santos, E. F., de Carvalho, P. V. R., & Gomes, J. O. (2022). Interactions between e-commerce users during the COVID-19 pandemic period: What came and what remained. *Work (Reading, Mass.)*, *73*(s1), S177-S187. https://doi.org/10.3233/WOR-211136

Dreher, F., & Ströbel, T. (2023). How Gamified Online Loyalty Programs enable and facilitate Value Co-Creation: A Case Study within a Sports-Related Service Context. *Journal of Service Theory and Practice*, *33*(5), 671-696. https://doi.org/10.1108/JSTP-10-2022-0229

Eaton, L., & Louw, J. (2000). Culture and Self in South Africa: Individualism-Collectivism Predictions. *The Journal of Social Psychology*, *140*, 210-217. https://doi.org/10.1080/00224540009600461

Eaton, P., Frank, B., Johnson, K., & Willoughby, S. (2019). Comparing Exploratory Factor Models of the Brief Electricity and Magnetism Assessment and the Conceptual Survey of Electricity and Magnetism. *Physical Review Physics Education Research*, *15*(2), 020133. https://doi.org/10.1103/PhysRevPhysEducRes.15.020133

eCommerceDB. (2023a). *Country Report - eCommerce in South Africa*. Statista. https://ecommercedb.com/reports/ecommerce-in-south-africa/562, https://ecommercedb.com/markets/za/all

eCommerceDB. (2023b). *eCommerce market in South Africa*. ECDB. https://ecommercedb.com/markets/za/all

Ellis, S., & Brown, M. (2017). *Hacking Growth: How Today's Fastest-Growing Companies Drive Breakout Success*. Virgin Books. (Virgin Books)

Feiz, D., Zarei, A., Maleki Minbashrazgah, M., & Shaabani, A. (2021). Typology of Growth Hacking Strategies Along the Growth Hacking Funnel. *Iranian Journal of Management Studies*, *14*(2), 331-346.

Ferreira Barbosa, H., García-Fernández, J., Pedragosa, V., & Cepeda-Carrion, G. (2022). The Use of Fitness Centre Apps and its Relation to Customer Satisfaction: a UTAUT2 perspective. *International Journal of Sports Marketing and Sponsorship*, *23*(5), 966-985. https://doi.org/10.1108/IJSMS-01-2021-0010

Field, A. (2013). *Discovering Statistics using IBM SPSS Statistics* (J. Seaman, Ed. 4 ed.). Sage Publications.

Franklin, S. B., Gibson, D. J., Robertson, P. A., Pohlmann, J. T., & Fralish, J. S. (1995). Parallel Analysis: A Method for Determining Significant Principal Components. *Journal of Vegetation Science*, *6*(1), 99-106.

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common Methods Variance detection in Business Research. *Journal of Business Research*, *69*(8), 3192-3198. https://doi.org/10.1016/j.jbusres.2015.12.008

Gaines, J. (2021). *How Are Habits Formed? The Psychology of Habit Formation*. positivepsychology.com. https://positivepsychology.com/how-habits-are-formed/

Galal, S. (2023). *E-commerce in Africa - Statistics & Facts*. Statista. https://www.statista.com/topics/7288/e-commerce-in-africa/#topicOverview

Gallo, A. (2014). The Value of Keeping the Right Customers. *Harvard Business Review*, *10*. https://hbr.org/2014/10/the-value-of-keeping-the-right-customers

Giannakos, M. N., Pateli, A. G., & Pappas, I. O. (2011). Identifying the Direct Effect of Experience and the Moderating Effect of Satisfaction in the Greek Online Market. *International Journal of E-Services and Mobile Applications (IJESMA)*, *3*(2), 39-58. https://doi.org/ 10.4018/978-1-4666-2654-6.ch005

Gillis, A. S. (2023). *The Application*. Techtarget. https://www.techtarget.com/searchsoftwarequality/definition/application

GlobalDataPoint. (2022). *Africa's e-commerce user growth expected to surge by 50% in three years' time*. *Global Data Point*. https://www.proquest.com/wire-feeds/africa-s-e-commerce-user-growth-expected-surge-50/docview/2629748074/se-2?accountid=15083

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213-236. https://doi.org/10.2307/249689

Gupta, D. (2018). FMCG Case Study. In *Applied Analytics through Case Studies Using SAS and R* (pp. 345-396). Springer.

Guzzo, T., Ferri, F., & Grifoni, P. (2016). A Model of E-commerce Adoption (MOCA): Consumer's Perceptions and Behaviours. *Behaviour & Information Technology*, *35*(3), 196-209. https://doi.org/10.1080/0144929X.2015.1132770

Hadi, N. U., Abdullah, N., & Sentosa, I. (2016). An Easy Approach to Exploratory Factor Analysis: Marketing Perspective. *Journal of Educational and Social Research*, *6*(1), 215. https://doi.org/10.5901/jesr.2016.v6n1p215

Hair, J. F., Money, A. H., Samouel, P., & Page, M. (2007). Research Methods for Business. *Education+Training*, *49*(4), 336-337. https://doi.org/10.1108/et.2007.49.4.336.2

Hair, J. J., Page, M., & Brunsveld, N. (2019). *Essentials of Business Research Methods* (M. E. Sharpe, Ed. Fourth ed.). Routledge.

Haji, K. (2021). eCommerce Development in Rural and Remote areas of BRICS Countries. *Journal of Integrative Agriculture*, *20*(4), 979-997. https://doi.org/https://doi.org/10.1016/S2095-3119(20)63451-7

Hajjar, S. T. (2018). Statistical Analysis: Internal-Consistency Reliability and Construct Validity. *International Journal of Quantitative and Qualitative Research Methods*, *6*(1), 46-57. (European Centre for Research Training and Development UK)

Hale, J. L., Householder, B. J., & Greene, K. L. (2002). *The Theory of Reasoned Action* (Vol. 14). books.google.com.

Hayton, J., Allen, D., & Scarpello, V. (2004). Factor Retention Decisions in Exploratory Factor Analysis: A Tutorial on Parallel Analysis. *Organizational Research Methods*, *7*(2), 191-205. https://doi.org/10.1177/1094428104263675

Hoffman, D. L., & Novak, T. P. (1996). Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations. *Journal of Marketing*, *60*(3), 14.M

Holton, E. F., & Burnett, M. F. (2005). *Research in Organizations: Foundations and Methods of Inquiry* (R. H. I. Swanson, Elwood F., Ed. First ed.). Berrett-Koehler Publishers Inc.

Hossain, M. A., & Quaddus, M. (2012). *Expectation–Confirmation Theory in Information System Research: A Review and Analysis* (Y. K. Dwivedi, Wade, M.R, Schneberger, S.L, Ed. Explaining and Predicting our Digital Society ed.). Springer. https://doi.org/10.1007/978-1-4419-6108-2

Huang, T. (2023). Expanding the UTAUT2 Framework to determine the drivers of Mobile Shopping Behaviour among Older Adults. *PloS One*, *18*(12), e0295581. https://doi.org/10.1371/journal.pone.0295581

Huiping, W., & Shing-On, L. (2017). Can Likert Scales be Treated as Interval Scales?—A Simulation Study. *Journal of Social Service Research*, *43*(4), 527-532 , https://doi.org/10.1080/01488376.2017.1329775

Human, G., Ungerer, M., & Azémia, J.-A. J. (2020). Mauritian Consumer Intentions to Adopt Online Grocery Shopping: An Extended decomposition of UTAUT2 with moderation. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, *29*(3), 15-37.

Hungilo, G. G., & Setyohadi, D. B. (2020). Factors Influencing Acceptance of Online Shopping in Tanzania using UTAUT2. *Journal of Internet Banking and Commerce*, *25*(1), 1-23.

Hutchinson, A. (2022). Pinterest Active Users Continue to Slide as it Loses Growth Momentum Sparked by Lockdowns. *Social Media Today*. https://www.proquest.com/trade-journals/pinterest-active-users-continue-slide-as-loses/docview/2627264646/se-2?accountid=15083

Hwang, E. C., & Mulyana, E. W. (2022). Analysis of factors Influencing Use Behavior on E-commerce Users in Batam City. *Enrichment: Journal of Management*, *12*(5), 4221-4229. https://doi.org/10.35335/enrichment.v12i5.883

Illidge, M. (2022). *How much 1GB of data costs in South Africa vs the World*. https://mybroadband.co.za/news/cellular/429334-how-much-1gb-of-data-costs-in-south-africa-vs-the-world.html

Irawan, R. (2023). *The Rise of E-commerce in FMCG: Opportunities and Challenges*. LinkedIn. https://www.linkedin.com/pulse/rise-e-commerce-fmcg-opportunities-challenges-rezky-irawan/

Jain, V., Malviya, B., & Arya, S. (2021). An Overview of Electronic Commerce (e-Commerce). *Journal of Contemporary Issues in Business and Government*, *27*(3), 665-670. https://doi.org/ 10.47750/cibg.2021.27.03.090

Jewels, T. J., & Timbrell, G. T. (2001). *Towards a Definition of B2C & B2B E-Commerce.* Proceedings of the Twelfth Australasian Conference on Information Systems,

Jinling, B. (2021). User Growth Model of Pinduoduo Based on SIR and Bass Model.*Advances in Economics, Business and Management Research* 2021 International Conference on Enterprise Management and Economic Development (ICEMED 2021),

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and Explained. *British Journal of Applied Science & Technology*, *7*(4), 396-403. https://doi.org/10.9734/BJAST/2015/14975

Kamer, L. (2023). *E-commerce in South Africa - Statistics & Facts*. Statista. https://www.statista.com/topics/11038/e-commerce-in-south-africa/#topicOverview

Kartikasari, Y., Sunaryo, S., & Yuniarinto, A. (2021). The Intention to Use E-Commerce to Purchase Green Cosmetics with a Modified UTAUT2 Approach. *Journal of Applied Management*, *19*(3), 605-615. https://doi.org/10. 21776/ub.jam.2021.019.03.13

Kemp, S. (2022). *Digital 2021: Executive Summary Report*. Hootsuite. https://www.hootsuite.com/pages/digital-trends-2021#c-274407

Kemp, S. (2023). *Digital 2023: South Africa*. Kepios. https://datareportal.com/reports/digital-2023-south-africa

Kenton, W. (2021). *Fast-Moving Consumer Goods (FMCG)*. Dotdash Meredith Publishing. https://www.investopedia.com/terms/f/fastmoving-consumer-goods-fmcg.asp

Kenton, W. (2023). *Customer: Definition and How to Study Their Behavior for Marketing*. Investopedia. https://www.investopedia.com/terms/c/customer.asp

Khalifa, M., & Liu, V. (2007). Online Consumer Retention: Contingent Effects of Online Shopping Habit and Online Shopping Experience. *European Journal of Information Systems*, *16*(6), 780-792. (Springer)

Khan, I. U., Hameed, Z., & Khan, S. U. (2017). Understanding Online Banking Adoption in a Developing Country: UTAUT2 with Cultural Moderators. *Journal of Global Information Management (JGIM)*, *25*(1), 43-65. https://doi.org/10.4018/JGIM.2017010103

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and Satisfaction, Two Stepping Stones for Successful E-commerce Relationships: A Longitudinal Exploration. *Information Systems Research*, *20*(2), 237-257.

Kim, S. S., Malhotra, N. K., & Narasimhan, S. (2005). Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison. *Information Systems Research*, *16*(4), 418-432. https://www.proquest.com/scholarly-journals/two-competing-perspectives-on-automatic-use/docview/208166110/se-2?accountid=15083

Klepek, M., & Bauerová, R. (2020). Why do retail customers hesitate for shopping grocery online? *Technological and Economic Development of Economy*, *26*(6), 1444-1462.

Klopping, I. M., & McKinney, E. (2004). Extending the Technology Acceptance Model and the Task-Technology Fit Model to Consumer E-Commerce. *Information Technology, Learning & Performance Journal*, *22*(1).

Koufaris, M. (2002). Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior. *Information Systems Research*, *13*(2), 205-223. https://doi.org/10.1287/isre.13.2.205.83

Kumar, A., & Anjaly, B. (2017). How to Measure Post-Purchase Customer Experience in Online Retailing? A scale development study [Post-purchase customer experience]. *International Journal of Retail & Distribution Management*, *45*(12), 1277-1297. https://doi.org/10.1108/IJRDM-01-2017-0002

Kumar, P., Agarwal, N., & Saraswat, H. (2021). E-commerce: a Catalyst of Marketing Especially on FMCG Product under COVID Pandemic. *Asian Journal of Advances in Research 8*(2), 1-11.

Kumar, V., & Ayodeji, O. G. (2021). E-retail factors for customer activation and retention: An empirical study from Indian e-commerce customers. *Journal of Retailing and Consumer Services*, *59*, 102399. https://doi.org/10.1016/j.jretconser.2020.102399

Lai, X. (2022). Research on Members Network Marketing Strategy Based on User Retention Growth Model. *Forest Chemicals Review*, 1811 – 1817.

Ledesma, R. D., Valero-Mora, P., & Macbeth, G. (2015). The Scree Test and the Number of Factors: A Dynamic Graphics Approach. *The Spanish Journal of Psychology*, *18*(E11), 1-10. https://doi.org/10.1017/sjp.2015.13

Lee, I., Choi, B., Kim, J., & Hong, S.-J. (2007). Culture-Technology Fit: Effects of Cultural Characteristics on the Post-Adoption Beliefs of Mobile Internet Users. *International Journal of Electronic Commerce*, *11*(4), 11-51. https://doi.org/10.2753/JEC1086-4415110401

Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12*(50), 752-780. https://doi.org/10.17705/1CAIS.01250

Leedy, P. D., & Ormrod, J. E. (2015). *Practical Research: Planning and Design* (11 ed.). Pearson Education Limited.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience throughout the Customer Journey. *Journal of Marketing*, *80*(6), 69-96. https://doi.org/10.1509/jm.15.0420

Li, M., & Tran, C. T. L. T. T. (2021). *A Case Study of Pinduoduo Strategy Based on SWOT Analysis* 1st International Symposium on Innovative Management and Economics (ISIME 2021),

Liang, H., & Cheah, S. M. (2020). Pinduoduo: Empowering Farmers with an E-commerce Platform. *Asian Management Insights*, *7*(2), 44-51. (Lee Kong Chian School of Business)

Liang, T.-P., & Huang, J.-S. (1998). An Empirical Study on Consumer Acceptance of Products in Electronic Markets: A Transaction Cost Model. *Decision Support Systems*, *24*(1), 29-43. https://doi.org/10.1016/s0167-9236(98)00061-X

Liew, E. J., Vaithilingam, S., & Nair, M. (2014). Facebook and socio-economic benefits in the developing world. *Behaviour & Information Technology*, *33*(4), 345-360.

Limayem, M., & Hirt, S. G. (2003). Force of Habit and Information Systems Usage: Theory and Initial Validation. *Journal of the Association for Information Systems*, *4*(1), 65-97. https://doi.org/10.17705/1jais.00030

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly*, *31*(4), 705-737. https://doi.org/10.2307/25148817 (Management Information Systems Research Center, University of Minnesota)

Lu, L. (2023). How far can the wild growth of Pinduoduo go? *Highlights in Business, Economics and Management*, *17*, 171-177. https://doi.org/10.54097/hbem.v17i.11158

Mak, H. Y., & Max Shen, Z. J. (2021). When Triple-A Supply Chains Meet Digitalization: The Case of JD. com's C2M Model. *Production and Operations Management*, *30*(3), 656-665. https://doi.org/10.1111/poms.13307

Malhotra, Y., & Galletta, D. F. (1999). Extending the Technology Acceptance Model to Account for Social Influence: Theoretical Bases and Empirical Validation. Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999. HICSS-32. Abstracts and CD-ROM of Full Papers,

Manfreda, K. L., Bosnjak, M., Berzelak, J., Haas, I., & Vehovar, V. (2008). Web Surveys versus other Survey Modes: A Meta-Analysis Comparing Response Rates. *International Journal of Market Research*, *50*(1), 79-104. https://doi.org/10.1177/147078530805000107

Maulidina, P. R., Sarno, R., Sungkono, K. R., & Giranita, T. A. (2020). Using Extended UTAUT2 Model to Determine Factors Influencing the Use of Shopee E-commerce. 2020 International Seminar on Application for Technology of Information and Communication (iSemantic),

McClure, D. (2007). *Startup Metrics for Pirates*. https://www.slideshare.net/dmc500hats/startup-metrics-for-pirates-long-version

McGaw, D. (2015). *AARRR! Pirate Metrics For Startups*. MacGaw.io. https://mcgaw.io/resources/aarrr-pirate-metrics-startups/#gs.239pzb

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation Analysis: Issues and Guidelines. *Journal of Applied Structural Equation Modeling*, *3*(1), 1-11. https://doi.org/10.47263/JASEM.3(1)01

Mertens, W., Pugliese, A., & Recker, J. (2017). *Quantitive Data Analysis: A Companion for Accounting and Information Systems Research*. Springer International Publishing. https://doi.org/10.1007/978-3-319-42700-3

Miao, M., Jalees, T., Zaman, S. I., Khan, S., Hanif, N.-u.-A., & Javed, M. K. (2022). The Influence of e-Customer Satisfaction, e-Trust and Perceived Value on Consumer's Repurchase Intention in B2C e-Commerce Segment. *Asia Pacific Journal of Marketing and Logistics*, *34*(10), 2184-2206. https://doi.org/10.1108/APJML-03-2021-0221 (Emerald Publishing Limited)

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. https://doi.org/10.1080/23311975.2021.1968206

Mohammed, Z., & Tejay, G. (2017). Examining Privacy Concerns and E-commerce Adoption in Developing Countries: The Impact of Culture in Shaping Individuals' Perceptions Toward Technology. *Computers & Security*, *67*, 254-265. https://doi.org/10.1016/j.cose.2017.03.001

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 173-239. https://doi.org/10.1287/isre.2.3.192

Mzekandaba, S. (2022). *Bold targets set for phase two of SA Connect*. IT Web. https://www.itweb.co.za/content/mYZRX79aKRr7OgA8

Mzekandaba, S. (2023). *R3bn budget boost for SA Connect, phase two*. *IT Web Business Technology Media Community*. https://www.itweb.co.za/content/Gb3Bw7WagoWq2k6V

Napitupulu, D., Kadar, J. A., & Jati, R. K. (2017). Validity Testing of Technology Acceptance Model based on Factor Analysis Approach. *Indonesian Journal of Electrical Engineering and Computer Science*, *5*(3), 697-704. https://doi.org/10.11591/ijeecs.v5.i3.pp697-704

NielsenIQ. (2023a). *E-commerce a Key Catalyst to South African CPG Growth in 2023*. NielsenIQ. https://nielseniq.com/global/en/insights/education/2023/e-commerce-a-key-catalyst-to-south-african-sector-growth-in-2023/

NielsenIQ. (2023b). *State of the Retail Nation: South Africa*. NielsenIQ. https://nielseniq.com/global/en/insights/analysis/2023/state-of-the-retail-nation-south-africa/

Ntloedibe, M., & Ngqinani, P. (2020). *Understanding the Living Standards Measure Segmentation in South Africa* U. S. D. o. Agriculture. https://www.fas.usda.gov/data/south-africa-understanding-living-standards-measure-segmentation-south-africa

Nurhayati-Wolff, H. (2023). *Number of Monthly Web Visits on Shopee in Indonesia from 1st quarter 2018 to 2nd quarter 2022*. Statista.

https://www.statista.com/statistics/1012548/indonesia-number-monthly-web-visits-shopee-quarter/

Nyoro, M. K., John W. ; Wanyembi, Gregory W.; Titus, Waithaka Stephen; Dinda, Wilkister Atieno. (2015). Review of Technology Acceptance Model Usage in Predicting e-Commerce Adoption. *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, *4*(1), 46-49. https://www.researchgate.net/profile/Michael-Nyoro/publication/339616625_Review_of_Technology_Acceptance_Model/links/5e5c81aa299bf1bdb84ad183/Review-of-Technology-Acceptance-Model.pdf (Mount Kenia University)

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, *17*(4), 460-469.

Orr, G. (2003). Diffusion of Innovations, by Everett Rogers (1995). *Academia.edu*, *21*.

Pal, A., De', R., Herath, T., & Rao, H. R. (2019). A Review of Contextual Factors Affecting Mobile Payment Adoption and Use. *Journal of Banking and Financial Technology*, *3*, 43-57. (Springerlink)

Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User Acceptance of Mobile Apps for Restaurants: An Expanded and Extended UTAUT2. *Sustainability*, *11*(4), 1210. https://doi.org/0.3390/su11041210

Park, J., Amendah, E., Lee, Y., & Hyun, H. (2019). M-payment Service: Interplay of Perceived Risk, Benefit, and Trust in Service Adoption. *Human factors and ergonomics in manufacturing & service industries*, *29*(1), 31-43. https://doi.org/10.1002/hfm.20750

Pasquali, M. (2023). *E-commerce Worldwide - Statistics & Facts*. Statista. https://www.statista.com/topics/871/online-shopping/#topicOverview

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, 115-143.

Pillai, S. (2019). *Shopee ups Entertainment Ante; still favours growth over Monetisation: Four-year-old e-commerce firm wants to enhance user stickiness amid intense pressure from competition*. *The Business Times*. https://www.proquest.com/newspapers/shopee-ups-entertainment-ante-still-favours/docview/2236138699/se-2?accountid=15083

Pink, M., & Djohan, N. (2021). Effect of Ecommerce Post-Purchase Activities on Customer Retention in Shopee Indonesia. *Enrichment: Journal of Management*, *12*(1), 519-526. https://doi.org/10.35335/enrichment.v12i1.259

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation Experiences: The Next Practice in Value Creation. *Journal of Interactive Marketing*, *18*(3), 5-14. https://doi.org/10.1002/dir.20015

Puspitaningsih, R., & Jati, H. K. (2023). Factors Influencing of Fintech Payment User using Unified Theory of Acceptance and Use of Technology 2 Model (UTAUT2) in Bandung. *AIP Conference Proceedings*, *2772*(1). https://doi.org/10.1063/5.0116062

Qianling, C., & Lan, D. (2016). Managing Mobile Market Users Based on the AARRR Model in the Age of Big Data. *Management Science and Engineering*, *10*(1), 58-66.

Quantilope. (2023). 5 Methods of Data Collection for Quantitative Research. https://www.quantilope.com/resources/glossary-data-collection-methods-quantitative-research

Raman, A., & Don, Y. (2013). Preservice Teachers' Acceptance of Learning Management Software: An Application of the UTAUT2 Model. *International Education Studies*, *6*(7), 157-164.

Ratih, H., Silalahi, S., & H Hendrayati, H. H. (2021). The Importance of Consumer Satisfaction for Ecommerce Users: How That Affects Consumer Behavior on Consumer Satisfaction? *Advances in Social Science, Education and Humanities Research*, *536*, 96-104.

Reio, J. T. G., & Shuck, B. (2015). Exploratory Factor Analysis: Implications for Theory, Research, and Practice. *Advances in Developing Human Resources*, *17*(1), 12-25. https://doi.org/10.1177/1523422314559804

Rodríguez-Ardura, I., & Meseguer-Artola, A. (2020). How to Prevent, Detect and Control Common Method Variance in Electronic Commerce Research. *15*(2), 1-5. https://doi.org/10.4067/S0718-18762020000200101

Rogers, E. M. (1981). Diffusion of Innovations: An Overview. *Use and Impact of Computers in Clinical Medicine.* https://doi.org/10.1007/978-1-4613-8674-2_9 (Computers and Medicine)

Rosset, S., Neumann, E., Eick, U., Vatnik, N., & Idan, Y. (2002). Customer Lifetime Value Modeling and its use for Customer Retention Planning. Proceedings of the eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,

Rouse, M. (2012). *Business-to-Government*. Technopedia. https://www.techopedia.com/definition/1425/business-to-government-b2g

Rudansky-Kloppers, S. (2014). Investigating Factors Influencing Customer Online Buying Satisfaction in Gauteng, South Africa. *International Business & Economics Research Journal (IBER)*, *13*(5), 1187-1198. https://doi.org/10.19030/iber.v13i5.8784

Sadan, V. (2017). Data Collection Methods in Quantitative Research. *Indian Journal of Continuing Nursing Education*, *18*(2), 58-63.

Saleh, M. (2022). *E-commerce in Africa - Statistics & Facts* (B2B) E-Commerce, Issue. https://www.statista.com/topics/7288/e-commerce-in-africa/#dossierKeyfigures

Samartha, V., Shenoy Basthikar, S., Hawaldar, I. T., Spulbar, C., Birau, R., & Filip, R. D. (2022). A Study on the Acceptance of Mobile-Banking Applications in India—Unified Theory of Acceptance and Sustainable Use of Technology Model (UTAUT). *Sustainability (Basel, Switzerland)*, *14*(21), 14506. https://doi.org/10.3390/su142114506

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research Methods for Business Students* (5 ed.). Pearson Education.

Savrul, M., & Kılıç, C. (2011). E-commerce as an Alternative Strategy in Recovery from the Recession. *Procedia-Social and Behavioral Sciences*, *24*, 247-259. https://doi.org/10.1016/j.sbspro.2011.09.055

Saxena, N., Gera, N., & Taneja, M. (2022). An Empirical Study on Facilitators and Inhibitors of Adoption of Mobile Banking in India. *Electronic Commerce Research*, *23*, 2573–2604. https://doi.org/10.1007/s10660-022-09556-6

Schindler, P. S. (2019). *Business Research Methods* (13 ed.). McGraw-Hill/Irwin.

Schwabe, C. (2023). *Socio-Economic Impact of Shopping Centers in Townships of South Africa*. Africascope-sa.com. https://africascope-sa.com/2023/07/19/socio-economic-impact-of-shopping-centers-in-townships-of-south-africa/

Sendpulse. (2023). *Retail Business*. Sendpulse. https://sendpulse.com/support/glossary/retail-business

Setiyani, L., Natalia, I., & Liswadi, G. T. (2023). Analysis of Behavioral Intentions of E-Commerce Shopee Users in Indonesia Using UTAUT2. *ADI Journal on Recent Innovation*, *4*(2), 160-171. https://doi.org/10.34306/ajri.v4i2.861

Shih-Chih, C., Huei-Huang, C., & Mei-Fang, C. (2009). Determinants of Satisfaction and Continuance Intention towards Self-Service Technologies. *Industrial Management & Data Systems*, *109*(9), 1248-1263. https://doi.org/https://doi.org/10.1108/02635570911002306

Singh, M., & Matsui, Y. (2017). How Long Tail and Trust Affect Online Shopping Behavior: An Extension to UTAUT2 framework. *Pacific Asia Journal of the Association for Information Systems*, *9*(4), 2. https://doi.org/10.17705/1pais.09401

Singh, S. (2023). *SPSS For Uninitiated: A Visual Odyssey for Mortals*. Udemy.com.

Solanki, M. R., & Dongaonkar, A. (2016). A Journey of Human Comfort: Web 1.0 to Web 4.0. *International Journal of Research and Scientific Innovation (IJRSI)*, *3*(9), 124-134.

Stacey, A. (2005). The Reliability and Validity of the Item Means and Standard Deviations of Ordinal Level Response Data. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, *14*(3), 2-25.

Statista. (2022). *eCommerce South-Africa*. Statista. https://www.statista.com/outlook/dmo/ecommerce/south-africa

StatisticsHowTo. (2023). *F Statistic / F Value: Simple Definition and Interpretation*. Statistics How To. https://www.statisticshowto.com/probability-and-statistics/f-statistic-value-test/

StatsSA. (2023). *Census 2022*. StatisticsSouthAfrica. https://census.statssa.gov.za/assets/documents/2022/P03014_Census_2022_Statistical_Release.pdf

Steyn, H., & Ellis, S. (2003). Practical Significance (effect sizes) versus or in Combination with Statistical Significance (P-values): Research Note. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, *12*(4), 51-53.

Stokes, R. (2018). *eMarketing: The Essential Guide to Marketing in a Digital World* (Vol. 6). Red & Yellow Creative School of Business. (Quirk eMarketing (Pty) Ltd)

Taherdoost, H., Sahibuddin, S., & Jalaliyoon, N. (2022). Exploratory Factor Analysis; Concepts and Theory. *Advances in applied and pure mathematics*, *27*, 375-382.

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer Acceptance and Use of Information Technology: A Meta-Analytic Evaluation of UTAUT2. *Information Systems Frontiers*, *23*, 987-1005.

Tang, K., Aik, N., & Choong, W. (2021). A Modified UTAUT in the Context of M-payment Usage Intention in Malaysia. *Journal of Applied Structural Equation Modeling*, *5*(1), 40-59. https://doi.org/10.47263/JASEM.5(1)05

Tavakol, M., & Dennick, R. (2011). Making Sense of Cronbach's Alpha. *International Journal of Medical Education*, *2*, 53-55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tavakol, M., & Wetzel, A. (2020). Factor Analysis: A Means for Theory and Instrument Development in Support of Construct Validity. *International Journal of Medical Education*, *11*, 245–247. https://doi.org/10.5116/ijme.5f96.0f4a

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research*, *6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15*(1), 125-143. https://doi.org/10.2307/249443

TingPeng, L., & JinShiang, H. (1998). An Empirical Study on Consumer Acceptance of Products in Electronic Markets: a Transaction Cost Model. *Decision Support Systems*, *24*(1), 29-43. https://doi.org/10.1016/S0167-9236(98)00061-X

Tredger, C. (2023). *Digitisation, Social Media fuelling rampant fraud in SA*. IT Web. https://www.itweb.co.za/content/KzQenMjyB9B7Zd2r

Vallerand, R. J. (1997). Toward a Hierarchical Model of Intrinsic and Extrinsic Motivation. In *Advances in Experimental Social Psychology* (Vol. 29, pp. 271-360). Elsevier. https://doi.org/10.1016/S0065-2601(08)60019-2

Van Droogenbroeck, E., & Van Hove, L. (2021). Adoption and Usage of E-grocery Shopping: A Context-Specific UTAUT2 model. *Sustainability*, *13*(8), 4144. https://doi.org/10.3390/su13084144

Van Wangenheim, F., & Bayón, T. (2007). The Chain from Customer Satisfaction via Word-of-Mouth Referrals to New Customer Acquisition. *Journal of the Academy of Marketing Science*, *35*, 233-249. https://doi.org/10.1007/s11747-007-0037-1 (Springerlink)

Vega-Vazquez, M., Revilla-Camacho, M. Á., & Cossío-Silva, F. J. (2013). The Value Co-Creation Process as a Determinant of Customer Satisfaction. *Management Decision*, *51*(10), 1945-1953. https://doi.org/10.1108/MD-04-2013-0227

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, *39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting Different Conceptualizations of System Use: The Competing Roles of Behavioral Intention, Facilitating Conditions, and Behavioral Expectation. *MIS Quarterly*, *32*(3), 483-502. https://doi.org/10.2307/25148853 (Management Information Systems Research Center, University of Minnesota)

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS*

Quarterly, *27*(3), 425-478. https://doi.org/10.2307/30036540 (Management Information Systems Research Center, University of Minnesota)

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412 (Management Information Systems Research Center, University of Minnesota)

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems*, *17*(5), 328-376.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. *Journal of Retailing*, *85*(1), 31-41. https://doi.org/10.1016/j.jretai.2008.11.001

Williams, B., Onsman, A., & Brown, T. (2010). Exploratory Factor Analysis: A Five-Step Guide for Novices. *Australasian Journal of Paramedicine*, *8*, 1-13. https://doi.org/10.33151/ajp.8.3.93 (Sage)

Wirtz, B. W., & Lihotzky, N. (2003). Customer Retention Management in the B2C Electronic Business. *Long Range Planning*, *36*(6), 517-532. https://doi.org/10.1016/j.lrp.2003.08.010

WoshipM. (2018). *AARRR*. WoshipM. https://www.woshipm.com/operate/887464.html

WTO. (2020). *E-commerce, Trade and the Covid-19 Pandemic* WorldTradeOrganization. https://www.wto.org/english/tratop_e/covid19_e/ecommerce_report_e.pdf

Wu, E. (2021). Chinese E-commerce site JD.com surges 17% as the Company reports record User Growth in the 2nd quarter and plays down impact of Tech crackdown. *Business Insider*. https://www.proquest.com/newspapers/chinese-e-commerce-site-jd-com-surges-17-as/docview/2563815368/se-2?accountid=15083

Yan, M., Filieri, R., & Gorton, M. (2021). Continuance Intention of Online Technologies: A Systematic Literature Review. *International Journal of Information Management*, *58*, 102315. https://doi.org/10.1016/j.ijinfomgt.2021.102315

Yan, Q., Ji, H., Chen, J., Wang, X., Gao, Y., Zhang, X., Wang, Y., & Zeng, M. (2022). Exploring the Promotion Method and Pathway of Energy Big Data Service Business. IOP Conference Series: Earth and Environmental Science, Yang, Z. X. (2010). Research on Trade Model of Transaction Costs based on Ecommerce. *Applied Mechanics and Materials*, *26-28*, 218-221. https://doi.org/10.4028/www.scientific.net/AMM.26-28.218

Yong, A. G., & Pearce, S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79-94. https://doi.org/10.20982/tqmp.09.2.p079

Zach. (2021). *The Durbin-Watson Test: Definition & Example*. Statology. https://www.statology.org/durbin-watson-test/

Zhang, G., Hattori, M., Trichtinger, L. A., & Wang, X. (2019). Target Rotation with both Factor Loadings and Factor Correlations. *Psychological Methods*, *24*(3), 390-402. https://doi.org/10.1037/met0000198

Zhang, J.-X., & Yang, H.-Y. (2019). Research on the Influencing Factors of Consumers' Purchase Behavior of Pinduoduo E-commerce Platform Based on the UTAUT Model. *2019 International Conference on Advanced Education and Management (ICAEM 2019)*.

Zhang, L. (2021). Research on Multi-user Growth Strategy of Pinduoduo Based on AARRR Model. 7th Annual International Conference on Social Science and Contemporary Humanity Development (SSCHD 2021),

Zhu, Y., Wei, Y., Zhou, Z., & Jiang, H. (2022). Consumers' Continuous Use Intention of O2O E-commerce Platform on Community: a Value Co-Creation Perspective. *Sustainability*, *14*(3), 1666.

APPENDIX A - Supporting Material: Chapter 4

1. Factor Analysis: Tables of Communalities

Table A1: Communalities - BI

Communalities – BI

	Initial	*Extraction
A9.1 BI_Become a regular user	1,000	0,706
A9.2 BI_Increase your basket size	1,000	0,814
A9.3 BI_Place more online orders	1,000	0,786

**Extraction Method: Principal Component Analysis*

Table A2: Communalities - UTAUT2 model (Venkatesh et al., 2012)

Communalities - UTAUT2 model

	Initial	*Extraction
A1.1PE_Website app useful	1,000	0,619
A1.2PE_Frees up time	1,000	0,731
A1.3PE_Shopping tasks quicker	1,000	0,694
A2.1EE_Learning to use is easy	1,000	0,687
A2.2EE_Quick and responsive	1,000	0,795
A2.3EE_Product info and pricing	1,000	0,728
A3.1SI_People influence my decision	1,000	0,762
A3.2SI_People who are important	1,000	0,584
A3.3SI_Status symbol	1,000	0,768
A4.1FC_Query resolution process	1,000	0,401
A4.2FC_Replacement Refund	1,000	0,755
A4.3FC_Flexible delivery pickup	1,000	0,779
A5.1PV_wifi to place order	1,000	0,637
A5.2PV_Pay a small delivery fee	1,000	0,435
A5.3PV_Free delivery of my order	1,000	0,437
A6.1HM_Browsing is enjoyable	1,000	0,765
A6.2HM_Exciting to order	1,000	0,745
A7.1Habit_Become a habit	1,000	0,444
A7.2Habit_Become a routine	1,000	0,607

**Extraction Method: Principal Component Analysis*

Table A3: Communalities - UG Construct

Communalities - UG Construct

	Initial	*Extraction
A10.1 Acquisition_Retailers advertise	1,000	0,755
A10.2 Acquisition_Info about benefits	1,000	0,720
A10.3 Acquisition_Visited and browsed	1,000	0,628
A12.1 Activation_Ease of registration	1,000	0,602
A12.2 Activation_Ease of navigation	1,000	0,667
A12.3 Activation_Simplicity order placement	1,000	0,692
A13.1 Reten_Indicators stock availability	1,000	0,697
A13.2 Reten_Delivery Selected timeslot	1,000	0,737
A13.3 Reten_Order accuracy	1,000	0,395
A14.1 Refer_Complete shopping tasks quickly	1,000	0,722
A14.2 Refer_Online product range	1,000	0,445
A14.3 Refer_The payment process is safe and secure	1,000	0,734
A15.1 Revenue_Loyalty points	1,000	0,758
A15.2 Revenue_Free 30day return order service	1,000	0,816
A15.3 Revenue_Cashbacks	1,000	0,845

**Extraction Method: Principal Component Analysis*

Table A4: Communalities – Satisfaction

Communalities – Satisfaction

	Initial	*Extraction
A8.1 Sat_The quality of the products	1,000	0,668
A8.2 Sat_Order accuracy	1,000	0,745
A8.3 Sat_The level of customer service	1,000	0,681
A8.4 Sat_Overall happiness	1,000	0,701

**Extraction Method: Principal Component Analysis*

2. Factor Analysis: Parallel Analysis

Table A5: Parallel Analysis - BI

Number of variables: 3
Number of subjects: 550
Number of replications: 100

Eigenvalue #	Random Eigenvalue	Standard Dev
1	1.0677	.0299
2	1.0002	.0186
3	0.9321	.0272

Table A6: Parallel Analysis - UTAUT2 model (Venkatesh et al., 2012)

Number of variables: 19
Number of subjects: 550
Number of replications: 100

Eigenvalue #	Random Eigenvalue	Standard Dev
1	1.3274	.0269
2	1.2753	.0239
3	1.2262	.0183
4	1.1886	.0207
5	1.1543	.0197
6	1.1142	.0167
7	1.0824	.0179
8	1.0505	.0152
9	1.0205	.0165
10	0.9919	.0140
11	0.9616	.0143
12	0.9307	.0142
13	0.9019	.0152
14	0.8743	.0163
15	0.8435	.0168
16	0.8140	.0165
17	0.7849	.0204
18	0.7510	.0202
19	0.7070	.0229

Table A7: Parallel Analysis - UG construct

Number of variables: 15
Number of subjects: 550
Number of replications: 100

Eigenvalue #	Random Eigenvalue	Standard Dev
1	1.2974	.0384
2	1.2264	.0259
3	1.1771	.0226
4	1.1361	.0190
5	1.0970	.0164
6	1.0619	.0166
7	1.0253	.0172
8	0.9909	.0170
9	0.9599	.0169
10	0.9265	.0161
11	0.8922	.0169
12	0.8595	.0179
13	0.8258	.0175
14	0.7871	.0235
15	0.7370	.0266

Table A8: Parallel Analysis - Satisfaction

Number of variables: 4
Number of subjects: 550
Number of replications: 100

Eigenvalue #	Random Eigenvalue	Standard Dev
1	1.0969	.0326
2	1.0264	.0205
3	0.9692	.0212
4	0.9076	.0298

3. Factor Analysis: Matrixes to test for Multicollinearity

Table A9: Component Correlation Matrix – UTAUT2 model (Venkatesh et al., 2012)

Component Correlation Matrix - UTAUT2 model

*Component	1	2	3	4	5	6
1	1,000	0,047	0,184	0,303	0,371	0,304
2	0,047	1,000	0,134	0,029	0,066	0,042
3	0,184	0,134	1,000	0,065	0,039	0,199
4	0,303	0,029	0,065	1,000	0,235	0,282
5	0,371	0,066	0,039	0,235	1,000	0,205
6	0,304	0,042	0,199	0,282	0,205	1,000

**Extraction Method: Principal Component Analysis*

Rotation Method: Oblimin with Kaiser Normalization

Table A10: Factor Correlation Matrix - UG Construct

Factor Correlation Matrix - UG Construct

	Retention	Revenue	Acquisition	Referral	Activation
***Factor**	**1**	**2**	**3**	**4**	**5**
Retention	1,000	-0,314	0,371	0,218	0,350
Revenue	-0,314	1,000	-0,104	-0,058	-0,243
Acquisition	0,371	-0,104	1,000	0,182	0,217
Referral	0,218	-0,058	0,182	1,000	0,190
Activation	0,350	-0,243	0,217	0,190	1,000

**Extraction Method: Generalized Least Squares*

Rotation Method: Oblimin with Kaiser Normalization

4. Multiple Regression Analysis – test for Homescedasticity

In the regression analysis between BI and UG, respondent numbers 262, 289 and 543 were identified as outliers (values < -3 or bigger > +3). Similarly, in the regression analysis between FC and UG, respondent numbers 215, 225, 341 and 359 were outliers and were removed from the database.

The outliers were excluded from the regression analysis. The Standardized Residuals were then plotted on a histogram and can be seen in Figure A1 and Figure A3, ranging from +3 to -3. The Standardised Residuals are also plotted on scatterplots, and a “cloud-like formation” ranging from – 3 to + 3 is visible in Figures A2 and A4.

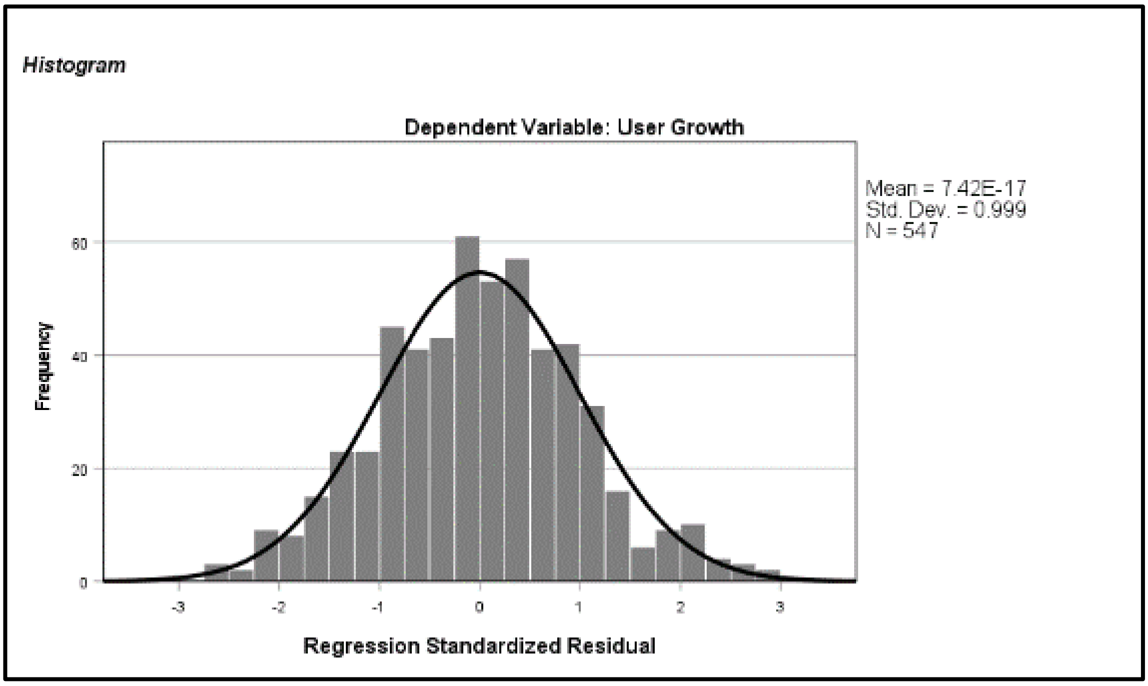


Figure A1: Histogram - Standardised Residuals for the regression between BI and UG

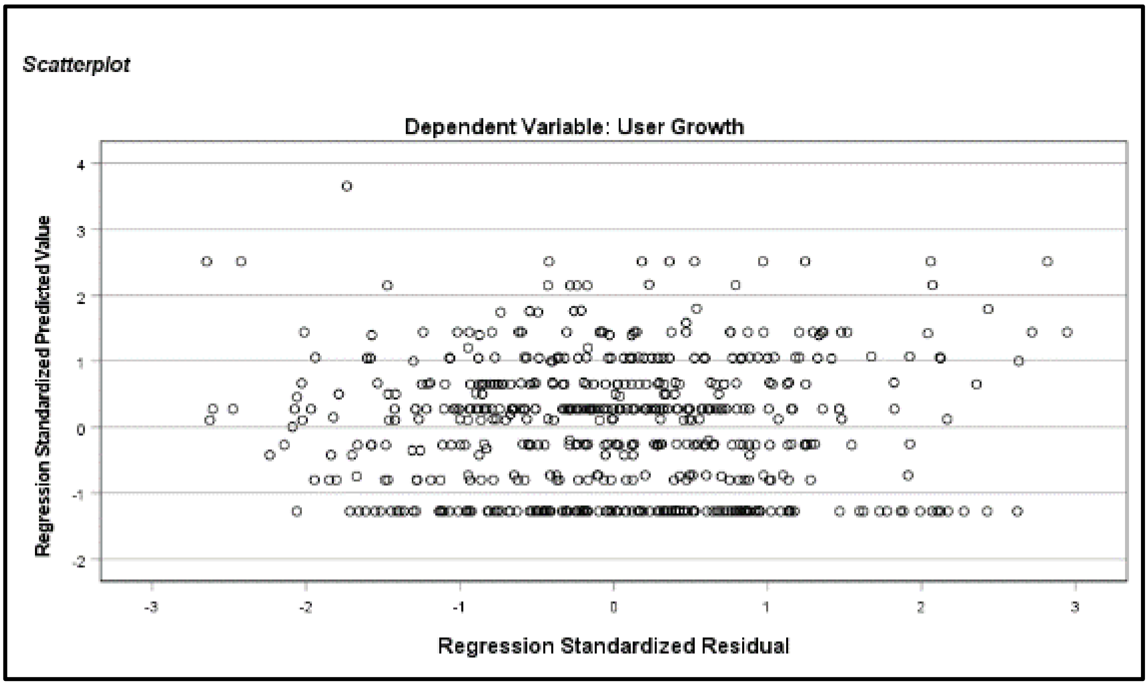


Figure A2: Scatterplot - Standardised Residuals for the regression between BI and UG

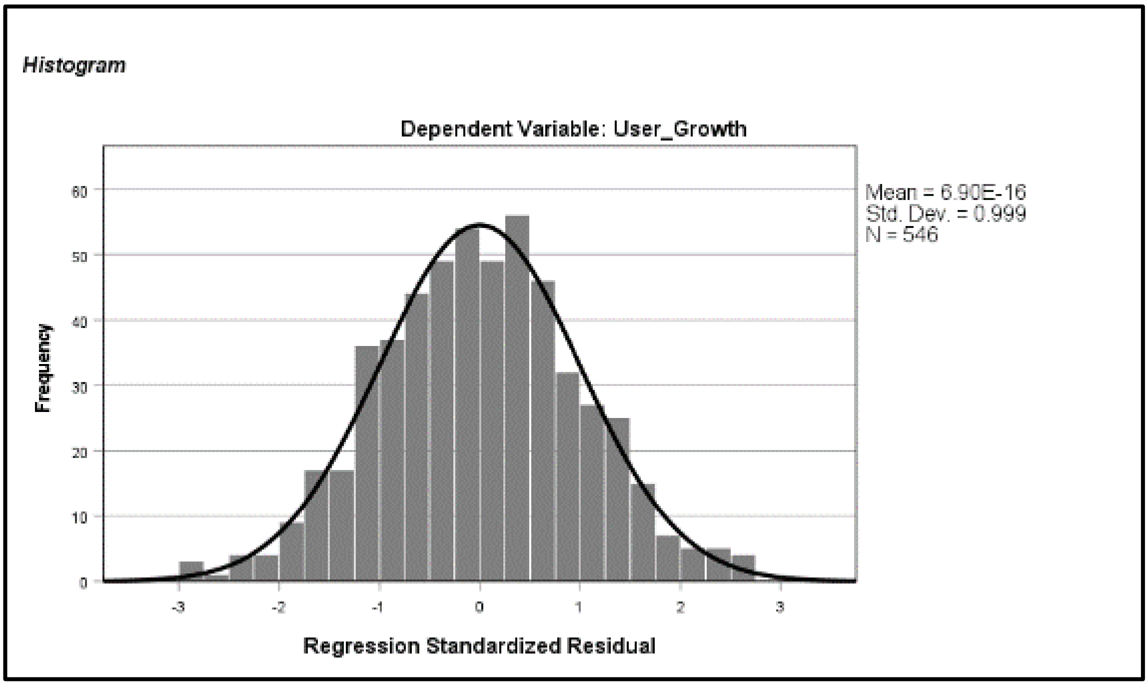


Figure A3: Histogram - Standardised Residuals for the regression between FC and UG

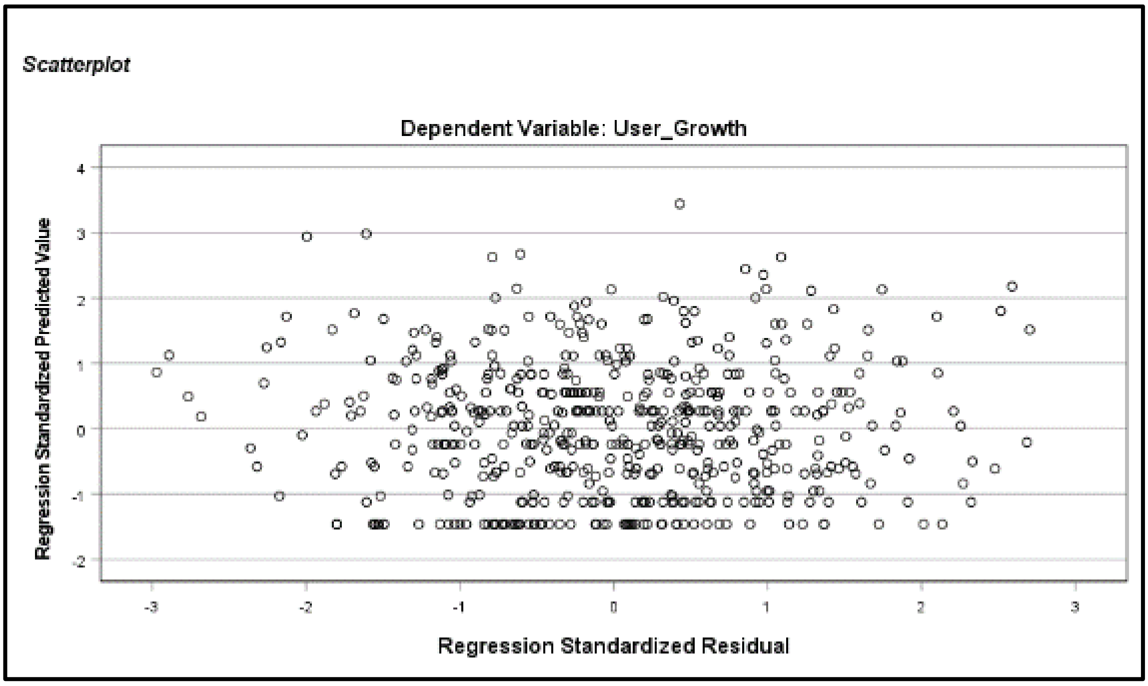


Figure A4: Scatterplot - Standardised Residuals for the regression between FC and UG

5. Correlation Analysis

Table A11: Correlations – BI and UG

Correlations – BI and UG Construct

		Retention	Revenue	Acquisition	Referral	Activation	BI
Retention	**Pearson Correlation**	--					
	N	550					
Revenue	**Pearson Correlation**	.400**	--				
	Sig. (2-tailed)	0,000					
	N	550	550				
Acquisition	**Pearson Correlation**	.374**	.378**	--			
	Sig. (2-tailed)	0,000	0,000				
	N	550	550	550			
Refer	**Pearson Correlation**	.395**	.394**	.214**	--		
	Sig. (2-tailed)	0,000	0,000	0,000			
	N	550	550	550	550		
Activation	**Pearson Correlation**	.311**	.245**	.244**	.169**	--	
	Sig. (2-tailed)	0,000	0,000	0,000	0,000		
	N	550	550	550	550	550	
BI	**Pearson Correlation**	.318**	.509**	.308**	.403**	.226**	--
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	
	N	550	550	550	550	550	550

6. Measures of Central Tendency

Table A12: Measures of Central Tendency: UTAUT2 model (Venkatesh et al., 2012)

UTAUT2 model										
		A1.1 PE_Website app useful	**A1.2 PE_Frees up time**	**A1.3 PE_Shopping tasks quicker**	**A2.1 EE_Learnin g to use is easy**	**A2.2 EE_Quick and responsive**	**A2.3 EE_Product info and pricing**	**A3.1 SI_People influence my decision**	**A3.2 SI_People who are important**	**A3.3 SI_Status symbol**
N	**550**	550	550	550	550	550	550	550	550	550
	0	0	0	0	0	0	0	0	0	0
Mean		-0,6327	-0,2499	-0,1879	-0,1004	-0,3786	-0,4229	0,4595	-0,0292	0,5465
Std. Error of Mean		0,03994	0,03143	0,03292	0,03313	0,03189	0,03193	0,04027	0,03976	0,04131
Median		-1,3211	0,0611	0,0607	0,0595	0,0722	-1,0821	0,7146	0,0619	0,7124
Std. Deviation		0,93666	0,73720	0,77200	0,77685	0,74793	0,74883	0,94442	0,93256	0,96873
Variance		0,877	0,543	0,596	0,603	0,559	0,561	0,892	0,870	0,938
Skewness		1,030	0,597	0,598	0,556	0,735	0,733	0,100	0,423	-0,044
Std. Error of Skewness		0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104
Kurtosis		0,124	-0,317	-0,089	-0,003	0,062	-0,085	-0,599	-0,662	-0,768
Std. Error of Kurtosis		0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208

UTAUT2 model (cont.)											
		A4.1 FC_Query resolution process	**A4.2 FC_Repla-cement Refund**	**A4.3 FC_Flexible delivery pickup**	**A5.1 PV_wifi to place order**	**A5.2 PV_Pay a small delivery fee**	**A5.3 PV_Free delivery of my order**	**A6.1 HM_Browsing is enjoyable**	**A6.2 HM_Exciting to order**	**A7.1 Habit_ Become a habit**	**A7.2 Habit_ Become a routine**
N	**Valid**	550	550	550	550	550	550	550	550	550	550
	Missing	0	0	0	0	0	0	0	0	0	0
Mean		-0,0768	-0,0562	-0,0360	-0,6221	-0,2061	-0,2332	0,8675	0,8850	1,6345	0,4089
Std. Error of Mean		0,02335	0,03772	0,03582	0,03710	0,03483	0,04109	0,03324	0,03225	0,03646	0,03838
Median		0,0500	0,0615	0,0607	-1,2656	0,0636	0,0708	0,7099	0,7102	1,9361	0,0726
Std. Deviation		0,54754	0,88467	0,84009	0,87009	0,81672	0,96362	0,77959	0,75623	0,85516	0,90000
Variance		0,300	0,783	0,706	0,757	0,667	0,929	0,608	0,572	0,731	0,810
Skewness		0,375	0,484	0,483	1,031	0,574	0,552	-0,020	-0,105	-0,531	0,211
Std. Error of Skewness		0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104
Kurtosis		0,198	-0,327	-0,228	0,250	-0,435	-0,657	-0,241	-0,133	0,253	-0,490
Std. Error of Kurtosis		0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208

Table A13: Measures of Central Tendency: AARRR model

AARRR Model (UG Construct)										
		A10.1 Acquisition_Retailers advertise	**A10.2 Acquisition_Info about benefits**	**A10.3 Acquisition_Visited and browsed**	**A12.1 Activation_ Ease of registration**	**A12.2 Activation_ Ease of navigation**	**A12.3 Activation_ Simplicity order placement**	**A13.1 Retention_ Indicators stock availability**	**A13.2 Retention_ Delivery Selected timeslot**	**A13.3 Retention _Order accuracy**
N	**Valid**	550	550	550	550	550	550	550	550	550
	Missing	0	0	0	0	0	0	0	0	0
Mean		0,7038	0,0147	-0,4832	-0,3109	-0,3899	-0,9157	-0,2303	-0,2278	0,2031
Std. Error of Mean		0,04806	0,03466	0,03442	0,03726	0,03823	0,03950	0,02709	0,02857	0,03647
Median		0,5529	-0,1416	-0,1479	-0,1502	-0,1483	-1,5889	-0,1538	-0,1538	-0,1324
Std. Deviation		1,12704	0,81287	0,80715	0,87387	0,89653	0,92646	0,63542	0,67000	0,85526
Variance		1,270	0,661	0,651	0,764	0,804	0,858	0,404	0,449	0,731
Skewness		-0,045	0,349	0,713	0,678	0,567	1,091	0,433	0,372	0,263
Std. Error of Skewness		0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104	0,104
Kurtosis		-0,706	0,046	0,433	0,494	-0,393	0,544	0,436	0,010	-0,293
Std. Error of Kurtosis		0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208	0,208

AARRR Model (Cont.)							
		A14.1 Refer_Complete shopping tasks quickly	**A14.2 Refer_Online product range**	**A14.3 Refer_The payment process is safe and secure**	**A15.1 Revenue_Loyalty points**	**A15.2 Revenue_Free 30day return order service**	**A15.3 Revenue_Cashbacks**
N	**Valid**	550	550	550	550	550	550
	Missing	0	0	0	0	0	0
Mean		0,5696	-0,3505	0,1282	0,2650	0,3077	0,4948
Std. Error of Mean		0,04489	0,04520	0,03258	0,03237	0,04078	0,04312
Median		0,5546	-0,1455	-0,1318	0,5560	0,5582	0,5557
Std. Deviation		1,05281	1,06005	0,76412	0,75916	0,95643	1,01123
Variance		1,108	1,124	0,584	0,576	0,915	1,023
Skewness		-0,099	0,410	0,019	0,051	0,064	-0,103
Std. Error of Skewness		0,104	0,104	0,104	0,104	0,104	0,104
Kurtosis		-0,804	-0,972	-0,535	-0,293	-0,602	-0,649
Std. Error of Kurtosis		0,208	0,208	0,208	0,208	0,208	0,208

Table A14: Measures of Central Tendency: BI and Satisfaction

Behavioural Intention and Satisfaction								
		A9.1BI_Become a regular user	**A9.2BI_Increase your basket size**	**A9.3BI_Place more online orders**	**A8.1Sat_The quality of the products**	**A8.2Sat_Order Accuracy**	**A8.3Sat_The level of customer service**	**A8.4Sat_ Overall happiness**
N	**Valid**	550	550	550	550	550	550	550
	Missing	0	0	0	0	0	0	0
Mean		-0,2105	0,2482	-0,0441	-0,3333	-0,6009	-0,3780	-0,4707
Std. Error of Mean		0,04184	0,04065	0,04306	0,02881	0,03440	0,03538	0,03502
Median		0,2226	0,2166	0,2161	0,0611	-1,2074	-1,1139	-1,1648
Mode		-1,16	0,22	-1,12	-0,97	-1,21	-1,11	-1,16
Std. Deviation		0,98116	0,95331	1,00994	0,67561	0,80669	0,82979	0,82126
Variance		0,963	0,909	1,020	0,456	0,651	0,689	0,674
Skewness		0,637	0,209	0,502	0,655	1,054	0,672	0,905
Std. Error of Skewness		0,104	0,104	0,104	0,104	0,104	0,104	0,104
Kurtosis		-0,348	-0,677	-0,472	-0,232	0,572	-0,617	0,485
Std. Error of Kurtosis		0,208	0,208	0,208	0,208	0,208	0,208	0,208

7. Summary Item Statistics

Table A15: Summary Item Statistics: UTAUT2 model (Venkatesh et al., 2012) and BI

Summary Item Statistics - UTAUT2 model and Behavioural Intention							
Performance Expectancy:	**Factor 1**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	0.521	0.464	0.555	0.092	1.197	0.002	3
Effort Expectancy:	**Factor 4**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	0.593	0.505	0.698	0.193	1.381	0.008	3
Social Influence:	**Factor 3**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	0.507	0.425	0.648	0.223	1.525	0.012	3
Facilitating Conditions:	**Factor 5**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	0.500	0.371	0.706	0.335	1.904	0.026	3
Price Value:	**Factor 6**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Scale Statistics	-0.4193						3
Hedonic Motivation:	**Factor 2**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	0.684	0.684	0.684	0.000	1.000	0.000	2
Behavioural Intention:	**Factor 7**						
	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.652	.594	.730	.136	1.230	.004	3

Table A16: Summary Item Statistics: UG Construct and Satisfaction

Summary Item Statistics - User Growth Construct and Satisfaction

Acquisition: **Factor 3**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.505	.505	.505	.000	1.000	.000	2

Activation: **Factor 5**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.440	.389	.511	.123	1.316	.003	3

Retention: **Factor 1**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.613	.613	.613	.000	1.000	.000	2

Revenue: **Factor 2**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.769	.769	.769	.000	1.000	.000	2

Referral: **Factor 4**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.689	.689	.689	.000	1.000	.000	2

Satisfaction: **Factor 1**

	Mean	Minimum	Maximum	Range	Maximum/Minimum	Variance	N of Items
Inter-Item Correlations	.598	.542	.640	.097	1.179	.001	4

8. Moderation Coefficients

Table A17: Moderation Coefficients of Satisfaction between BI and UG Construct

Satisfaction as a Moderator between Behavioural Intention and the User Growth Construct					
Acquisition					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,1223	0,0346	3.5381	0,0004	0,0544, 0,1902
BI (X)	0,1650	0,038	4,3458	0,0000	0,0904, 0,2396
Satisfaction (W)	0,1344	0,0435	3,0924	0,0021	0,0490, 0,2197
Interaction	0,1028	0,0450	2,2849	0,0227	0,0144, 0,1912
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(Acquisition*Satis-faction)	0,0089	5,2206	1,0000	546,0000	0,0227
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,2707	0,0733	0,3900	14,3905	0,0000
Activation					
	coeff	**SE**	**t**	**p**	**CI**
Constant	-0,3184	0,0341	-9,3501	0,0000	-0,3853,-0,2515
BI (X)	0,0924	0,0374	2,4715	0,0138	0,0190, 0,1659
Satisfaction (W)	0,5065	0,0428	11,8341	0,0000	0,4224, 0,5906
Interaction	0,0347	0,0443	0,7821	0,4345	-0,0524, 0,1217
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(Activation*Satis-faction)	0,0008	0,6116	1	546	0,4345
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,5079	0,2580	0,3784	63,2684	0,0000
Retention					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,0946	0,0253	3,7348	0,0002	0,0448, 0,1443
BI (X)	0,2112	0,0278	7,5942	0,0000	0,1566, 0,2659
Satisfaction (W)	0,1502	0,0318	4,7187	0,0000	0,0877, 0,2128
Interaction	0,0027	0,0330	0,0828	0,9430	-0,0620, 0,0675
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(Retention*Satis-faction)	0	0,0069	1,0000	546,0000	0,934
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,4485	0,2011	0,2093	45,8264	0,0000

Table A18: Moderation Coefficients of Satisfaction between BI and UG Construct (cont.)

Satisfaction as a Moderator between Behavioural Intention and the User Growth Construct					
Revenue					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,4715	0,0432	10,9039	0,0000	0,3866, 0,5564
BI (X)	0,5375	0,0475	11,31	0,0000	0,4442, 0,6308
Satisfaction (W)	0,1564	0,0544	2,877	0,0042	0,0497, 0,2632
Interaction	0,0039	0,0563	0,0686	0,9453	-0,1067, 0,1144
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(Revenue*Satis-faction)	0	0,0047	1,0000	546,0000	0,9453
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,5398	0,2914	0,6102	74,8544	0,0000
Referral					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,1363	0,0391	3,4838	0,0005	0,0595, 0,2132
BI (X)	0,1881	0,0430	4,3776	0,0000	0,1037, 0,2725
Satisfaction (W)	0,1189	0,0492	2,4178	0,0159	0,0223, 0,2155
Interaction	0,1678	0,0509	3,2956	0,0010	0,0678, 0,2679
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(Referral*Satis-faction)	0,0186	10,861	1,0000	546,0000	0,001
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,2576	0,0664	0,4996	12,9351	0,0000
UG Construct					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,1013	0,0187	5,4195	0,0000	0,0646, 0,1380
BI (X)	0,2389	0,0205	11,6389	0,0000	0,1985, 0,2792
Satisfaction (W)	0,2133	0,0235	9,0812	0,0000	0,1672, 0,2594
Interaction	0,0624	0,0243	2,5649	0,0106	0,0146, 0,1102
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(UG*Satisfaction)	0,0074	6,5785	1,0000	546,0000	0,0106
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,6222	0,3871	0,1139	114,9363	0,0000

Table A19: Moderation Coefficients of Age between BI and UTAUT2 model (Venkatesh et al., 2012)

Age as a Moderator between Behavioural Intention and the UTAUT2 Construct					
Performance Expectancy					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,0481	0,1345	0,3579	0,7205	-0,2160, 0,3123
Performance Expectancy (X)	0,2543	0,1746	1,4563	0,1459	-0,0887, 0,5973
Age (W)	0,0286	0,0340	0,8404	0,4010	-0,0383, 0,0955
Interaction	0,0526	0,0450	1,1674	0,2436	-0,0359, 0,1410
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Age)	0,0022	1,3627	1,00000	546,0000	0,2436
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,3575	0,1278	0,6486	26,6716	0,0000
Effort Expectancy					
	coeff	**SE**	**t**	**p**	**CI**
Constant	-0,0897	0,1434	-0,6256	0,5319	-0,3714, 0,1920
Effort Expectancy (X)	0,2440	0,2024	1,2057	0,2285	-0,1535, 0,6415
Age (W)	0,0409	0,037	1,1056	0,2694	-0,0318, 0,1136
Interaction	-0,0091	0,0521	-0,175	0,8611	-0,1115, 0,0932
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Age)	0,0001	0,0306	1,0000	546,0000	0,8611
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,1685	0,0284	0,7226	5,3196	0,0013
Social Influence					
	coeff	**SE**	**t**	**p**	**CI**
Constant	-0,1494	0,1407	-1,0615	0,2889	-0,4259, 0,1271
Social Influence (X)	0,0232	0,1688	0,1375	0,8907	-0,3083, 0,3547
Age (W)	0,0251	0,0373	0,6726	0,5015	-0,0481, 0,0983
Interaction	0,0372	0,0440	0,8440	0,3991	-0,0493, 0,1236
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Age)	0,0013	0,7123	1	546	0,3391
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,1597	0,0255	0,7247	4,7660	0,0027
Facilitating Conditions					
	coeff	**SE**	**t**	**p**	**CI**
Constant	-0,1208	0,1127	-1,0716	0,2844	-0,3421, 0,1006
Facilitating Conditions (X)	0,6486	0,1473	4,4026	0,0000	0,3592, 0,9380
Age (W)	0,0503	0,0293	1,7165	0,0866	-0,0073, 0,1079
Interaction	0,0080	0,0378	-0,2106	0,8333	-0,0823, 0,0663
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Age)	0,0001	0,0443	1	546	0,8333
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,5279	0,2787	0,5364	70,3274	0,0000

__Table A20: Moderation Coefficients of Gender between BI and UTAUT2 model (Venkatesh et al., 2012)__

Gender as a Moderator between Behavioural Intention and the UTAUT2 Construct					
Performance Expectancy					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,3598	0,1198	3,0029	0,0028	0,1244, 0,5951
Performance Expectancy (X)	0,5846	0,1574	3,7131	0,0002	0,2753, 0,8939
Gender (W)	-0,1387	0,0787	-1,7624	0,0786	-0,2933, 0,0159
Interaction	-0,098	0,1032	-0,9493	0,3429	-0,3008, 0,1048
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Gender)	0,0014	0,9012	1,00000	543,0000	0,3429
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,3622	0,1312	0,6436	27,3273	0,0000
Effort Expectancy					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,3075	0,1246	2,4677	0,0139	0,0627, 0,5523
Effort Expectancy (X)	0,2264	0,1717	1,3185	0,1879	-0,1109, 0,5638
Gender (W)	-0,1634	0,0802	-2,0369	0,0421	-0,3209, 0,0058
Interaction	-0,0124	0,1127	-0,1103	0,9122	-0,2339, 0,2090
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Gender)	0,0000	0,0122	1,0000	543,0000	0,9122
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,1866	0,0348	0,7150	6,5289	0,0002
Social Influence					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,0871	0,1279	0,681	0,4962	-0,1642, 0,3385
Social Influence (X)	0,3584	0,1456	2,4608	0,0142	0,0723, 0,6445
Gender (W)	-0,0966	0,0789	-1,223	0,2219	-0,2516, 0,0585
Interaction	-0,1361	0,0941	-1,4464	0,1487	-0,3210, 0,0487
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Gender)	0,0037	2,092	1	543	0,1487
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,1850	0,0342	0,7154	6,4175	0,0003
Facilitating Conditions					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,1686	0,0993	1,6981	0,0901	-0,0264, 0,3636
Facilitating Conditions (X)	0,5722	0,1343	4,2606	0,0000	0,3084, 0,8360
Gender (W)	-0,0657	0,0634	-1,0356	0,3008	-0,1903, 0,0589
Interaction	0,0330	0,0862	0,3831	0,7018	-0,1363, 0,2023
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Gender)	0,0002	0,1468	1,00000	543,00000	0,7018
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,5334	0,2845	0,5300	71,9651	0,0000

Table A21: Moderation Coefficients of Experience between BI and UTAUT2 model (Venkatesh et al., 2012)

Experience as a Moderator between Behavioural Intention and the UTAUT2 Construct					
Effort Expectancy					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,4779	0,1444	3,3102	0,0010	0,1943, 0,7615
Effort Expectancy (X)	0,2896	0,2115	1,3695	0,1714	-0,1258, -0,7050
Experience (W)	-0,0989	0,0330	-2,9942	0,0029	-0,1638, -0,0340
Interaction	-0,0207	0,0477	-0,4353	0,6635	-0,1144, -0,0729
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Experience)	0,0003	0,1895	1,0000	546,0000	0,6635
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,2038	0,0415	0,7128	7,8851	0
Social Influence					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,4166	0,1527	2,7288	0,0066	0,1167, 0,7164
Social Influence (X)	0,1311	0,1824	0,7184	0,4728	-0,2273, -0,4894
Experience (W)	-0,1118	0,0350	-3,1897	0,0015	-0,1806, -0,0429
Interaction	0,0096	0,0414	0,2329	0,8159	-0,0716, -0,0909
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Experience)	0,0001	0,0542	1,0000	546,0000	0,8159
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,2068	0,0428	0,7119	8,1313	0,0000
Facilitating Conditions					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,2719	0,1210	2,2467	0,0251	0,0342, 0,5095
Facilitating Conditions (X)	0,4485	0,1483	3,0247	0,0026	0,1572, 0,7398
Experience (W)	-0,0477	0,0276	-1,7285	0,0845	-0,1020, -0,0065
Interaction	0,0387	0,0345	1,1240	0,2615	-0,0290, -0,1064
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(BI*Experience)	0,0017	1,2633	1,0000	546,0000	0,2615
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,5296	0,2804	0,5351	70,9343	0,0000

Table A22: Moderation Coefficients of Satisfaction between FC and UG Construct

Satisfaction as Moderator between Facilitating Conditions and the UG Construct					
FC and UG					
	coeff	**SE**	**t**	**p**	**CI**
Constant	0,1280	0,0175	7,3046	0,0000	0,0935, 0,1624
FC (X)	0,3096	0,0238	12,9907	0,0000	0,2628, 0,3564
Satisfaction (W)	0,2047	0,0224	9,1301	0,0000	0,1606, 0,2487
Interaction	0,0633	0,0282	2,2414	0,0254	0,0078, 0,1187
Test of highest order unconditional interactions:					
	R2-chng	**F**	**dfl**	**df2**	**p**
X*W(UG*Satisfaction)	0,0053	5,0238	1,0000	546,0000	0,0254
Model Summary	**R**	**R-squared**	**MSE**	**F**	**p**
	0,6524	0,4256	0,1068	134,8536	0,0000

APPENDIX B - Consistency table: research questions, hypothesis statements, data collection and data analysis

RQ No.	Research Question	Hypothesis no.	Hypothesis Statement	Data collection detail	Data analysis method
1	Which determinants influence a customer’s behavioural intention to use B2C e-commerce platforms in South Africa?	1	PE influences customers’ BI to use B2C e-commerce platforms.	Questions 5.1, 5.2 and 5.3	Factor Analysis, Regression Analysis
		2	EE influences customers’ BI to use B2C e-commerce platforms.	Questions 4.2, 4.3, 4.4	
		3	SI influences customers’ BI to use B2C e-commerce platforms.	Questions 5.4, 5.5 and 5.6	
		4	FC influences customers’ BI to use B2C e-commerce platforms.	Questions 6.1, 6.2 and 6.3	
1	Which determinants influence a customer’s behavioural intention to use B2C e-commerce platforms in South Africa?	5	HM influences customers' BI to use B2C e-commerce platforms.	Questions 7.2, 7.3	Factor Analysis, Regression Analysis.
		6	Habit influences customers' BI to use B2C e-commerce platforms.	Questions 7.4, 7.5	
		7	PV influences customers' BI to use B2C e-commerce platforms.	Questions 8.1, 8.2, 8.3	
		8	Age will moderate the effect of PE, EE, SI and FC on customers’ BI to use B2C e-commerce platforms.	Question 1.2	Descriptive and Inferential Statistics.

RQ No.	Research Question	Hypothesis no.	Hypothesis Statement	Data collection detail	Data analysis method
		9	Gender will moderate the effect of PE, EE, SI and FC on customers' BI to use B2C e-commerce platforms.	Question 1.1	
		10	Experience will moderate the effect of EE, SI and FC on customers' BI to use B2C e-commerce platforms.	Question 3.4	
2	To what extent do customers' behavioural intentions influence UG in B2C e-commerce platforms in South Africa?	11	Customers' BI influences acquisition in becoming aware of B2C e-commerce platforms.	Questions 4.1.1, 4.1.2, 4.1.3	Factor Analysis, Correlation Analysis.
2	To what extent do customers' behavioural intentions influence UG in B2C e-commerce platforms in South Africa?	12	Customers' BI influences activation in the adoption of B2C e-commerce platforms.	Questions 4.5.1, 4.5.2, 4.5.3	Factor Analysis, Correlation Analysis.
		13	Customers' BI influences retention in reusing B2C e-commerce platforms.	Questions 7.1.1, 7.1.2, 7.1.3	
		14	Customers' BI influences the referral to B2C e-commerce platforms.	Questions 8.4.1, 8.4.2, 8.4.3	
		15	Customers' BI is influenced by the revenue received (benefits) from reusing B2C e-commerce platforms.	Questions 8.5.1, 8.5.2, 8.5.3	
2	To what extent do customers' behavioural intentions influence UG in B2C e-commerce platforms in South Africa?	16	Customers' BI influences user growth in B2C e-commerce platforms.	Questions 9.2.1, 9.2.2, 9.2.3	Factor Analysis, Correlation Analysis, Mediation Analysis.
		17	Customers' habits affect user growth in B2C e-commerce platforms.	Questions 7.4, 7.5	

RQ No.	Research Question	Hypothesis no.	Hypothesis Statement	Data collection detail	Data analysis method
		18	Facilitating conditions (FC) affects user growth in B2C e-commerce platforms.	Questions 6.1, 6.2 and 6.3	
3	To what extent does satisfaction affect behavioural intention to use B2C e-commerce platforms in South Africa?	19	Customers' BI to use B2C e-commerce platforms is moderated by satisfaction.	Questions 9.2.1, 9.2.2, 9.2.3	
		20	The effect of FC on UG in B2C e-commerce platforms is moderated by satisfaction.	Questions 6.1, 6.2 and 6.3 Questions 9.1.1, 9.1.2, 9.1.3, 9.1.4	Factor Analysis, Regression Analysis, and Mediation Analysis.

APPENDIX C - Proposed schedule and timelines

Below are the estimated timelines for the completion of the research report:

Date	Activity
2022.06.30	Submit Research Proposal to Wits Business School (WBS) Research Panel.
2022.07.07	Present Proposal to WBS panel.
2022.07.13	Research Proposal Title approval.
2022.07.26	Proposal Defence outcome.
2022.08.29	Revised Title submitted.
2022.09.23	Revised Title approved.
2022.11.10	Resubmit the Proposal for panel approval after updates have been incorporated.
2022.11.22	Panel approves revised Proposal.
2023.02.21	Ethics approval was received.
2023.03.31	Approval to conduct research at the University received from the Registrar.
2023.04.01 – 2023.07.31	Data collection.
2023.08.01 – 2024.12.31	Finalisation of results and Research Report.
2024.01.01 – 2024.02.15	Editing and Supervisor approval.
2024.02.29	Submission of final Research Report.

APPENDIX D - Research Project Information Sheet

Wits Business School
Masters of Management in Digital Business Research Survey

My name is Liesl Viljoen-Nel. I am a Master's student in Digital Business at Wits Business School, and I am conducting a research study about user behaviour and user growth in Business-to-Consumer (B2C) e-commerce platforms in the FMCG (fast moving consumer goods) industry in South Africa. The aim of this study is to understand the factors or determinants that will influence a user to start and continue buying products on an e-commerce website/application. The study title is:

"Determinants of User Growth in B2C E-Commerce Platforms in South Africa".

I am inviting you to participate in this research survey by answering an online questionnaire that will take an estimated 15 minutes of your time. Your participation in this research study is voluntary. The data collected will be treated with the strictest confidentiality, and all the required steps will be taken to ensure that your responses remain anonymous and non-traceable throughout the research process.

If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University of Witwatersrand Human Research Ethics Committee (Non-Medical) by telephone +27(0) 11 717 1408 or email hrecnon-medical@wits.ac.za.

This research study will be written up as a research report. On request, you are able to receive a copy of the research report.

If you have any questions during or afterwards about this research study, feel free to contact me or my Supervisor at the details listed below.

Contact details of master's candidate:
Ms Liesl Viljoen-Nel
Email: 443960@students.wits.ac.za
Mobile No. +27 82 760 5720
Contact details of the Research Supervisor:
Prof. Nixon Ochara, PhD.
Email: nixon.ochara@wits.ac.za

APPENDIX E - Participant Agreement Form

Wits Business School

Masters of Management in Digital Business Research Survey

Topic: Determinants of User Growth in B2C E-Commerce Platforms in South Africa

The data collection will be treated with the strictest confidentiality, and all the required steps will be taken to ensure the respondents' anonymity and non-traceability throughout the research process. If needed, respondents can request a summary of the research report.

By proceeding to complete this survey, you agree that you are anonymously and voluntarily participating in this survey.

I agree. ☐ I do not agree. ☐

Thank you in advance for your feedback.

Contact details of Masters' candidate:

Ms Liesl Viljoen-Nel

Email: 443960@students.wits.ac.za

Mobile No. +27 82 760 5720

Contact details of Research Supervisor:

Prof. Nixon Ochara, Ph.D.

Email: nixon.ochara@wits.ac.za

Tel: +27 11 717 3543

APPENDIX F - Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

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

Ethics Clearance Certificate

Ethics protocol number: WBS/DB443960/568

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (belo

Project title	Determinants of user growth in B2C e-commerce platforms in South Africa
Investigator / Researcher	Mrs Liesl Viljoen
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2023-02-21
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

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

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

Viljoen
Signature

2023|02|21
Date:

APPENDIX G - Approval to conduct Research at the University

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

OFFICE OF THE DEPUTY REGISTRAR

31 March 2023

Liesl Viljoen
Student Number (443960)
Master of Management
Wits Business School

TO WHOM IT MAY CONCERN

"Determinants of user growth in B2C e-commerce platforms in South Africa ."

This letter serves to confirm that the above project has received permission to be conducted on University premises, and/or involving staff and/or students of the University as research participants. In undertaking this research, you agree to abide by all University regulations for conducting research on campus and to respect participants' rights to withdraw from participation at any time.

If you are conducting research on certain student cohorts, year groups or courses within specific Schools and within the teaching term, permission must be sought from Heads of School or individual academics.

Ethical clearance has been obtained. (Protocol number: WBS/DB443960/S68)

Research Expiration: (Research submission date)

NPotgieter

Nicoleen Potgieter
University Deputy Registrar

Private Bag 3, WITS, 2050, South Africa | T +27 11 717 1204/8 | E nicoleen.potgieter@wits.ac.za | www.wits.ac.za

IYUNIVESITHI YASEWITWATERSRAND | YUNIVESITHI YA WITWATERSRAND

100 1922 2022

APPENDIX H - Research Instrument

A. Introduction

Wits Business School
Masters of Management in Digital Business Research Survey

My name is Liesl Viljoen-Nel. I am a Master's student in Digital Business at Wits Business School. I am conducting a research study about user behaviour and user growth in Business-to-Consumer (B2C) e-commerce platforms in the fast-moving consumer goods (FMCG) industry in South Africa. The study title is **"Determinants of User Growth in B2C E-Commerce Platforms in South Africa"**

I am inviting you to participate in this research survey by answering an online questionnaire that will take an estimated 10 minutes of your time.

Your participation in this research study is voluntary. The data collected will be treated with the strictest confidentiality, and all the required steps will be taken to ensure that your responses remain anonymous and non-traceable throughout the research process. The required institutional clearance for this study was obtained from the University of Witwatersrand.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor at the details listed below.

Contact details of masters' candidate:
Ms Liesl Viljoen-Nel
email: 443960@students.wits.ac.za
Mobile No. +27 82 760 5720
Contact details of the Research Supervisor:
Prof. Nixon Ochara, PhD.
email: nixon.ochara@wits.ac.za

Consent

By proceeding to complete this survey, you agree that you are anonymously and voluntarily participating in this survey.

◯ Yes, I consent to participate in the survey (1)

◯ No, I do not consent to participate in the survey (2)

Skip To: End of Survey If B. Consent = 2

Instructions:

The following questionnaire contains a list of statements to determine your online purchase behaviours for fast-moving consumer goods.

Fast-moving consumer goods includes fresh, baked and frozen foods, alcoholic and non- alcoholic beverages, medication, cleaning products, self-care products and stationery.

Platforms where you can typically shop online for these products includes Checkers Sixty60, Pick 'n Pay ASAP!, Woolies Dash!, www.makro.co.za, www.clicks.co.za, www.dischem.co.za, Takealot and OneDayOnly to name a few.

Please select the most appropriate choice.

Section 1

Section 1: Demographic Questions

Gender

1.1 Please select your gender

Male	Female	Non-binary	I prefer not to say

Age

1.2 Please select your age

17 yrs or younger *(If this option is selected, the respondent will exit the survey)*	18 – 30 years	31 – 40 years	41 – 50 years	51 – 60 years	61 – 70 years	71 + years

Ethnic Group

1.3 Please select your race or ethnic group

African	Asian	Coloured	Indian	Mixed Race	White	Other

Location

1.4 Please select your current location of residence in South Africa

Eastern Cape	Free State	Gauteng	KwaZulu-Natal	Limpopo	Mpumalanga	Northern Cape	North West	Western Cape	Other

Section 2

Section 2: Education and Occupation

Education

2.1 Please select your highest level of education obtained

High school	Matric Certificate	Diploma	Bachelor's Degree	Postgraduate Degree or higher	Other

Income

2.2 Please select your approximate before tax income bracket

< R9,999 per month	R10,000 - R25,000 per month	R26,000 - R50,000 per month	R51,000 - R75,000 per month	R76,000 + per month

Section 3

Section 3: Shopping Habits and Experience

Internet Usage

3.1 On average, how often do you use the Internet to shop online?

Once per week	More than once per week	Every two weeks	Once a month	Every three months	Occasionally - when there are big sales (Easter, Black Friday)	Seldom	I don't shop online *(If this option is selected, the respondent will exit the survey)*

Shopping duration

3.2 In general, how much time do you spend doing online shopping/browsing per week?

± 30 minutes	± 45 minutes	± 60 minutes	± 90 minutes	More than 2 hours

Shopping places

3.3 On average, how many different online shopping websites or apps do you shop from in a month?

1 to 3 websites/apps	4 to 6 websites/apps	7 to 10 websites/apps	More than 11 websites or apps

Online Experience

3.4 For approximately how long have you been shopping online?

For less than six months	7 -11 months	1 - 2 years	3 - 4 years	5 -10 years	More than 10 years

Section 4

Section 4: *This block of questions explores how you become aware and start using an e-commerce website/app.*

4.1 I am aware of e-commerce websites or apps because

4.1.1 Retailers advertise them on TV, radio and in newspapers	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
4.1.2 I have gathered enough information about their benefits - timesaving, cost-saving, available 24/7	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
4.1.3 I have visited some websites and apps and have browsed through the available products	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

4.2 Learning to use my preferred retailers' e-commerce website/app is easy

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

4.3 My preferred retailers' e-commerce website/app is quick and responsive when searching and adding products to my basket

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

4.4 My preferred website/app's online product information & pricing supports me to evaluate and compare prices between products prior to buying online

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

4.5 My adoption of a website or app is determined by:

4.5.1 Ease of the online registration	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
4.5.2 Ease of online navigation - search and selecting of products	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
4.5.3 Simplicity of order placement	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

Section 5

Section 5: *This block of questions will review your expectations of an e-commerce website/app and the impact of your social circle on your usage of a website/app.*

5.1 I find the e-commerce website/app of my preferred retailer useful (handy/ helpful/ effective)

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

5.2 Shopping for my groceries, self-care or other products online frees up time to achieve things that are important to me

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

5.3 Online shopping helps me accomplish my shopping tasks quicker

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

5.4 People who influence my decision-making think that I should shop for my products online by using an e-commerce website/app

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

5.5 People (friends/ family/ co-workers) who are important to me think that I should be ordering my products online

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

5.6 Using an e-commerce website/app is a status symbol in my social networks (Facebook, Instagram, X, LinkedIn)

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

Section 6

Section 6: *This block of questions will review your expectations of customer service when shopping online.*

6.1 My usage of an e-commerce website/app is dependent on the availability of a query resolution process via online messaging/ telephone /email customer support

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

6.2 It is important that my preferred e-commerce website/app facilitates valid replacement or refund requests of my order

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

6.3 I order on my preferred e-commerce website/app since it provides me with flexible delivery/pick up options

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

Section 7

Section 7: *This block of questions will review your usage behaviours of a website/app.*

7.1 My decision to reuse a website/app is impacted by

7.1.1 Indicators that shows stock availability as I compile my basket	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
7.1.2 Order delivery that takes place in my selected time slot	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
7.1.3 Order accuracy (products & quantities) are delivered as placed	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

7.2 Browsing through an e-commerce website/app is enjoyable

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

7.3 I find it exciting to order my products through an e-commerce website/app

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

7.4 Ordering on my preferred e-commerce website/app has become a habit for me

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

7.5 Placing my online orders for food, beverages, self-care products, books etc. has become a routine for me

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

Section 8

Section 8: *The next block of questions will evaluate your view on pricing and intention to re-use or refer to a website/app.*

8.1 Using a secure internet connection/WIFI to place my online order (with free delivery) is more economical than the return travelling cost and time to shop instore

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

8.2 I will rather pay a small delivery fee, than increasing my order value to enable me to qualify for free delivery of my order

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

8.3 I prefer to buy from e-commerce websites/apps that offers free delivery of my order

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

8.4 I will refer my preferred e-commerce website/app if

8.4.1 It enables me to complete my shopping tasks quickly	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
8.4.2 I am happy with the online product range at different price points	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
8.4.3 The payment process is safe and secure	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

8.5 I choose to use a website or app with the possibility of receiving the following benefits

8.5.1 Loyalty points on all online purchases	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
8.5.2 The availability of a free 30-day return order service	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
8.5.3 The potential cash backs that I can receive through my insurance/med aid/gym/mobile operator	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

Section 9

Section 9: *The last block of questions will aim to understand your satisfaction and increased usage of an e-commerce website/app.*

9.1 A satisfactory experience with my preferred e-commerce website/app has been impacted by

9.1.1 The quality of the products offered online	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
9.1.2 Order accuracy - the retailer delivers what I have ordered	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
9.1.3 The level of customer service received	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
9.1.4 My overall happiness with the online shopping experience	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

9.2 In future, will you ...

9.2.1 Become a regular user of your preferred retailers' website/app?	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)
9.2.2 Increase your basket size and the variety of products that you order online?	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)

9.2.3 Place more online orders as you become more comfortable with the online shopping process?	Strongly agree (1), Agree 2), Somewhat agree (3), Neither agree nor disagree (4), Somewhat disagree (5), Disagree (6), Strongly disagree (7)