E-CONSUMER AWARENESS OF DIGITAL CONSUMERISM CONCERNING FREE DATA RESOURCE EXPLOITATION

Thesis submitted in fulfilment of the requirements of the degree of Doctor of Philosophy in Management Sciences Specialising in Marketing in the Department of Marketing and Retail Management, Faculty of Management Sciences at the Durban University of Technology

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DEDICATION

This work is dedicated to my family and all the citizens of the world. I thank my parents for their resounding motivation, advice, guidance, love, and support. As a result, I have grown from a humble beginning to strength, which has motivated me to persevere and achieve the goals set out for my life. The completion of this thesis is only one of those goals. Thank you for your unrelenting support, unconditional love, and continuous inspiration. I love you, always!

ABSTRACT

The ubiquity of digital technology with powerful smart equipment has transformed digital marketing, paving the way for digital consumerism. Electronic consumer data is being freely exploited at an exponential rate through constant company surveillance for the purpose of predicting profits. E-consumer online behavioural data is progressively becoming a valuable asset for precise, granular online targeting. However, e-consumers are oblivious to the fact that their digital traces are being monitored in the process of navigating the internet. Additionally, e-consumers are unaware that their autonomy is being eroded by unfair, capitalistic digital surveillance and profiling technology. The aim of the study is to assess e-consumers awareness of the influence of digital consumerism on free data resource exploitation.

A cross-sectional mixed method research design using a validated Likert-type scale questionnaire survey was administered to a non-probability convenience sample of 400 respondents. Thereafter, interviews were conducted using purposive sampling of participants until sufficient data was collected based on the point of saturation. The saturation point was reached after interviewing 20 participants. Online survey data was analysed by SPSS 28 computer software for descriptive and inferential statistics and AMOS was administered for structural equation modelling (SEM). The data from the interviews was analysed using NVivo pattern matching and content analysis.

The results reveal that while some e-consumers are aware of free data exploitation, most e-consumers do not notice that their online behavioural data is being harvested and exploited by online retailers. The findings may assist digitalised companies to initiate loyalty programmes by compensating e-consumer data resource input. Further studies should be undertaken to explore the remediation models for free data exploitation. A remediation strategy by online retailers to recognise e-consumers data input is paramount with the current, rapid growth of digitalisation in today's data-driven economy.

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LIST OF ACRONYMS

AFI: Absolute fit index

AI: Artificial Intelligence

AMOS: Analysis of moment structures

ANOVA: Analysis of variance

API: Application programming interface

AVE: Average variance extracted

B2B: Business-to-business

B2C: Business to consumer

CASIC: Computer-assisted survey information collection

CDT: Cognitive dissonance theory

CFA: Confirmatory factor analysis

CFI: Comparative fit index

CMIN/DF: Minimum chi-square value discrepancy per degree of freedom

CR: Composite reliability

EE: E-consumer empowerment

EF: Effects

EFA: Exploratory factor analysis

eWOM: Electronic word of mouth

GFI: Goodness of fit index

IDP: Integrated development programme

IP: Internet protocol

KMO: Kaiser-Meyer Okin

ML: Machine learning

NUDIST: Non-numerical unstructured data indexing, searching and theorising

PCT: Privacy calculus theory

PI: Purchase intention

PLS-SEM: Partial least squares structural equation modelling

PMT: Protection motivation theory

PR: Perceived risk

PRE: Power-responsibility equilibrium

PRT: Perceived risk theory

PT: Perceived trust

QDAS: Qualitative data analysis software

RMSEA: Root mean square error of approximation

SEM: Structural equation modelling

SLT: Social learning theory

SPSS: Statistical package for social sciences

TAM: Technology acceptance model

TLI: Tucker-Lewis's index

TPB: Theory of planned behaviour

TRA: Theory of reasoned action

UGC: User-generated content

UGT: Uses and gratification theory

CHAPTER 1. INTRODUCTION

1:1 INTRODUCTION

E-consumer data resource exploitation is gaining traction in the growing data-driven economies of developed and developing countries. While e-consumers are conducting online shopping, they seem to be unaware that behind the scenes, online traders are harvesting their free browsing behavioural data for free. Free data resource exploitation is the use of online traces that are left by e-consumers during online shopping. This chapter covers a summary of the entire thesis, where the context and scope of the research are predominant. Chapter 2 covers the effects of digital consumerism free data resource exploitation. Chapter 3 covers the influence of perceived risk and perceived trust on e-consumers. Chapter 4 discusses the influence of purchase intention and shopping experience on e-consumers. Chapter 5 describes the ideal research methodology for the study. Chapter 6 covers the findings, analyses, and interpretation of the study, while Chapter 7 covers the discussion and conclusion of the study. The background of the study is discussed in the next section.

1:2 BACKGROUND

The new industrial revolution is characterised by the growing ubiquity of internet services. Inherent in this is the rapid data capturing powerful technologies of artificial intelligence (AI) and machine learning (ML), which have transformed marketing (Yeung 2018: 258). Digital marketing is advancing within the marketplace, with 40% of purchases in developing countries taking place on the online platform, where deliveries are made directly to the consumer's address or at a convenient collection point (UNDP 2018: 1). This development has ushered in technological surveillance of electronic consumers (e-consumers) to facilitate analytical improvements in order to satisfy e-consumer needs (Govender 2019: 26). E-consumers' activities involve any business-to-consumer (B2C) or business-to-business (B2B) transactions conducted on the internet (Nasution, Rossanty, Ariffin and Zaina 2019: 14). Hirt, Kuhl and Satzger (2019: 93) maintain that companies harvest data relating to trends in order to tailor services to customers who are clustered according to their matching profiles. E-consumers are unaware that, behind the scenes, online traders are harvesting their valuable data resources.

Hung-Joubert and Van Huyssteen (2017: 363) assert that e-consumer internet browsing, searching, and online purchases leave a trail of data footprints that fosters marketers' ability to make accurate predictions. South Africa has 54% of its population engaging in online activities (Brink, Heyns and Kilbourn 2019: 3) in search of information and making online purchases, which has contributed to digital consumerism. Due to a high level of automation to track online activities, e-consumers' autonomy is threatened by large- scale monitoring (Carmon, Schrift, Wertenbroch and Yang 2019: 1). Sharda, Delen and Turban (2018: 157) assert that e-consumer data resources are valuable for predictive and prescriptive decisions made by managers. Economically digitalised companies are benefiting from e-consumer data resources. No studies have covered e-consumer awareness of free data resource exploitation.

1:3 PROBLEM STATEMENT

Most e-consumers are held captive as their personal data, likes, friends and locations are monitored by sophisticated applications like TripAdvisor (Van der Schyff and Flowerday 2019: 3). Behind the scenes, e-consumers are unaware of the complex networks and big data mining equipment that monitor habits, behaviour, social relations, and preferences, which shape predictions for the benefit of surveillance capitalists (Antunes and Maia 2018: 192). In this study, the use of e-consumer information to make predictions is referred to as free e-consumers' data exploitation. Recent studies, as indicated by Kanwal, Pitafi, Akhtar and Irfan (2019: 190), have amassed a plethora of research on online privacy, consent, measures to protect personal data, and online purchase behaviour. However, this study is not about privacy concerns, surveillance, profiling, or predictions based on consumer online purchase behaviour. Nonetheless, the harvesting of e-consumer data is beneficial to e-consumers because their preferences can be easily identified and addressed by online traders.

The problem of concern is the exploitation of e-consumers' valuable data as free input resources to make predictions that boost online companies' value and improve performance. Therefore, the study focuses on free data resource exploitation of e-consumers, which is ubiquitous in developed countries and steadily spreading in developing countries like South Africa, where there is a high level of poor digital literacy (Pade-Khene 2018: 3). Remote surveillance of the e- consumers data resources compromises e-consumer sovereignty. E- consumers are unaware that they are under surveillance as they risk performing online transactions on the World Wide Web. Perceived risk is worrisome to e- consumers faced with uncertainty of the unknown expected results from the online activities, which may include financial loss (Salim, Alfansi, Darta, Anggarawati, and Amin 2019: 4). E-consumers develop online trust without realising that online traders are harvesting their data resources.

Having noted this cognitive conscience, e-consumers submit their valuable information online after minimising the risk and gaining some degree of trust. Therefore, e-consumers are principally concerned about trust and the risk of not getting their online purchases successfully, rather than free data resource exploitation. Coupled with a lack of awareness of free data exploitation, e-consumers may be influenced by perceived risk and perceived trust to share their valuable data assets online, endangering consumer autonomy. E-consumer awareness of free data resource exploitation requires a thorough investigation in order to establish a redress mechanism to recognise the value of online shopper's data in the growing digitalised economies. Nonetheless, e-consumer data harvesting is useful in developing strategies that can improve customer services. In the next section, the rationale of the study is explained.

1:4 RATIONALE OF THE STUDY

From the preceding section, it is clear that digitalisation has infiltrated conventional marketing practice, giving way to digital marketing where e-consumer data has become a valuable resource for the success of online trade (Van der Schyff and Flowerday 2019: 3). Unlike conventional consumer data, e-consumer data is granular, thereby attracting online traders to harvest the richer e-consumer data almost on an epic scale. Nevertheless, e-consumers seem to be unaware that their precious data resources are progressively being extracted by online traders for predictions. Online retail companies are still lagging behind in acknowledging that e-consumer data input is exploited for profitable predictions. This current study seeks to illuminate a remediation strategy towards the recognition of the value of e-consumer granular data resources, while embracing e-consumer data optimisation, which is necessary for strengthening customer relations in the exponentially growing data-driven digital economy. There is a gap in e-consumer awareness while data is a valuable resource to online traders. The aim and objectives in the next section serve as a conduit in pursuit of the remediation strategy to restrain free e-consumer data exploitation.

1:5 AIM AND OBJECTIVES

E-consumers autonomy is steadily being eroded by exploitative digitalised entities that manipulate the online users' valuable data assets for economic gain. There is constant nudging of on-board e-consumers by the online companies without e-consumers' knowledge (Carmon *et al.* 2019: 3). In the digital environment, e-consumers are increasingly disclosing their information resources (data assets) in order to transact effectively online, which has resulted in the phenomenon of free data exploitation (Salim *et al.* 2019: 42). There is a need for digitalised companies to develop remediation strategies to overcome e-consumer data exploitation. When e-consumers use online services to search for products, purchase goods, upload content on social networks, or click on a certain advertisement, they are unknowingly offering free data resources ready to be exploited for prediction (Ruckenstein and Granroth 2019: 1).

There is an escalating e-consumer lack of awareness of free data resource exploitation conducted by digitalised companies without compensation to the owner of the data resources. Dawson (2020: 244) contends that the source of data forms part of data management, where companies use the data resources for informed decision-making, especially in digital marketing. A remediation strategy to restrain free data exploitation is necessary. The aim of this study is to evaluate e- consumers' awareness of digital consumerism involving free data resource exploitation with the following objectives:

- To assess e-consumers' awareness of the effects of digital consumerism: This objective targets the core issue of e-consumer awareness, examining the extent to which individuals are cognisant of the implications of their digital interactions and the potential exploitation of their data.

- To determine the influence of perceived risk on e-consumers: This objective acknowledges the role of perceived risk in influencing e-consumer behaviour. It suggests a desire to understand how concerns related to data security and privacy impact the decision-making process of e-consumers.
- To determine the influence of perceived trust on e-consumers: Trust is a critical factor in digital transactions. This objective aims to explore how the perceived trustworthiness of digital entities influences e-consumer behaviour, particularly in the context of data sharing.
- To investigate the influence of e-consumer purchase intention: This objective delves into the relationship between e-consumer intentions to purchase and their awareness of digital consumerism, aiming to uncover the factors that drive e-consumer decision-making, and
- To investigate the influence of the e-consumer's shopping experience. The shopping experience is a multifaceted aspect of e-consumer behaviour. This objective seeks to understand how the overall online shopping experience influences e-consumer awareness and behaviour in the realm of data exploitation.

Globalisation, facilitated by digital consumerism, is bringing citizens all over the world together by means of online media and cultural transformation (De Mooij 2019: 322). Digital consumerism has grossly changed the way e-consumers perform online transactions with digitalised entities (Ventre and Kolbe 2020: 1). E-consumers are unsuspectingly innocent in the provision of their data resources to online companies, which has sparked the negative consequences of data exploitation (Wang 2018:60). In the next section, the conceptual framework is covered.

1:6 CONCEPTUAL FRAMEWORK

According to Yeung (2018: 267), consumerism is free market capitalism characterised by mass production, mass customisation, mass consumption, and mass promotion, where individuals are pre-occupied with material possessions through the purchase of consumer goods. Data resource exploitation in the current study is the use of e-consumer information to make predictions due to the fact that e-consumers are a major source of big data rich in volume and variability, enabling online entities to exploit these data resources for free without the e-consumer's knowledge (Antunes and Maia 2018: 192). Consumer data resources are valuable assets that facilitate demand forecasting in order to generate huge profits. Digitalised retail companies freely predict and prescribe with guidance from surveillance of online consumer behaviour by matching e-consumer data traces (Ruckenstein and Granroth 2019: 3).

Furthermore, Hirt, Kuhl and Satzger (2019: 100) affirm that digitalised companies are crawling into online users' information using Application Programming Interface (API) technology that classifies e-consumers to maximise free data resource exploitation. E-Consumers are unaware that their data assets are being exploited by online organisations for economic gain. Although the surveillance of e-consumers helps in making targeted predictions, e-consumers ought to be considered for their data input in order to mitigate the problem of data exploitation. In the next sub-section, a succinct briefing of the effects of digital consumerism concerning free e-consumer data exploitation is covered.

1:6:1 Effects

The profiling of online shoppers by online companies for re-targeting based on previous browsing behavioural patterns is met with discomfort on the side of online users (Ruckenstein and Granroth 2019: 5). Online retail firms embed algorithms that monitor e-consumer behaviour, where, for example, a shopper with a smoking habit receives annoying commercials promoting e-cigarettes (Carmon *et al.* 2019: 3). Digitalised retailers can detect when e-consumers need to replace older online purchased products triggering annoying commercials' new replacements (Govender 2019: 27). In some cases, algorithms produce digital noise by making false predictions that fall short of the volatility of online shopper behaviour (Ruckenstein and Granroth 2019: 9). Online firms that harvest behavioural patterns based on previous online transactions execute false predictions without e-consumers' knowledge.

Antunes and Maia (2018: 195) caution that the scale of digital consumerism fails to restrict self-disclosure online. But proponents of data harvesting from e-consumers cling to the premise that data harvesting saves e-consumers from irrelevant offers by predicting e-consumers' choices (Yeung 2018: 260). Nonetheless, predicting for e-consumers takes away the autonomy of freedom of choice, restricting shoppers to the predicted alternatives. Carmon *et al.* (2019: 1) hold the same view as Yeung (2018: 260) that online firms recommend what e-consumers should purchase based on past online behaviour. E-consumer digital transparency reflects social life, friends, and likes (Antunes and Maia 2018: 194). Online shoppers do not realise that their autonomy is slowly being wiped out by digital consumerism. A remediation mechanism is necessary to value e-consumers' data resources that are exploited by online traders. Perceived risk as an influence on e-consumers' decisions to transact online is explained in brief in the next sub-section.

1:6:2 Perceived risk

Van der Schyff and Flowerday (2019: 4) state that the risk of disclosing data resources is downplayed provided that the transaction benefits e-consumers with consideration in return. When the benefit exceeds the cost of giving out personal data, e-consumers compromise cognitive severity, leading to online self-disclosure (Nel and Boshoff 2019: 17). Perceived risk is considered by online shoppers if they transact with a particular online company. Once the transaction is successful, the risk is ignored (Nel and Boshoff 2019: 16). Also, reputable brands can be associated with credibility and ethical behaviour, which positively influence perceived risk (Wang 2019: 60).

Contrary to popular belief, online retailers with credible brands obtain e-consumer confidence leading to the disclosure of personal data assets. E-consumers are worried about the perceived risks of non-delivery and financial loss and are unaware of data asset disclosure (Salim *et al*. 2019: 42). The major e-consumer concern is the negative uncertainty about product quality and hidden costs of online orders, which discourage online shopping and reduce the incidence of free data resource exploitation (Ventre and Kolbe 2020: 4). Consequently, digital companies should not be complacent about e-consumers ignorance by taking advantage of it to exploit online users' data. A remediation mechanism needs to be established to acknowledge e-consumer data resource input. Perceived trust, explained in the next sub-section, is gained once the online risks are minimised.

1:6:3 Perceived trust

Perceived trust is a prerequisite for online transactions and depends on the track record of companies (Ventre and Kolbe 2020: 2). Ocel and Arslan (2019: 1104) share the view that e-consumers trust companies that ensure online protection and privacy, which leads to e-consumers wilfully giving away their data resources. On this note, e-consumers are more likely to divulge their data resources if there is a positive review of the online entity they are dealing with. Kotler and Keller (2016: 134) contend that digitalised companies monitor conversations and comments consumers make about the products when measuring the level of trust.

E-consumers immediately share their positive or negative electronic word-of-mouth (eWOM) by posting reviews on social networks (Li, Xie and Zhang 2020: 1). Prior studies indicate that eWOM, through posts, comments and opinions shared on multiple social platforms, strengthens or weakens e-consumer confidence as well as trust (Ventre and Kolbe 2020: 3). Online users are willing to give away their information to digitalised companies based on their level of trust. A remediation strategy should be established by digitalised companies for the use of e-consumers' data for business predictions. Once e-consumers gain trust, there is a possibility that they will develop online purchase intentions, as explained in the next sub-section.

1:6:4 Purchase intention

E-consumer purchase intention, as articulated by Kim (2020: 2), is an expression of commitment due to attitude towards buying a product or service online. Nasution *et al.* (2019: 17) concur that e-consumer purchase intention depends on an attitude shaped by the advantages and disadvantages of shopping online. Digitalised companies estimate that online growth is based on the purchase intention of e-consumers (Ha, Nguyen, Nguyen and Nguyen 2019: 1451). E-consumers are monitored while searching for information, even when they do not make a purchase (De Mooij 2019: 34). Digitalised companies track how visitors navigate page views, search words, cart abandonment, and look inside the online shopping cart in order to predict pur- chase intention (Sharda, Delen, and Turban 2018: 323).

Ha *et al.* (2019: 1452) add that e-consumer purchase intention is conceptualised as a subjective attitude that can trigger an online purchase. Digitalised companies make predictions based on e-consumer purchase intention by analysing web file logs and page visitor paths (Dawson 2020: 188). Digitalised companies therefore exploit e-consumer data resources for free in order to make economic predictions. E-consumers are not aware that their data resources are an input for digitalised retail companies to make predictions. Socially responsible digital corporations ought to seek remediation mechanisms to compensate for the use of e-consumers' data resources. In the next sub-section, the shopping experience of online purchases is explained.

1:6:5 Shopping experience

Javed and Wu (2019: 2) are of the opinion that a positive online consumer experience is an indicator of satisfaction, where consumer confidence is enhanced by online purchase options involving exchanges, cancellations and refunds that foster buyers' gratification. Therefore, a positive experience lures e-consumers to divulge their data resources with full confidence, permitting free exploitation of e- consumer data by digitalised companies. It is worth noting that the positive experience allows for openness, addiction, and self-disclosure as articulated by Kanwal *et al.* (2019: 189). E-consumers share their experiences on the internet unaware that companies use their personal data for free in order to create value (Van Rensburg 2016: 276). Digitalised companies track online experiences on online social platforms and use them for free to make future predictions without the e-consumer's awareness (Dawson 2020: 80). Digitalised companies are continuously benefiting from e-consumer data resources without paying any reward to online users. E- consumer empowerment is explained next.

1:6:6 E-consumer empowerment

Antunes and Maia (2018: 190) caution that the freedom of technology that supports big data mining of e-consumers' data resources has taken control of human digital behaviour with a scheme that repetitively uses algorithms to standardise thoughts. This wave of technology has eroded e-consumer independence in such a way that online users are no longer making their own choices. The sophisticated algorithms predict e-consumers choices automatically without feedback from the masses, who endure irrelevant offers (Yeung 2018: 260). The sovereignty that marketing experts have emphasised for decades–that the customer is a king–is collapsing with exponential digital consumerism.

Digitalised companies exploit the digital captivity of e-consumers through continuous data resource tracking for economic value. Although big data mining of e-consumers is aimed at profiling consumers to enable micro-targeting strategies so that different profiles are approached differently, the autonomy of e-consumers is highly compromised (Antunes and Maia 2018: 195). Therefore, the remediation strategy to mitigate free data resource exploitation to restore the autonomy of the e-consumer in the digital environment is paramount. The conceptual framework works hand-in-hand with the theoretical framework explained in the next section.

1:7 THEORETICAL FRAMEWORK

In the current study, the theory of reasoned action TRA assumes that individual action to perform transactions online is determined by perception, norms, and behavioural attitudes towards technology (Van Schyff and Flowerday 2019: 3). The TRA is inclined towards online consumer comments and content that retailers exploit on digital platforms. Individual rational online behaviour unwittingly permits data disclosure, which enables retailers to embark on free data exploitation. The TRA is crucial in explaining how online shoppers' beliefs influence online shopping decisions based on perception and online shopping behavioural aspects (Sharma 2019: 1164). Along with TRA, Perceived Risk Theory (PRT) developed by Bauer (Mwencha and Muathe 2019: 172), is very important in guiding this study to determine how risk influences e-consumer awareness of free data resource exploitation.

Additionally, the theory of planned behaviour (TPB) has been used by several researchers to predict complex individual behavioural intentions (Lim and Weissmann 2021: 3). Certainly, the TPB is, in most cases, used in conjunction with the technology acceptance model (TAM) when investigating the mediators of online purchase intention and online shopping experience (Baeshen 2021: 100). Moreover, Ghosal, Biswas, Prasad, and Behera 2020: 1401) concur that all theoretical influences on online consumer data disclosure are centred on the TAM in that online consumers must accept the online technology.

Humans are subjected to theoretical and practical reasoning by ignoring cognitivist interpretations even when they know the repercussions of their decisions, but due to the passion of achieving a certain goal, individuals fail to avoid harm (Rabinoff 2018:

100). Ha (2020: 2029) affirm that TAM originally developed by Davis in 1985 as a reinforcement of TRA, is useful in contrasting technological influences and behavioural control. The TRA, TPB and TAM shape attitudes towards the intentions to purchase online, especially if online shoppers positively perceive usefulness and ease of online technology (Choi and Park 2020: 4). Having explained the theoretical framework underpinning this current study, the scope of the study is explained in the next section.

1:8 SCOPE OF THE STUDY

This current study includes online shoppers who reside in the eThekwini municipality and online traders based in the eThekwini municipality, South Africa. In total, the larger population from, which e-consumers are to be selected is close to one million (eThekwini municipality IDP 2018:38). Pentz, Du Preez and Swiegers (2020: 231) state that South Africa reported approximately 48% active internet users in 2018, but not all internet users engage in online shopping. Notably, within digital marketing, the digital phenomenon of this study is about digital traces in the form of browsing behaviour that companies aggregate, filter and exploit for profitable decision-making. As part of marketing, the digital marketing environment covers e-consumers as well as online traders. Therefore, the scope of this study encompasses the collaboration of views from online shoppers and online traders in order to illuminate e-consumer awareness of free data resource exploitation. In the next section, the structure of the thesis is briefly explained.

1:9 THESIS STRUCTURE

The structure of the thesis of the current study is arranged according to the standards of academic guidelines. The first chapter introducing the study is followed by three literature review chapters, followed by the methodology chapter, the findings, analyses, and interpretation, and the discussion and conclusion summarising the entire study. A succinct explanation of the chapter is covered in the next sub-sections.

1:9:1 Chapter 1. Introduction

This chapter contained the background, rationale, aim and objectives, conceptual framework, and theoretical frameworks of the study, as well as the chapter's summary. This chapter also served as an introduction to the entire study and the context of the study.

1:9:2 Chapter 2. Digital consumerism

This chapter covers the information that has already been covered that relates to digital consumerism and its positive and negative effects concerning the consumer and highlighting the research gaps. The concept of digital consumerism is gaining traction due to the evolution of the internet connection. Web technology is also covered in this chapter, as digital consumerism is facilitated by the activities on retailers' websites. Finally, the phenomenon of e-consumer free data resource exploitation and e-consumer awareness of free data resource exploitation are covered in detail.

1:9:3 Chapter 3. Free Data resource exploitation

In this chapter, perceived risk and perceived trust in relation to free data resource exploitation are discussed to establish research gaps. Furthermore, in this chapter, the influence of e-consumer awareness of free data exploitation in relation to perceived risk and perceived trust is discussed. The factors linking perceived risk and perceived trust are also determined in this chapter.

1:9:4 Chapter 4. Remediation of data exploitation

In this chapter, the influence of e-consumer awareness of free data resource exploitation in relation to purchase intention and shopping experience is discussed to illuminate their influence on e-consumer awareness of free data resource exploitation in a bid to suggest remediation strategies. The remediation discourse focuses on the digital culture from the perspective of purchase intention and shopping experience. A positive shopping experience prompts e-consumers to continue developing re-purchase intentions, leading to online self-disclosures and free data resource exploitation. This chapter of the literature review focuses on remediation strategies concerning the influence of digital consumerism in a bid to identify research gaps.

1:9:5 Chapter 5. Research Methodology

This chapter is about the selection of a suitable research methodology for this study. A detailed plan of the empirical study, techniques methods of data collection and analysis are explained in this chapter. A relevant research design is discussed, starting. with the logic of inquiry and followed by the research paradigm. The mixed methods approach of the current study is subsequently elaborated on in terms of typology, shortcomings, and rationale.

1:9:6 Chapter 6. Findings, analysis, and interpretation

Empirical data from the online survey and qualitative interviews are summarised, analysed and interpreted in this chapter. A positivist and interpretivist pragmatic approach was adopted with the quantitative survey and the qualitative interview. Descriptive and inferential statistics involving structural equation modelling are covered in this chapter.

1:9:7 Chapter 7. Discussion and conclusion

In this chapter, the results will be discussed in relation to the aim and objectives of the study, citing the implications. This final chapter of research also summarises the entire study, from the research problem to the implications of the study. The chapter is organised as follows: after the introduction, the summary of the theoretical study is discussed. Then the summary of the empirical study is discussed in conjunction with managerial implications and further research. Recommendations based on e-consumer empowerment in relation to the entire study are discussed. Then the conclusion is drawn based on the theoretical and empirical study.

1.10 CONCLUSION

This chapter aimed to discuss the overall context of the study from a broad perspective before focusing on the South African context. Specific issues discussed in the chapter include the background, problem statement, rationale, conceptual framework, theoretical framework, scope, and thesis structure of the study. In this current study, free e-consumer data exploitation is a phenomenon in the digital environment that is affecting all online companies. E-consumer awareness of digital consumerism concerning free data exploitation is the core of the study to enable remediation strategies. In the data-driven digital economy with its reliance on e-consumer data to make predictions and decisions in digital economics.

CHAPTER 2. DIGITAL CONSUMERISM

2:1 INTRODUCTION

This chapter discusses literature focusing on digital consumerism and its effects. The purpose of this discussion is to lay a solid foundation for the study by clarifying the context of the specific components of the effects of digital consumerism concerning free data resource exploitation. This chapter commences with a review of the conceptualisation of the effects of free data resource exploitation. The entire chapter is organised into 14 sections. After the introduction in Section 2.1 and the theoretical background in 2.2, understanding the framework, an overview of digital consumerism in 2.3, the rise of digital consumerism in 2.4, the website trajectory in 2.5, social engagements in 2.6, smart devices in 2.7, the electronic consumer in 2.8, the electronic retailer in 2.9, e-tailing surveillance in 2.10, surveillance steps in 2.11, the positive effects in 2.12, and the negative effects in 2.13 are critical for creating a platform in subsequent chapters. Therefore, this chapter focuses on providing a broad understanding of the study with a focus on e-consumer awareness of the effects of free data exploitation by online retailers. Finally, the concluding remarks in Section 2.14 provide a foundation for Chapter 3. But first, in the next section, the theoretical background is discussed.

2:2 THEORETICAL BACKGROUND

The uses and gratification theory (UGT) explain the motives that drive individuals to disclose their useful data resources online (Irshad, Ahmed and Malik 2020: 2). Van der Schyff and Flowerday (2019: 4) describe the UGT as a theory that is concerned with consumer online engagements, social interactions, and self-disclosure characterised by social cohesive motivation. However, UGT backed up by the TRA is seemingly inclined towards online consumer comments and content that retailers exploit on digital platforms (Irshad, Ahmed and Malik 2020: 3). The TRA assumes that individual action to perform transactions online is determined by perception, norms, and behavioural attitudes towards technology (Van Schyff and Flowerday 2019: 3). Individual rational online behaviour unwittingly permits data disclosure, which enables retailers to embark on free data exploitation. As consumers interact on digital platforms for various reasons, they inadvertently disclose their valuable data resources to online retailers' exploitation traps.

Furthermore, Plangger and Montecchi (2020: 34) assert that subjective norms, past behavioural attitudes and perceived controls are major actors in consumer surveillance, which facilitates online consumer data resource exploitation. These factors will be discussed in detail in Chapter 3. On the other hand, Ghosal *et al.* 2020: 1401) argue that all theoretical influences on online consumer data disclosure are centred on TAM, in that online consumers must accept the online technology first before visiting online shopping portals and social platforms. Retailers who can afford digital technology lure online consumers with goal-directed online purchase behaviour to inadvertently overwrite consumer power on retailer's website, leading to data resource exploitation (Bornschein, Schmidt and Mairer 2020: 137). Park and Lee (2019: 2) add that the digital technology that embraces e-consumer digital power allows information sharing and convenient online shopping. The sharing of information online exposes e-consumers to data disclosure that prompts data exploitation.

Online shopping technology is progressively being accepted by consumers, considering convenience and time-saving factors (Ghosal *et al.* 2020: 1402). Consequently, online consumer data resource exploitation is attributed to the retailer's affordance theory (AT), which refers to the ability of online retailers to exploit real-time data and respond with ambidextrous means to predict behavioural patterns (De Luca Herhausen, Troilo and Rossi 2020: 3). Digital retailers benefiting from online consumer data resource exploitation have digital capabilities, require impervious attention to monitor online content to engage with online consumers and invest in new digital capabilities timeously (Verhoef and Bilmolt 2019: 4). Therefore, as online consumers consider the convenience of online technology, they unwittingly disclose their data resources to online retailers, who end up exploiting consumer data resources for business growth. So, the summary of the theoretical assumptions in this chapter illuminates online consumer data resources disclosure, leading to data exploitation by online retailers. In the next section, an overview of digital consumerism is discussed.

2:3 OVERVIEW OF DIGITAL CONSUMERISM

Consumerism is a societal concept that seeks to protect the consumer in a business environment, whereas digital consumerism involves the protection and empowerment of online consumers in the digital environment (Park and Lee 2019: 20). In 2017, South Africa reported a total of R1 trillion worth of retail sales of, which online retail maintains a strong presence (Pentz, Du Preez and Swiegers 2020: 229). Chipp, Ismail and Meiring (2017: 38) add that South Africa is rapidly growing its online trade as dominant retail giant like Takealot, that merged with Kalahari in 2015 is taking advantage of new opportunities in the digital environment. Online retailing, as asserted by Hung-Jourbert and Erdis (2019: 211), is growing exponentially at a rate of 30% year on year in South Africa as consumers get accustomed to digital technology. Albeit South Africa's digital shopping activities indicate progress, the overall online market is still in its infant stage (Pentz, du Du Preez and Swiegers 2020: 230). However, online consumers are unaware that digitalised retailers are trailing consumer personal data and behavioural patterns online.

Moreover, being the largest African online retailing country, South African retailers like Mr. Price and Pick n Pay have adopted one form of online orders to supplement the physical brick-and-mortar stores, which offer offline onsite trade (Chipp, Ismail and Meiring 2017: 64). As consumers get more engaged in online shopping, online retail companies are boosting their capabilities to collect online consumer data to expand predictive business models (Rust 2020: 16). Research about online consumer awareness of free data exploitation is in its infancy. To understand the phenomenon of data exploitation of online consumers in a capitalist economy, one needs to grasp the rise of digital consumerism, elaborated on in the next section of the study.

2:4 THE RISE OF DIGITAL CONSUMERISM

In the second half of the 20th century, multiple companies started to migrate from analogue to digitalisation where individual online data concerning consumer online behaviour became valuable for targeting advertisements and manipulating online consumers (Clarke 2019: 59). After the development of personal computers by International Business Machines (IBM) in the 1970s, the Internet Protocol (IP) that identifies online users was developed in the 1980s followed by Web 1.0 in 1991 (Sponder and Khan 2018: 4). This technological development fuelled the growth of online consumer tracking without the awareness of the consumer. By 1974, the term internet had gained popularity thanks to the inventor Vint Cerf, an American computer scientist who is presently the internet evangelist working as a senior executive at the headquarters of Google (Ryan 2017: 9). Chipp, Ismail and Meiring (2017: 4) add that, as the most important business development since the industrial revolution, the internet has become a dominant conduit of digital convergence to facilitate the extraction of useful consumer data. Online consumers are not aware that while they are transacting online, a vast amount of personal data is collected by online companies for business decision-making and economic growth.

The continuous reliance on digital connectivity by online consumers has rendered online users vulnerable to personal data harvesting by digitalised retailers to facilitate predictive models (Petrescu, Krishen and Bui 2020: 675). Farman, Comello and Edwards (2020: 299) affirm that the growing surveillance of online activities and the collection of personal data is principally for the purpose of commercial precision in targeting online consumers. As the internet crossed international borders, the development of the World Wide Web, which is a tiny portion of the internet, led to the rise of hyperlinks that enable consumers to browse for information on the web (Chipp, Ismail and Meiring 2017: 6). As consumers search for information on the web, they inadvertently leave behind a digital footprint of massive data, which entices online retailers to exploit it at zero or marginal cost. Plangger and Montecchi (2020: 32) add that the surveillance of online users' insights relating to preferences and behavioural and demographic characteristics is paramount for customisation, which benefits both retailers and consumers. Unbeknown to online consumers, retailers exploit online users' data for selfish economic benefit without rewarding the users who generate the valuable data.

Furthermore, when consumers purchase goods online, order goods, or communicate with the suppliers, the first-hand information is captured for free for future use in forecasting (Chipp, Ismail and Meiring 2017:81). Although online consumers benefit indirectly from customisation, they still have to exchange payment for the customised product; therefore, it is the retailer who benefits directly from the exploitation of consumer data without the consumers' awareness. Consumer awareness of data exploitation through surveillance in the digital economy has not been fully investigated based on a handful of related literature studies. Apart from the other components of the digital ecosystem, such as email, the Web has contributed enormously to free data exploitation. While transacting online, consumers are unaware that their data is exploited for re-targeting. Consumers deserve to be recognised for their data input, which may increase their willingness to disclose data for the purpose of precise targeting that is profitable. The website trajectory is explained in the next section of this study.

2:5 WEBSITE TRAJECTORY

Unlike the conventional business models of brick-and-mortar, the website is the most important online address with, which digital marketers interact with online consumers (Chipp, Ismail and Meiring 2017: 14). The website, which forms 1% of the entire ecosystem of the internet, started with Web 1.0 for read only, web 2.0 for read and write as well as social media, Web 3.0 for live streaming, and now Web 4.0, encompassing all the web developments as well as artificial intelligence (Sponder and Khan 2018: 5). Furthermore, web beacons and cookies track online consumer browser fingerprints by screening through customer activities as well as data points of interest in order to predict consumer demand (Clarke 2019: 63). Online retailers have embraced artificial intelligence, which has led to machine learning technology that extracts consumer behaviour for marketing analysis (Petrescu, Krishen and Bui 2020: 676). Bornschein, Schmidt and Maier (2020: 135) caution against the unrestricted power that digital retailers have over online consumers by tracking their behaviour and click paths on the website that trigger cookies to easily identify unsuspecting online consumer profiles. Little is known about online consumer awareness of free resources data exploitation facilitated by the web's trajectory.

Nearly all the successful retailers in South Africa, for example, Makro and Pick n Pay, have an alternative online channel where consumers browse for products online end up buying them at the physical brick-and-mortar collection point (Chipp, Ismail and Meiring 2017: 87). Retailers trail online consumer search footprints using the Uniform Resource Locator (URL), which is attached to the emails of online users to help locate internet users' data easily (Sponder and Khan 2018: 9). The exploitation of free e-consumer data resources for targeting and prediction is now a major tool used by retailers to reach out to all corners of e-consumer hideouts. However, e-consumers are seemingly unaware that behind the scenes, they are being followed in a bid to harvest their precious data resources, which have contributed to the growth of digital consumerism in the growing data-driven digital economy. The web's trajectory can be explained based on web traffic, web content, and web advertising. These elements are explained in the next sub-sections.

2:5:1 Web traffic

The use of algorithms to redirect the web traffic of online consumers to the retailer's website permits the tyranny of data manipulation, committing online users to succumb to human behavioural tracking, which highly benefits retailers (Lipschultz 2020: 4). Online consumers are unaware of digital retailers' monitoring capabilities and manipulation of web traffic. When Tim Bernes-Lee developed the cross-referencing hypertext link on the 6th of August 1991, the number of web page owners grew by 342 081 active website owners, but presently, there are over a billion websites that include retail owners like Amazon (Ryan 2017: 10). The Bernes-Lee's development contributed enormously to the birth of present-day digital marketing as consumers started searching for products and services online, which in turn led to innocent online consumer data disclosure. This development further led to the expansion of digital business dealings, allowing online retailers to prey on vulnerable consumers' data in order to gain a digital competitive advantage.

Web page visitors are constantly under surveillance, permitting retailers to profile unique visitors, returning visitors, serious online shoppers and customer preferences in order to streamline the exploitative sales forecasts that are profitable to retailers (Juska 2018: 179). Cuellar and Huq (2019: 1290) reviewed the argument of Zuboff, Professor Emerita of Harvard University in the United State, that behavioural surplus (data not related to a business transaction) is harvested to guide automated predictions that benefit consumers by concluding that the harvest largely benefits the retailers. Online consumer data is freely accessed by consumers without any form of reward to the consumer who generates the valuable data. As ascertained by Gokcek, Carikcioglu and Yuksel (2019: 119), online retailers are striving to prevent consumers from switching from one website to another by using specialised technology to track online movements of consumers in a bid to increase the profitability index and turn searchers into actual online shoppers. Consumers do not notice the constant monitoring aimed at data exploitation during their online purchase journey.

Websites in digital marketing form the central pillar where online consumers express their opinions and reviews that propel retailers to adjust forecasts, steering towards consumer reviews (Park and Lee 2019: 3). Since retailers benefit from the data sets of online consumers, so too should the consumers who are the owners of the data, but due to lack of awareness among online consumers, the trend of data exploitation is still far from over in the growing digital era. Sponder and Khan (2018: 71) articulate that first-party data from sales and emails, second-party data from retailers' affiliates, and third-party data like behavioural patterns are all extracts harvested from the digital platforms and exploited by retailers without the knowledge of the consumers. Consumers are unaware that their data input expressed on websites is of great value to online retailers, who benefit freely from consumer data. Web content is discussed in the next sub-section.

2:5:2 Web content

The likelihood of being visited on the website address is practically determined by the keyword search and content placed before the consumer, which can be created after navigating the consumer journey online (Lipschultz 2020: 43). Additionally, retailer websites are used to monitor consumer trends, sometimes in a bid to develop keywords and content that can optimise online visibility, maximising top viewership to get higher returns by targeting consumers based on their popular searches (Sponder and Khan 2018: 24). Websites as online premises of retailers are of core value, especially when the content conforms to consumer needs and can transform web traffic into potential buyers, because the goal of retail websites is to maximise sales, encourage repeat visits and bookings, and build trust that can enable data harvest (Ryan 2017: 39). Online consumer data is used to develop the best content and keywords to optimise viewership; however, consumers are not aware of the value of their data input in developing useful content. E-consumers are unaware that retailers' search criteria are designed after exploiting consumer data, without, which retailers are faced with a hard time developing search keywords and content that can attract web page views and web searches that convert to sales through web advertising.

2:5:3 Web advertising

In 2019, South Africa reported 31.18 million online users and 4.73 million browses daily for only the month of March, based on the findings of the Advertising Bureau of South Africa (Pentz, Du Preez and Swiegers 2020: 231). The Advertising Bureau of South Africa further indicates a large base of online users exposed to retailers for data exploitation and targeting. Websites are embedded with viewer monitoring data formats that are responsible for generating online consumer data relating to customer online experience, images, text, and files downloaded by visitors (Clarke 2019: 64). Online consumers are subject to relentless monitoring (Farman, Comello and Edwards 2020: 300) of their past browsing data footprint, which helps to develop a profitable online advertisement campaign. Although some retailer websites contain a small faint bar on the edge of the web page informing the user of data tracking and collection (Bornschein, Schmidt and Maier 2020: 136), most websites track consumer data without notification. This data harvesting technology is unknown by the consumers from whom the collection is made.

Furthermore, online retailers are collecting vast amounts of consumer data by developing hidden subscription opt-ins where consumers click on the subscription links, which enable retailers to collect consumer information that can aid in profitable advertising (Chipp, Ismail and Meiring 2017: 90). Additionally, retailers have developed tag management facilities on the websites to track, sort and harvest online consumer data, especially through affiliated retail companies' websites (Sponder and Khan 2018: 149). Tracking begins when the online user receives a commercial email and clicks on it, thereby driving the consumer to the retailer's website link designed with a question mark character (?) of, which the subsequent characters represent the tracking code on the browser (Lipschultz 2020: 12). Websites are designed by retailers to push for notifications and pop-ups that lure online users into disclosing their precious data to exploitative retailers (Tong, Luo and Xu 2020: 67). E-consumers are unaware that their browsing data is exploited by online retailers for retargeting.

Digital companies like Uber have websites that automatically collect consumer information related to their rides and drop-offs and share this information in real-time using the Application Programme Interface (API), enabling online consumer data sharing of inter-linked services (Kopalle, Kumar and Subramaniam 2020: 116). Examples of interlinked companies using online services include airlines, accommodations and restaurants. Reviews analysed by Cuellar and Huq (2019: 1318) in the famous book of Zuboff relating to surveillance capitalism indicate disturbing revelations concerning the exploitation of online consumers and require further investigations. Even when the online consumer is browsing for information, the tracking system on the website automatically identifies the preferences of the online user and targets them using the search criteria (Busca and Bertrandias 2020: 1). The website as a source of consumer data is the main component of digital marketing, which acts as a shopping window for online consumers. Websites save online shoppers' data, which is later exploited by online retailers without the awareness of the consumer. In the subsequent section of this study, social engagements linked to data exploitation are discussed.

2:6 SOCIAL ENGAGEMENTS

Sponder and Khan (2018: 57) view social engagements as peer-to-peer communication that allows consumers to participate in user-generated conversations. Consumers who find engaging socially offline difficult often find it much easier to associate comfortably through online social engagements (Chipp, Ismail and Meiring 2017: 122). Park and Lee (2019: 4) recognise the inter-dependence and connectedness of consumers as a collectivist social setting of a cohesive group that provides high content of data that helps online retailers shape their decisions based on social engagements. Online retailers track consumer data on social networks and exploit it for business growth. For example, numerous advertisements on social networks are based on online consumer social engagement data harvested from multiple integrated social media platforms (Farman, Comello and Edwards 2020: 299). Consumers have no knowledge that their social engagements are part of a retailer's valuable data input. Social engagements can be discussed in terms of social posts and the influence of digital platforms will be explained in the next sub-sections.

2:6:1 Social posts

Online retailers claim that social posts are data from the public domain (Clark 2019:64) but data from consumer social posts on social network platforms is truly generated by online consumers who are not aware that their data posts add value to retailing. Understanding social posts that include comments, likes, tweets and views alerts online retailers to predict future trends, intentions, wishes and future online purchases of consumers (Sponder and Khan 2018: 175). Retailers in turn engage on social networks by weighing in on feedback from social group posts, gaining more useful insights from the consumer through friendly social engagements that benefit the retailer (Chipp, Ismail and Meiring 2017: 140). Retailers, as asserted by Juska (2018: 181), are monitoring social posts to obtain consumer reactions to online strategies in order to update the necessary adjustments depending on the negativity or positivity of the comments. When consumers submit posts on the social platforms, they are unaware that they are providing precious data to online retailers for free.

Ryan (2017: 126) shares the same view regarding the robust monitoring of online consumer posts and interactions on social platforms as an important activity for retailers to grasp consumer perceptions and trends in order to guide precise predictions. Online retailers spend a lot of time listening to and reading constructive conversations, opinions, and criticisms to revise their digital strategy. In so doing, online consumers are not aware the comments they post are a data input beneficial to the business decision-making of online retailers. If online retailers benefit from the consumer-generated data posts, so too should the online consumers benefit as owners of the data input in order to even out the retailers' data exploitation.

2:6:2 Digital platforms

The age of digitalisation has propelled retailers to target digital platforms to curve out individual behaviour and offer tailored promotions based on the profile harvest of the digital platforms (Ma and Sun 2020: 490). Touch points on the digital platforms are monitored in order to segment hedonic purchases from utilitarian purchases, considering purchase behaviour where hedonic consumers appear to be more engaging than utilitarian consumers (Li, Abbasi, Cheema and Abraham 2020: 128). Therefore, hedonic online consumers are more vulnerable to data exploitation due to their tendency to engage more on digital platforms. The digital appetite for hedonic consumers prompts inadvertent free data disclosure online, which attract online retailers to exploit the free data resources hanging on the digital platforms.

Furthermore, Chipp, Ismail and Meiring (2017: 141) distinguish digital platforms that have a high degree of factual and emotional consumer data disclosure, thereby tracking reliable real-time data for decision-making on the fly. Online retailers monitor credible blogs with themes on WordPress and YouTube to extract behavioural data without the awareness of online consumers (Sponder and Khan 2018: 58). The vast amount of data harvested from digital platforms is exploited by online retailers for advertisements that boost sales. Online consumers, as providers of useful data on digital platforms, ought to be rewarded for their data input. Consumers use smart devices, which are regarded as conduits for data exploitation by online retailers. Also, consumers are targeted based on their innocent data disclosures exploited by firms on the digital platforms without their knowledge. In the next section, the role of smart devices in the exploitation of consumer data is discussed.

2:7 SMART DEVICES

Smart devices are regarded by Cuellar and Huq (2019: 1288) as vicious self-tracking electronic gadgets that record consumer habits, movements and personal behaviour. Without consumer access to smart devices, it would be virtually impossible to track and exploit consumer data. The 7.59 billion global population has 4 billion internet users actively using smart devices that facilitate consumer data exploitation by retailers sophisticated data harvest technology (Lipschultz 2020: 6). South Africans are gradually moving away from traditional personal computers to smart portable mobile devices (Pentz, Du Preez and Swiegers 2020: 231). However, consumers are unaware that the smart devices they are holding are conduits for data tracking, which triggers data exploitation by online retailers.

Smart devices harvest a huge amount of consumer data, especially when they are linked to machines that are embedded with intelligence learning technology in real-time (Petrescu, Krishen and Bui 2020: 677). This is evident in the works of Sponder and Khan (2018: 10), where smart devices are regarded as providers of around-the-clock access to consumer hyper-content data with connectivity to the internet providing the internet protocol (IP) address that algorithms use for monitoring. Consumers do not notice that behind the scenes, online retailers are trailing their data, with the help of consumer smart devices. Smart devices function with software applications that are discussed in the next section.

2:7:1 Device Applications (apps)

Online consumers with internet connectivity download online retailer app, and once the download is complete, tracking begins depending on the link to content on the app downloaded (Ryan 2017: 185). User friendly-retailer app provide unique and superior online consumer engagements with the retailers, bring the consumer much closer to the retailer than ever before (Van Heerde, Dinner and Neslin 2019: 421). The installed app on the devices has the capability to track internet search behaviour and consumer movements to assist in directing promotions and offers in real-time (Tong, Luo and Xu 2020: 66). For example, digitalised companies such as Uber can only access consumer data using the device app model that has successfully enabled the company to monitor data points of its customers, thereafter, exploiting user data to target future advertisement campaigns via the device app registration details (Kopella, Kumar and Subramanian 2020: 188). Ryan (2017: 180) reported that in 2014, 30 billion WhatsApp messages were sent every day, which allows online retailers to extract data from the linked app to the retailer's digital platform. Consumers are not aware that the downloaded retailer app are linked to their personal profiles, ready to be exploited by the retailers.

Van Heerde, Dinner and Neslin (2019: 422) caution that app link online consumers to retailers' websites, allowing retailers to directly link to app users' accounts, gaining open access to personal data that is eventually exploited by the retailers in decision-making. When consumers install apps on their devices, they cannot recognise that the app defaults to accessing to personal data and profiles. For example, the push notification after downloading the app responds to the data tracking of the app user (Tong, Luo and Xu 2020: 67). Firms are now installing apps like TripAdvisor that have the capability of harvesting e-consumer data resources regarding location, personal traits, and behaviour linked to the user profile (Van der Schyff and Flowerday 2019:

2). Consumers simply install apps without realising that they are being lured into parting with their valuable data to exploitative retailer's app traps for data tracking.

The apps are used by retailers to triangulate online consumers with smart android devices tracking online consumer movements using cell towers connected to the Radar (Cuellar and Huq 2019: 1289). In a study conducted by Van Heerde, Dinner and Neslin (2019: 420), it was found that device app increases online consumer engagements, which include brand recommendations and product features that attract online shopping intentions. There is a tendency for consumers to first install apps like the Amazon or Walmart prior to actual online shopping, which triggers retailers to automatically start monitoring movements on the app and dropping targeted advertisements on unsuspecting consumers (Sponder and Khan 2018: 12). The device app installation requires registration on the internet, which is covered in the next section. E-consumers are innocently lured into voluntary self-disclosures, leading to free data resource exploitation.

2:7:2 E-mail registration

Online consumers shopping with smart devices must complete an initial online registration using their personal emails, thereafter, allowing online retailers to monitor consumer wish lists, content viewed, checkouts, payment information, purchases, and cart abandonment (Lipschultz 2020: 87). Once the email is registered on the device, online consumers searching for the products are intercepted with offers, new products, and upgrades through email tracking (Ryan 2017: 155). The consumer remains unaware that the email registration on the smart device is a gateway to retailers monitoring of the search movements that attract retail offers. Once the customer opts in with the registered email on the device, subscriptions and new feeds are automatically linked to the tracking software. As a prerequisite, consumers are obliged to register with the email before accessing the App Store to access the retailer App. Retailers download the app with the email, which is later used for monitoring without the consumer's knowledge (Van Heerde, Dinner and Neslin 2019: 425). Online consumers are unaware that their online registration details are exploited for tailored online commercial advertisements that benefit retailers in terms of revenue. In the next section, the electronic consumer is discussed in detail.

2:8 ELECTRONIC CONSUMER (E-CONSUMER)

It has been emphasised in the preceding sections that online consumers are those who use the internet to shop for goods and search for information. In this section and subsequent sections of the study, reference is made to e-consumers as creatures with hyper-connectivity in the cyber world who are fascinated with technology in the digital environment involving online shopping (Ryan 2017: 26). The terms online consumer and e-consumer can virtually be used interchangeably. However, some scholars refer to e-consumers as digital natives with digital technology savvy, segregating online consumers with less digital literacy as digital immigrants (Chipp, Ismail and Meiring 2017: 114). Together with digital immigrants, digital natives are vulnerable to constant monitoring on arrival in the digital world and are followed to the path of product search, destination points, and the point of actual purchase (Sponder and Khan 2018: 111).

Therefore, it is worth noting that not all online consumers are e-consumers because e-consumers are a category of online consumers who provide relevant online data to the digital ecosystem (Kopalle, Kumar and Subramaniam 2020: 116). In fact, e-consumers generate enormous amounts of valuable data, making them distinct from the large crowd of online consumers in general (Cuellar and Huq 2019: 1305). Retailers exploit rich e-consumer data to make predictions and target online promotions. In the next section, e-consumer data resources are explained.

2:8:1 E-consumer data resources

E-consumer data resources include all the digital footprints that are left by online users when search for information until they complete their online shopping experience (Lipschultz 2020: 29). Kuchta (2020: 35) believes e-consumer data resources to be the most valuable asset that supports decision-making in digital marketing activities. Also, Cueller and Huq (2019: 1333) refer to e-consumer data resources as a new asset category digitalised companies have recognised that include all useful consumer data extracts in the digital environment. Bornschein, Schmidt and Maier (2020: 135) raised concerns over the shift of power regarding e-consumer data resources from e-consumers to retailers, who have taken advantage of this valuable asset owned by e-consumers. Online retailers often exploit e-consumer data resources without the awareness of the consumers, who are the owners of the resources and deserve to be rewarded for their data resources usage.

Farman, Comello and Edwards (2020: 299) are concerned as to how e-consumer data resource exploitation continues without the knowledge of the e-consumers who own the data resources. However, online retailers should not remain complacent about the low level of e-consumer awareness of data resource exploitation by retailers. It would be ideal if there were a remediation mechanism in the digital ecosystem to recognise the valuable data input e-consumers provide online retailers on a regular basis. The behaviour of e-consumers online has facilitated the exploitation of e-consumer data resources by retailers. In the next section, a brief discussion of e-consumer behaviour is covered, and a full account will be covered in Chapter 3 of this study.

2:8:2 E-consumer behaviour

E-consumer behaviour is greatly influenced by demographic, psychological and technological factors (Chipp, Ismail and Meiring 2017: 112). A succinct introduction to e-consumer behaviour is covered in this section pending a detailed discussion in Chapter 3. The rapid growth of business-to-consumer and business-to-business digital transformation is shaping the behaviour of e-consumers (Sponder and Khan 2018: 4). Technical aspects, for example, web technology is one of the core influencers of e-consumer behaviour as digital marketing is centred on websites to run digital campaigns (Hung-Jourbert and Erdis 2019: 211). E-consumer awareness of data exploitation is largely influenced by the demographic factors surrounding the willingness to disclose data online (Farman, Comello and Edward 2020: 301). For example, in the gender category, females are more engaged on digital platforms, and therefore, they search for information, thereby making them powerless to avoid the internet, while males merely emphasise the importance of digitalisation (Chipp, Ismail and Meiring 2017: 115). Gender has an influence on e-consumer awareness of free data resource exploitation.

Therefore, females are more vulnerable to data resource exploitation without their awareness. On the other hand, Lipschultz (2020: 278) points to the demographic category of the young generation as the driving force of digitalisation, virtually enjoying everything on the digital platform. Pentz, Du Preez and Swiegers (2020: 235) share the same belief that the young generation is impulsive, has a high online purchasing power, tends to be hedonic, and is constantly looking for positive influence online, rendering them inadvertently vulnerable to disclosing data for retailer exploitation. Furthermore, levels of income and education influence e-consumer engagement on the digital platforms in that, high-income groups tend to have good education involving computer literacy, thereby engaging on the internet with ease while having access to smart devices and internet connectivity (Chipp, Ismail Meiring 2017:117). It is, therefore, worth noting that e-consumers with better education and/or income will engage more on the digital platform and are more vulnerable to data disclosure and exploitation than the uneducated or low-income earners.

Apart from the demographic variables, Ryan (2017: 38) identifies aspects like the website as an online premise where e-consumers search for information and make bookings and purchases; hence, the technical appearance of the website influences e-consumer behaviour online. Additionally, Hung-Jourbert and Erdis (2019: 212) support the view that the quality of websites heavily influences e-consumers to disclose personal data on the digital platform. Retailers' websites also offer digital engagements, directly influencing visitors to disclose personal and behavioural data (Van Heerde, Dinner and Neslin 2019: 422). Depending on the design of the website, e-consumers behave differently on different websites, and therefore, websites have a formidable influence on e-consumer' behavioural exposure to exploitation.

The growth of shopping portals consisting of a wide range of products online has also influenced e-consumer behaviour by stimulating impulse behaviour and increasing cognitive reactions towards online shopping, in turn increasing data disclosure and embracing data exploitation (Ghosal *et al.* 2020: 1401). Behavioural outcomes of e-consumers are also determined by emotional and psychological factors like perception intertwined with demographic and technological factors (Irshad, Ahmad and Malik 2020: 5). The psychological factors bordering on perception will be discussed extensively in Chapter 3. The dynamic e-consumer behaviour is evolving every time newcomers tap into the digital markets, and therefore, it is not easy to track behaviour without machine learning technology (Ryan 2017: 27). Perception is shaped by e-consumer innovativeness, self-efficacy towards technology, and the ability to avoid cyber risks (Chipp, Ismail and Meiring 2017: 118). E-consumers who engage on portals and websites are unwittingly influenced to disclose data, which leads to exploitation by online retailers.

The attitude towards technology is influenced by e-consumer innovation, perception and willingness to engage on digital platforms (Grandhi, Patwa and Saleem 2020: 3). Perception and other cognitive factors are central to this study and deserve to be exhaustively discussed in the next chapter. Last but not least, e-consumer behaviour is also influenced by socio-cultural factors interlaced with psychological and technological factors. E-consumers social lives and living patterns affect their online behaviour as globalisation coupled with digitalisation is shaping cultural values (Pentz, Du Preez and Swiegers 2020: 234). People with collectivistic cultures engage more than those with individualistic cultures, making the collectivists more relevant on social platforms by posting reviews and behavioural data that is exploited by retailers online (Park and Lee 2019: 5). E-consumers are not aware that cultural engagements on digital platforms are exploited by online retailers for predictions.

Social platforms are a source of behavioural data and personal profile data that retailers use to target e-consumers after navigating the social posts, comments, and complaints (Clarke 2019: 64). Social e-consumer behaviour causes e-consumers to innocently share views and experiences, which constitute data points for retailers to exploit on the digital platform. In the community, some members do not participate on social platforms, whereas reference groups usually engage on digital platforms through continuous postings that are used as data input by the online retailers (Chipp, Ismail and Meiring 2017: 141). Online retailers monitor the socio-cultural values of e-consumers in a bid to extract social behavioural data for decision-making that can affect a collective group. In the next section, e-consumer journal online is explained.

2:8:3 E-consumer journey

The digital ecosystem of which e-consumer is part involves web technology, internet connectivity, and smart devices (Kopalle, Kumar and Subramaniam 2020: 114). In the digital ecosystem, the e-consumer journey starts with numerous stages from information search on the internet up to the moment of purchase and post-purchase (Li *et al.* 2020: 1). The internet in the digital ecosystem is the main pool of e-consumer data regarding habits and preferences, especially with retail giants like Amazon, which paves the path of an e-consumer journal by locking in consumers during the journey and connecting previous purchases to allocate personalised offers in real-time (Chipp, Ismail and Meiring 2017: 13). During the stages of the e-consumer journal, without consumer knowledge, online retailers are trailing all the movements by harvesting relevant data based on search behaviour to payment or cart abandonment.

Uber and Alibaba, inter alia, appear to regard the digital ecosystem as their native habitat, where they stick around to monitor the traffic on e-consumer journey routes and stopovers (Kopalle, Kumar and Subramaniam 2020: 115). AS e-consumers journey through the digital ecosystem, they are unaware that online retailers are following their path and navigating their digital footprint, thereby leading to tracking for data exploitation. Technology has made it possible for e-consumers to unwittingly provide free data to online retailers, who exploit shoppers' data to predict demand. Having introduced retail surveillance activity, the next section of the study focuses on data exploitation through surveillance techniques.

2:9 ELECTRONIC RETAILER (E-TAILING) SURVEILLANCE

The age of digitalisation has resulted in a coherent era of data-driven market structure with the expansion of technology and the internet (Cuellar and Huq 2019: 1284). Surveillance capitalism is defined as the acquisition, storage, and exploitation of personal data involving characteristics, attributes, behaviour and attitudes for profitability in a given economy (Plangger and Montecchi 2020: 32). E-tailing activities fit the definition of surveillance capitalism by far. E-consumers are unaware of the new wave of surveillance capitalism, as much as they are exposed to full-time surveillance with the use of sophisticated machines that aid digital marketers to profile and target e-consumers using automation.

The argument that surveillance capitalism involving the acquisition of behavioural surplus is principally aimed at behavioural modification using predictive models that are beneficial to e-consumers is somehow acceptable (Cuellar and Huq 2019:1288). However, e-consumers do not know that they are under surveillance while they are transacting online and are unaware that digitalised retailers are exploiting their data resources for prediction, which largely benefits online retailers. Clarke (2019: 59) confirms that surveillance has become a business policy where large quantities of e-consumer data resources are exploited in order to manipulate consumer behaviour to develop contemporary predictive models that generate revenue. In fact, consumers have no clue whether, behind the scenes, they are under constant surveillance for the purpose of data resource exploitation.

Farman, Comello and Edwards (2020: 300) warn that e-consumers awareness of surveillance will be met with a negative reaction of discomfort; therefore, digital marketers have to develop early mechanisms that can reduce the emotional hazard. Besides, Plangger and Montecchi (2020: 330) are of the view that, albeit surveillance risks e-customer relationships with online retailers, companies need to know what consumers think, feel and how they behave in order to develop an optimal strategy. Nonetheless, retailers benefit profitably because consumer surveillance provides e-tailing data input that should be assigned value to remunerate the e-consumer data resources utilised by online retailers. With little doubt, the awareness of e-consumer surveillance might result in future ramifications relating to unrest as a result of uncovering data resource exploitation.

Furthermore, the epistemic harvest of e-consumer data resources is done by a computational toolkit using artificial intelligence that generates forecasts using precise content (Cuellar and Huq 2019: 1290). Digitalised companies exploit e-consumer data resources to innovate, remain competitive, and evaluate strategies aimed at consumer satisfaction (Plangger and Montecchi 2020: 32). The systematic surveillance termed dataveillance by Clarke (2019:61) has been recommended as a cost-effective marketing policy that reduces e-consumers to statistical skeletons that can offer real-time assessment to drive rapid action. Ruckenstein and Granroth (2019: 2) regard dataveillance as the exploitation of personal data that includes behaviour, likes, posts and downloads, which are of economic value for decision-making. The policy of surveillance therefore benefits the online retailer at the expense of innocent e-consumers. E-consumers are not aware of this cost-effective alternative to systematic personal data surveillance.

Cuellar and Huq (2019: 1292) argue that the unfair e-tailing surveillance practice of acquiring e-consumer data resources is a sporulating fungus that is addictive. By the same token, Ruskenstein and Granroth (2019: 2) agree that retailers' addictive accumulation of data from e-consumers leaves online users with no option but to become prey to data-generating subjects. Cuellar and Huq (2019: 1292), however, add that surveillance should not be reduced to deontological harm because the harvest of data is solely for the purpose of business growth and not aimed at scrapping e-consumers. Whatever the purpose may be, e-tailing surveillance can be interpreted as exploitative because it is aimed at adding value to the business, as consumers are kept in the dark, yet they own the data resources that add value.

Research by Farman, Comello and Edwards (2020: 299) indicates a chain of marketing tactics where surveillance has exposed e-consumers to targeted advertisements, which have negative effects that will be discussed in detail in the subsequent section. On the other hand, Cuellar and Huq (2019: 1311) caution that surveillance ought not to be deemed a business activity that has no meaningful increment to e-consumer wellbeing in consideration of positive contributions towards meeting consumer granular needs. In contrast, the argument proposed by Ruckenstein and Granroth (2019: 4) that surveillance destroys e-consumer corporate relationships puts digital retailers in a worrisome state of disarray. Although at the moment e-consumers are not aware that behind the corporate image, there is a stigma of data resource exploitation through surveillance, it may reach a point where e-consumers will become aware of the phenomena of data resource exploitation, which might be met with unrest in a fully-fledged digital economy.

Plangger and Montecchi (2020: 33) warn that whether e-consumers are aware of surveillance and data resource exploitation or not, routine data surveillance activity risks consumer relationships coupled with mistrust that can damage digital retailers' reputations for some time. Cuellar and Huq's (2019: 1333) argument recognise e-consumer data resources as a new asset class, whose extraction may result in a negative spillover, but the rules for data ownership and disposal should not be restricted to individual ownership but a collection for public use. However, e-consumers deserve to be aware of the phenomenon of data exploitation as they invest in the process of online surveillance, which involves the use of smart devices and internet connectivity paid for in advance by e-consumers. There are various steps that can be undertaken concerning the surveillance process for electronic retailing.

2:10 E-TAILING SURVEILLANCE STEPS

Managers adopt different steps to harvest insights into consumer behaviour using marketing intelligence to gain a competitive advantage in the digital environment (Plangger and Montecchi 2020: 32). Depending on the nature of the business, numerous steps can be taken to extract valuable data using surveillance alternatives. The following steps related to electronic retailing are discussed in the subsequent sub-sections: e-tailing, planning for relevant data, data crawling, profiling, and targeting.

2:10:1 E-tailing

Chipp, Ismail and Meiring (2017: 50) describe e-tailing as the use of the internet to trade goods and services as retailers. Pentz, Du Preez and Swiegers (2020: 229) affirm that South African retailers are now widening their online presence as e-consumers are progressively yearning for tailored online experiences. E-tailing firms are braced with unrestricted power to exploit e-consumer data resources through numerous digital technologies of surveillance enabled by website cookie generators (Bornschein, Schmidt and Mairer 2020: 135). With all the power e-tailing firms have, e-consumers are not aware of the magnitude of e-tailing surveillance resulting in data resource exploitation. E-tailing takes three business models that include business-to-consumer (B2C) like Takealot, business-to-business (B2B) like Amazon dealing with UPS couriers, and the shared-economy model like Uber collaborating with airline companies (Chipp, Ismail and Meiring 2017: 22). Depending on the model selected, surveillance of e-consumer data benefits e-tailing firms without the e-consumers' knowledge. However, sorting the relevant data is crucial for optimising e-consumer data resource exploitation.

2:10:2 Relevant data

To avoid the burden of piling useless data, electronic retailers have to classify and sort structured data from unstructured data, which is marred by a clutter of posts, images, and visuals uploaded on digital platforms (Sponder and Khan 2018: 14). During surveillance, online retailers are capable of identifying hedonic browsers that merely engage in electronic window shopping (Chipp, Ismail and Meiring 2017: 94).

The digital environment is amassed with a plethora of data, but not all data is relevant to electronic retailers; therefore, digital marketers are tasked with planning to target data that has value to the goals of the organisation (Kopalle, Kumar and Subramaniam 2020: 117). One can infer that airport online booking data can be relevant to the hospitality industry and tourism (Chipp, Ismail and Meiring 2017: 127). Notably, the vast amount of data under surveillance may not be useful for sound decision-making, which calls for careful planning for retailers to focus on relevant data.

Tong, Luo and Xu (2020: 14) contend that the design of the surveillance toolkit should be able to push notifications based on the target market and capture content that is highly relevant for e-tailing growth. For example, Amazon deliberately accumulates historical consumer search information that can be amplified to target the same customer browsing again and make offers best suited to the prospective customer to attract repeat business (Kopalle, Kumar and Subramaniam 2020: 118). While Amazon is accumulating relevant data, e-consumers are not aware that data disclosed to the Amazon digital platform is used to retarget them. After planning for relevant data, the crawling begins.

2:10:3 Data crawling

Sponder and Khan (2018: 21) refer to data crawling as a technical process of collecting information from the website, like a spider having a wide range of avenues to crawl for prey in all directions in real-time. Lipschultz (2020: 87) contends that 80% of online consumers outbound browsing faces data crawling. Juska (2018: 45) adds that crawling may involve revisiting the records of opt-ins and online consumer registrations of members that are among the target market. The surveillance of these online registrations links the email registered to the opinions, social content, experiences and recommendations on the social platforms (Ryan 2017: 111). Cuellar and Huq (2019: 1289) describe crawling as a gross expropriation of e-consumer experience executed through the acquisition of behavioural surplus generated by human interactions with self-tracking smart devices that can crawl data involving domestic habits, movements and life patterns. While e-consumers are interacting with electronic retailers, they inadvertently disclose their data resources, allowing retailers to crawl in a bid to exploit consumer data for decision-making.

Retailers are developing the technology that is embedded on the website dedicated to a backend crawl into online shoppers by identifying behavioural patterns (Hirt, Kuhl and Satzger 2019: 100). Data crawling involves first-party data, which is data crawled from customer business interactions; second-party data is crawled from affiliated companies; and third-party data crawled from behavioural aspects of e-consumers (Sponder and Khan 2018: 71). The first-party data acquired from business transactions, such as emails, physical addresses, contact details and demographic data can lead to the acquisition of second-party and third-party data by means of crawling (Clarke 2019: 63). Therefore, the most tedious data to crawl is third-party data because it deals with the behavioural surplus of the consumer, which would be the best data to exploit for decision-making. With all the three types of data, e-consumers are not aware that retailers are crawling customer data. Once the data crawling is set running, retailers start to create profiles, which facilitate easy targeting.

2:10:4 Profiling

Collaborative filtering of e-consumers purchases data leads to profiling to enable specialised marketing campaigns; for example, millennials prefer to use mobile technology with side-panel advertisements rather than online pop-up advertisements (Behera, Gunasekaran, Gupta and Kamboj 2020: 3). On the other hand, e-consumers using retailer App that have on-click instant access may not be responsive to any other form of engagement due to their heterogeneity in favouring user-friendly retailer App (Van Heerde, Dinner and Neslin 2019: 421). Electronic retailers make better use of the profiling classifier technology that enables the building of micro-blogs capable of detecting and grouping e-consumer trends and matching them with demographics in order to allocate product offers and tailored services (Hirt, Kuhl Satzger 2019: 94). Juska (2018: 45) acknowledges that profiling is also done by geofencing and creating boundaries for clusters of e-consumers based on product search history and opt-in online registration, which facilitate easy profiling. E-consumers are not aware that retailers' profile them in order to maximise data exploitation for precise decision-making and targeting.

In other instances, electronic retailers use Marketo Marking Automation (MMA) to identify and profile online visitors who are mostly using email to enable email marketing based on the classified profile of email users (Sponder and Khan 2018: 161). Unlike the brick-and-mortar physical store, where traditional segmentation enables consumer profiling, e-consumers are not seen and have a high degree of vanishing into the cyber space compared to other competitive electronic retailers, which makes e-consumer profiling quite complicated (Ryan 2017: 27). Hirt, Kuhl and Satzger (2019; 95) suggest automated profiling in real-time to immediately classify and harvest online visitors' gender, age, personality and other psychological attributes. The free data resources exploited enable online retailers to strengthen profitable predictions. Once the profiling of e-consumers is set, retailers embark on targeting.

2:10:5 Targeting

Profiling e-consumers lessens the task of electronic retailers' targeting capabilities with precision in the dynamic digital environment. Tong, Luo and Xu (2020: 66) recommend that the ideal digital platforms to target the youth profile are Snapchat, YouTube, and WhatsApp by presenting suitable content that is appealing to the young generation. Unlike conventional targeting based on homogenous groups, it is sometimes ideal to target e-consumers based on individual-by-individual profiles, which constitutes a high degree of personalisation by matching offers using machine learning algorithms (Ma and Sun 2020: 490). According to statistica.com, over 50% of e-consumers use mobile App, with 197 billion downloads of online shopping-related activities, this sends a signal to retailers to target e-consumers using mobile marketing (Tong, Luo Xu 2020: 67). In fact, e-consumer data is exploited mainly for the benefit of the company, although consumers may enjoy specialised targeting, which necessitates e-consumer awareness of the mutual benefits of data exploitation.

The targeting of e-consumers via mobile marketing requires retailers to send mobile billboards and banners to e-consumers' smart mobile devices, considering global mobile phone usage in 2015 was 7.1 billion, as reported by the International Communications Union (Ryan 2017: 179). Retailers use behavioural targeting, utilising a combination of data from e-consumers, to retarget advertisements that boost sales and product awareness (Farman, Comello and Edwards 2020: 311; Ruckenstein and Granroth 2019: 4). Electronic retailers use tagging, especially the hashtag, on digital platforms to target online user profiles (Sponder and Khan 2018: 61). E-consumers are unaware that their data from their mobile interactions online is being used to target them. In the next section of this study, an overview of the effects of digital consumerism on data resource exploitation is discussed.

2:11 POSITIVE EFFECTS

The positive effects of digital consumerism involving e-consumer data resource exploitation include mass customisation, e-tailing predictions, and digital innovation, which are all of value to e-tailing success in the digital age. These factors are discussed in the following sub-sections:

2:11:1 Mass customisation

Mass customisation is a marketing activity that seeks to bring consumers closer to the organisation with individualised services and tailored products (Zhang, Fiore, Zhang and Liu 2020: 1). Digital consumerism concerning e-consumer data resource exploitation ushers in abundant consumer data through the online surveillance activities that bring with it a new consumer experience (Lang, Xia and Liu 2020: 2). Mass customisation inexorably espouses e-consumer personalised marketing, which is facilitated by tracking online behavioural surplus that has helped to understand the consumer much better (Rust 2020: 19). The monitoring of e-consumers is viewed by Kopella, Kumar and Subramaniam (2020: 115) as a blessing in disguise due to the fact that the exploitation of e-consumer tracked data resources irks consumers but at the same time enables firms to extend tailored services directly to e-consumers. Furthermore, tracking e-consumers based on their browsing history illuminates information about hidden conditions of e-consumers that require customised discriminatory marketing practices that automatically match e-consumer potential (Bornschein, Schmidt and Mairer 2020: 139). E-consumers are unaware that digital retailers track behavioural data in order to customise services.

South African electronic retailers are getting much closer to e-consumers with free customised deliveries; for example, Netflorist.co.za offers 24-hour customised delivery thanks to consumer monitoring (Chipp, Ismail and Meiring 2017: 66). Also, Mr Price and Pick n Pay allow online orders followed by pick up in brick-and-mortar stores. The acceleration of e-consumer data exploitation offers web-based interactions, enabling e-tailing to provide products that are reflective of personal preference due to the rigorous behavioural data surveillance (Zang *et al.* 2020: 1). E-consumer data resource exploitation provides individualised behavioural data with identifiable attributes that attract customised target offerings, optimising consumer need satisfaction (Farman, Comello and Edwards 2020: 301). Mass customisation offers unique consumer value at an affordable price, which maintains customer loyalty in an efficient way (Lang, Xia and Liu 2020: 3). E-consumers are unaware that digital surveillance assists retailers to maximise consumer experience and satisfaction through massive customisation.

Rust (2020: 20) is of the view that consumers like personalised attention by addressing distinctive requirements through the exploitation of e-consumer data resources by tracking customer behaviour. Mass customisation through digital consumerism involving data exploitation allows the inter-dependence of e-consumers and online retailers, which is fundamental for real-time guidance on product usage and optimising consumption (Kopalle, Kumar and Subramaniam 2020: 119). Digital retailers identify e-consumers through data monitoring and classify potential customers, which increases their ambition to focus on urgent needs through mass customisation (Grandhi, Patwa and Saleem 2020: 5). With the surveillance of e-consumers, attractive opportunities often automatically appear in e-consumers inboxes, like price specials that are allocated based on e-consumer profile (Clarke 2019: 66). Additionally, e-consumer data trailing exposes willing customers who are ready to pay a premium for the mass customised product, which gives capable consumers a sense of accomplishment that their exact need has been met (Zhang *et al.* 2020: 2). E-consumers do not know that through data resource exploitation, retailers are able to determine what offers fit best with individual capacity.

By tracking e-consumer behaviour, mass customisation of the products can easily be applied in order to display the uniqueness of each individual customer, which provides a memorable and exciting experience and increased customer perceived product value (Lang, Xia and Liu 2020: 2). Mass customisation enables the supply of products that match e-consumer data harvest, thereby reducing the cost of producing goods with no customer orientation (Kopalle, Kumar and Subramaniam 2020: 120). Modern-day e-consumer in the digital age desists from standardised products in preference to customisation, necessitating e-tailers to use the available technology to monitor behavioural patterns matching customer product requirements (Grandhi, Patwa and Saleem 2020: 1). Unknown to e-consumers, retailers track consumer data resources in order to customise consumer experiences, thereby increasing loyalty. However, retailers benefit massively due to the fact that it is the e-consumer who purchases the customised product. Therefore, mass customisation to a small extent indirectly benefits the consumer by getting personalised products and services, but still at a cost.

2:11:2 E-tailing prediction

E-consumer data monitoring provides fine-grained insights into behavioural characteristics that help to make accurate predictions based on the browsing history of consumers (Tong, Luo and Xu 2020: 74). Surveillance, as asserted by Cueller and Huq 2019: 1293), weeds out uncertainties, making predictions of e-consumer behaviour more accurate and precise. With minimum human interference, online retailers use machine learning technology to perform meta-predictions with the aid of classifiers that are able to compare similarities and compute probabilities of future outcomes (Hirt, Kuhl and Satzger 2019: 97). Unbeknownst to e-consumers, retailers track and exploit e-consumer data resources for prediction that benefits digital retailers and helps them to grow their businesses.

Ma and Sun (2020: 489) argue that, while machine learning during e-consumer surveillance may produce a high level of predictive accuracy, it often fails to cope with the dynamics and heterogeneity of e-consumers, leading to false predictions. Previously, retailers by constrained with making predictions using the usual statistical business models, but as artificial intelligence intensifies, e-tailing focuses on building logical predictive models using machine learning backed by data tracking (Ma and Sun 2020: 482). Digital business models enable firms to expand digital capabilities that can add value to e-consumers as well as stakeholders in general (Verhoef and Bijmolt 2019: 343). However, Cueller and Huq (2019: 1317) criticise the activity of e-consumer data tracking as a process of instrumentalisation of e-consumer behaviour with the aim of making predictions that render human life scrapped for Marxist exploitation. One may not be able to support the argument because the retailer's goal is to predict business growth at the expense of excessive e-consumers data resources harvesting.

The machine learning technology cuts out similar e-consumer behavioural patterns, locations and movements to reproduce future fine-grained behavioural data with algorithms that automatically predict future possibilities for decision-making (Tong, Luo and Xu 2020: 74). Once e-consumer data is extracted during surveillance, the predictive classifier can, for example, correlate gender data based on historical behaviour, make accurate future demographic implications and guide decisions (Hirt, Kuhl and Satzger 2019: 98). Impractical manual data collection in the digital age has now been replaced with artificial intelligence that can handle vast amounts of structured and unstructured e-consumer data, enabling real-time prediction and decision-making (Kuchta 2020: 36). Cuellar and Huq (2019: 1309) are of the view that the surveillance of e-consumer behavioural surplus permits the creation of valuable prediction products that reflect the interior psychological factors of innocent humans. E-consumer reliance on internet connectivity is a recipe for data tracking used by retailers to gain intelligence on individual behaviour, which helps in prediction and forecasting that increase revenue.

Albeit algorithms are initially created by humans during the programming stage and are subject to bias, they can handle e-consumer data harvest, identify unique patterns, and predict future consumer purchases by assimilating useful undetectable historical data (Tong, Luo and Xu 2020: 75). Electronic retailers are developing predictive models based on e-consumer data exploitation to enhance digital competition as well as digital transformation as consumers are increasingly embracing digitalisation (Verhoef and Bijmolt 2019: 343). Therefore, e-consumer data resources are a raw material for developing predictive models, which add value to digitalised retailers and confirm data exploitation unknown to e-consumers. However, Cueller and Huq (2019: 1325) insist that the surveillance of individuals should not be overlooked without considering the improvements it can offer to humans in the future in terms of prediction products. But even if e-consumer data exploitation through surveillance brings good things in the future, e-consumers are entitled to be aware of the activity and have their contribution recognised.

Chipp, Ismail and Meiring (2017: 157) contend that, with the burden of making sense through vast amounts of real-time e-consumer data on digital platforms, less effort is vested in prediction, and therefore, retailers prefer nowcasting to forecasting. Nevertheless, tracking e-consumer records on past purchases and web search history may help to anticipate the most likely demand from different segments of e-consumers engaging online (Ryan 2017: 157). Although data resource exploitation can be viewed as toxic, e-consumer surveillance leading to prediction is a necessary harm with desirable fruits that bring in new products that are intended to satisfy future consumer demand (Cueller and Huq 2019: 1314). Nonetheless, e-consumer data resources are used to make such predictions without consumer knowledge. Therefore, e-consumers ought to be considered for their data resources relevant to the future growth of electronic retailers. A remediation mechanism is necessary to value relevant e-consumer data input.

2:11:3 Digital innovation

Retailers are investing in data harvesting to become competitive performers in providing superior services and products in the growing data-driven economy (De Luca *et al.* 2020: 2). The tracking and profiling of consumers enable retailers to innovate efficient and affordable services; for example, Uber has innovated a new taxi fare model based on what consumers can afford for a ride (Valletti and Wu 2020: 309). This Uber innovation scraps the old system of pre-set journey taxi fares, which can over charge short journey consumers. Kaushik (2020:3) affirms that understanding consumer experience at a conceptual level with the help of technology is crucial to serving customers in a coherent and efficient manner. E-consumer data resource exploitation provides a new category of capital for creating new products and improving service delivery in the digital environment (Sadowski 2019: 3). Little is known about e-consumer awareness of the role of data exploitation by online retailers.

Trailing e-consumer behavioural patterns has also led to improved digital services and increased consumer engagements through the development of high-level technology. Innovation is the process of developing new ways of satisfying the unmet needs of consumers based on the available opportunities to upgrade the status quo (Purchase and Volery 2020: 763). Digital innovation is, however, based on the affordance theory, which states that the ability to achieve one's goals depends on the affordance of the actors to achieve the specified target (De Luca *et al.* 2020: 3). Therefore, online retailers should have the capacity to track relevant e-consumer data in order to make proper innovative decisions. In the developing economies of Africa and Asia, the increase in monitoring capacity of digitalised retailers has led firms to disguise themselves as being socially responsible by extending internet broad-band services to marginalised rural communities to widen the e-consumer data exploitation base (Sadowski 2019: 3). E-consumers awareness of data exploitation by e-tailing firms for the purpose of innovation requires further investigation to ratify the rationale for data tracking.

As retailers expand services to markets through innovation, electronic consumers are upgrading recommender engines on website portals that endorse and put forward the goods to purchase while tracking internet browsing consumers (Behera *et al.* 2020: 2). Lang, Xia and Liu (2020: 3) contend that with continuous e-consumer monitoring, new fashionable products are being developed based on consumer data on digital platforms. E-consumer data exploitation has enabled firms to develop new technology by restructuring mass distribution channelling to multi-channel technology using omni-channelling e-tailing strategies with new ways of interacting with individual consumers (Purchase and Volery 2020: 777). Mu, Lennon and Liu (2020: 11) add that e-tailing surveillance of the omni-channel e-consumer base has improved real-time interactions with consumers through live chat and call-back services that have facilitated data harvest. Little is known about e-consumer awareness of the positive effects relating to innovation accelerated by data resource exploitation by electronic retailers.

Purchase and Volery (2020: 775) allege that with the increased monitoring of e-consumers, retailers are expanding brand visibility by extending existing parent brands that receive positive online reviews by simply adding series or numbers; for example, iPhone-11 brand innovation. Some companies are innovating new products not to increase revenue but for the purpose of harvesting and monitoring e-consumer data during the testing and full launch of the new product (Sadowski 2019: 4). With the high level of e-consumer profiling during data exploitation, new digital technologies are being developed to make targeted offers to consumers (Valletti and Wu 2020:

309). Data exploitation has enabled online retailers to track consumers and open direct communications, eliminating media companies allowing retailers to optimise the use of powerful in-house consumer data bases that facilitate the smooth execution of programmes (Purchase and Volery 2020: 779). E-consumer data resource exploitation has also led to the birth of real-time digital marketing, where the tracking and monitoring of online consumers enable firms to meet customer needs as they emerge, but online firms benefit excessively from free e-consumer data.

The exploitation of e-consumer data resources has resulted in the strengthening of consumer-centricity and granularity with real-time collaboration based on e-consumer sentiments beyond tweets and likes as more retailers are going digital with the new social distancing needs (Gairika 2020: 1). As digitalisation is growing at a faster rate, e-consumers are facing difficulties in anonymising their data resources and the concealment is becoming costlier to consumers as they end up missing out on online offers, resulting in a data disclosure trap (Valletti and Wu 2020: 310). As a result, e-consumers unwittingly disclose their data resources, unaware that retailers benefit from the data harvested for innovation that brings more e-tailing revenue.

2:12 NEGATIVE EFFECTS

The negative effects are a threat to e-tailers' relationships with e-consumers in such a way that as consumers become savvier and more aware of the value of data, they start to realise that their data resources are being exploited. The negative effects include the decline in e-consumer sovereignty, unsolicited commercials, and behaviour manipulation. These factors are discussed in detail in the following sub-sections.

2:12:1 E-consumer sovereignty

Power involves the asymmetric control of resources, which is inextricably associated with having the freedom of choice to dispose of or exchange resources in a capitalist free enterprise economy (Bornschein, Schmidt and Mairer 2020: 137). Ruckenstein and Granroth (2019: 2) caution that e-consumer autonomy is threatened by corporate surveillance, which has rendered e-consumers powerless over digging deep into their social lives and behavioural surplus. Clarke (2019: 62) refers to this phenomenon as a form of exploitation by taking advantage of one's resources to unfairly benefit while over-looking the owner of the resources. E-consumer data resource exploitation is often met with a negative attitude as it erodes the power of online consumers, which can result in irreversible negative consequences for digital retailers (Farman, Comello and Edwards 2020: 299). Online consumers are becoming more vulnerable to data resource disclosure as the sovereignty they have kept since the birth of marketing is getting out of hand to surveillance capitalists, diminishing cultural power, discursive power, and data power (Park and Lee 2019: 3). However, not all e-consumers are unaware that their power is being eroded by retailers' activities in e-consumer data resource exploitation, which might result in unrest, thereby testing the future of e-tailing.

On the other hand, Cueller and Huq (2019: 1318) argue that at no marginal incremental effort, e-consumers never intend to create the data resources on the digital platform and have no alternative use for the data resources which question the right of ownership. Even if they do not intend to create the data resources, they generate this data and should have a right of ownership. They should not give retailers a free pass to exploitation. Bornschein, Schmidt and Maier (2020: 137) state that e-consumers have no power or choice as to how websites automatically harvest their valuable data resources while transacting online as the data extraction is not transparent, increasing vulnerability. Clarke (2019: 67) articulates that the threat of surveillance as a component of digital consumerism goes beyond reproach in that, there is no chilling effect on encroaching on the power of consumers by screening behavioural aspects. Farman, Comello and Edwards (2020: 302) warn that consumers who become aware of surveillance feel too identifiable with their autonomy compromised citing the violation of societal norms. However, based on the existing literature, consumer knowledge of e-consumer data resource exploitation at the moment is still limited.

Bornschein, Schmidt and Maier (2020: 135) add that consumers feel controlled and powerless as they become aware of data resource exploitation by retailers. Plangger and Montecchi (2020: 2) are of the view that although surveillance is met with a negative attitude by e-consumers, it does not always translate into negative behaviour towards the retailers, but feel like of loss of autonomy, which can turn out to be catastrophic in the future. Astonishingly, Cuellar and Huq (2019: 1318) argue in favour of surveillance, noting that data monitoring should not be a cause of concern because e-consumer data only becomes valuable if it is exploited as a collective rather than individual data sets, making it a public resource. Therefore, e-consumers should not claim loss of power over the ownership of the data resources due to the fact that data is used as a collective and consumers are not aware of its accumulation. This is a dangerous argument that threatens the relationship of e-consumers with electronic retailers as consumers become aware of data resource exploitation.

Additionally, public debates are intensifying with respect to the ongoing tracking of e-consumers by digitalised companies, raising concerns of declining consumer autonomy due to data resource exploitation (Ruckenstein and Granroth 2019: 2). In some instances, retailers are discriminating on the basis of unattractiveness by blacklisting e-consumers who are rendered to be of less or no potential during the tracking and profiling (Clarke 2019: 67). Ryan (2017: 369) confirms that the exploitation of consumer data through monitoring is affecting human psychology and reducing the power of self-confidence. Clarke (2019: 68) reiterates that e-consumer data resource exploitation is progressively undermining sovereignty by diminishing self-determination, resulting in psychic numbing of consumers.

In contrast, Cueller and Huq (2019: 1315) sarcastically articulate that the loss of e-consumer control over data resources to the hands of capitalists does not exhaust humanity. Sadly, the tyranny of electronic retailers' data exploitation through surveillance is worrisome to at least those consumers who have a vague sense of digital consumerism. However, more research is needed to investigate e-consumer awareness of data resource exploitation in a bid to establish digitalised remediation strategies to maintain consumer dignity.

2:12:2 Unsolicited commercials

Sponder and Khan (2018: 44) emphasise that digitalised retailers track e-consumers' demographics, interests, locations, and behavioural surplus in a bid to allocate target advertisements (ads), which can sometimes be met with discomfort. E-consumer online email registration attracts e-tailing data tracking activities aimed at frequently sending special offers based on consumer browsing history (Ryan 2017: 155).

Unfortunately, the study conducted by Farman, Comello and Edwards (2020: 306) found that e-consumers get aggravated, angry and irritated with ads popping up on their digital profiles. Tong, Luo and Xu (2020: 70) contend that consumers have a positive response to brand commercials sent via short message systems (SMS). But Ruckenstein and Granroth (2019: 5) disagree by warning that algorithm-driven commercials are regarded as digital noise and are blocked by consumers. E-consumers are surprised as to how they become targets for unsolicited commercials that are automatically generated by the data monitoring technology of online retailers on digital platforms.

Grandhi, Patwa and Saleem (2020: 2) allege that the growing digital platforms fuelling the harvest of e-consumer data provide enormously useful insights that online retailers exploit to send commercials that are based on e-consumer behaviour. The empowerment of e-consumers considers that fact that e-consumers should not be objects of unsolicited ad targets using their data resources that are exploited by online retailers to generate sales revenue (Irshad, Ahmad and Malik 2020: 4). Retailers take advantage of consumers' low level of awareness of e-consumer data resource exploitation, which has rendered e-consumers helpless. As consumers navigate the internet, they are unaware that the commercials that keep popping up are automatically generated by e-consumer data resource exploitation through tracking.

Unsolicited commercials tend to stimulate unnecessary impulse buying where e-consumers are coerced to press the purchase button as they are browsing the internet putting consumers in an uncomfortable vulnerable situation (Clarke 2019: 67). The pop-ups keep flashing on e-consumers' digital profile show-casing new products, which may be unwanted by e-consumers browsing for similar products (Sponder and Khan 2018: 45). The creepy unsolicited ads that keep popping up make e-consumers enraged with the sensation that while they are searching for products online, they are being watched. Grandhi, Patwa and Saleem (2020: 5) state that e-consumers should be targeted on the digital platform based on their own data resources, but e-consumers are not please to be targets of unsolicited commercials as discussed is the preceding paragraph. Additionally, Cueller and Huq expound that the targeting of commercials is now more granular and precise, thanks to the effort of consumer surveillance activity. However, the commercials targeting e-consumers at a distinct granular level can be met with negative reaction as consumers are unaware as to how they become targets of unsolicited commercials.

Incidentally, e-consumers are not aware that online retailers share consumer data with affiliated third parties who send ads to completely unknown e-consumers undermining the fundamental values of e-consumer data (Lip Schultz 2020: 173). Furthermore, there is a possibility of mistargeting e-consumers with unsolicited commercials based on the errors of surveillance algorithms that may not match the actual e-consumer profile, triggering unwarranted and annoying ads (Clarke 2019: 67). Ruckenstein and Granroth (2019: 8) argue that sometimes tracking algorithms do not always interpret correctly especially when they logically group consumers, thereby sending unwanted commercials that leave e-consumers disillusioned with the entire digital environment. Some of the ads are a mismatch to the websites they navigate, as they are not aware that behind the scenes, the surveillance algorithms are automatically updating according to the browsing behaviour (Farman, Comello and Edwards 2020:304). Innocent e-consumers are helplessly surprised to see commercials posted to their digital platforms.

Electronic retailers use mobile marketing to send personalised push notifications based on the data harvested pertaining to behavioural segmentation and location data using the global positioning system (GPS) tracking movements (Tong, Luo, Xu 2020: 64). E-consumers react positively and negatively to online advertisement but most of the commercials are irrelevant to e-consumers making the disturbance unbearable (Ruckinstein and Granroth 2019: 3). Most persuasive unsolicited commercials threaten online consumer peace and are rejected, which has a negative effect on retailers (Farman, Comello and Edwards 2020: 299). Consumers are not aware of the origin of the unsolicited commercials.

2:12:3 Behavioural manipulation

Behavioural surplus (e-consumer data not related to business transactions) is monitored and harvested in order to manipulate e-consumer behaviour towards the retailer’s goals (Cuellar and Huq 2019: 1288). As discussed earlier in reference to Sponder and Khan (2018: 72), unlike the first- and second-hand data, which is generated by daily business transactions, behavioural data referred to as third-party data, is exploited for the purpose of manipulating e-consumers towards retailers' offerings. Once the tracking and harvesting of e-consumer data is saved on the retailer's data base, retailers begin the advertisement campaigns intended to manipulate e-consumer behaviour to lure customers' commitment to purchase products online (Farman, Comello and Edwards 2020: 311). The unrelenting surveillance has led to the development of behavioural management teams within the retail organisations assigned to manipulate behaviour towards the company's products by tearing away the interior sanctuary of e-consumer pre-existing psychology (Cuellar and Huq 2019: 1309). There is scanty research about consumer awareness of e-consumer data exploitation by online retailers pre-occupied with the idea of manipulating behaviour.

Kendell (2020: 52) warns that behavioural manipulation deprives e-consumers of choice by influencing purchase behaviour towards retailers' product offerings, diminishing consumers' rational behaviour during online shopping (Lorenz-Spreen, Lewandowsky, Sunstein and Hertwig 2020: 1104). E-consumers are unaware that their behaviour is automatically manipulated by the tracking algorithms. Cuellar and Huq (2019: 1291) refer to behavioural manipulation as behavioural modification involving surveillance intended to herd and tune as well as condition consumers to stimulate shopping. While the positive effects largely benefit the retailers, as discussed in the previous section, the negative effects affect the e-consumer relationship with the retailers in the digital environment, which poses a threat to retailers.

2:13 CONCLUSION

This chapter aimed to discuss the effects of digital consumerism concerning e-consumer awareness of free data resource exploitation from a broad perspective, and then focus on the South African context. The evolution of digital consumerism has led to the recognition of e-consumer data resource exploitation by electronic retailers. Specific issues discussed in the chapter include e-consumer behavioural monitoring and awareness of the effects of free e-consumer data exploitation. This chapter also explained how e-consumer data is harvested in the era of digital consumerism practised in South Africa. It emerged that online consumer data harvesting in South

Africa is practised using conventional and digital means. The chapter further indicated that there are still significant challenges besetting e-consumer awareness of free data exploitation. The challenges include the inability to improvise a remediation strategy against free data exploitation. Having set the digital consumerism context, the next chapter focuses on discussing the influence of perception on e-consumers in the environment of free data exploitation.

CHAPTER 3. FREE DATA RESOURCE EXPLOITATION

3:1 INTRODUCTION

In Chapter 2, digital consumerism and its effects in relation to e-consumer awareness of free data exploitation were discussed. This chapter discusses literature focusing on the influence of perceived risk and perceived trust on e-consumers. The purpose of this discussion is to lay a solid foundation for the study by clarifying and putting into context the specific components of perceived risk and perceived trust relating to e-consumer awareness of free data exploitation. This chapter commences with a review of the conceptualisation of perception. An outline of the theory is provided to set the background for a discussion of free data exploitation and then provide a discourse to understand the framework critical for creating the foundation for the next chapter. The chapter is arranged in nine sections. Section 3.1 covers the introduction, 3.2 discusses the conceptual and theoretical background, 3.3 covers perception, 3.4 discusses perceived risk, 3.5 explains the facets of perceived risk, 3.6 describes perceived risk relievers, 3.7 covers the discourse of perceived trust, 3.8 discusses perceived trust and Section 3.9 covers the conclusion. Therefore, this chapter focuses on providing a broad understanding of free data exploitation with a focus on perceived risk and perceived trust, but first, the theoretical and conceptual background are discussed in the next section.

3:2 THEORETICAL AND CONCEPTUAL BACKGROUND

Rabinoff (2018: 43) relates perception to the central role of reasoning in guiding individuals to apply meaningful decisions to fair treatment of the human soul. In studies related to perception and online shopping behavioural aspects, the theory of reasoned action (TRA) is crucial in explaining how online shoppers' beliefs influence online shopping decisions (Sharma 2019: 1164). To conceptualise this theory, unsuspecting e-consumers' perceptions are compromised by the confrontation of data disclosure requirements favouring e-retailers with stronger power to control online user data resources for free exploitation (Grosso, Castaldo, Li and Lariviere 2020: 525). Individuals act on what is immediately pleasant (Rabinoff 2018: 103) irrespective of rational perceptions acquired prior to the decision-making.

Power has a fundamental grip on human manipulation, culminating in the dependency and control of vulnerable e-consumers, leading to free data resource exploitation undetected by online shoppers (Bornschein, Schmidt and Maier 2020: 137). The analogy of human perception relies on intellectual power to function towards the desired goals (Rabinoff 2018: 56). Additionally, the power-responsibility equilibrium (PRE) theory is used to explain the balance between power and responsibility (Bandara, Fernando and Akter 2020: 3). Notably, the unbalanced e-consumer-e-retailer relationship favouring online retailers explains how those who have power exploit the vulnerable. E-consumer shopping decisions ultimately result in self-disclosures, facilitating free data resource exploitation without the awareness of e-consumers.

The perceived risk theory (PRT) developed by Bauer (Mwencha and Muathe 2019: 172) is very important in guiding this study to determine how risk influences e-consumer awareness of free data resource exploitation. According to Balogh and Meszaros (2020: 15), Professor Raymond Bauer, a famous Harvard Business Scholar in 1960 warned of the dangerous consequences of perceived risk in consumer behaviour. Humans are subjected to theoretical and practical reasoning by ignoring cognitivist interpretations even when they know the repercussions of their decisions, but due to the passion of achieving a certain goal, individuals fail to avoid harm (Rabinoff 2018: 100). Another useful theory for this study is the social learning theory (SLT) developed by Albert Bandura suggesting that individuals learn from each other by bridging subjective cognitive beliefs with social behaviour, enhancing trust (Rajani and Nakhat 2019: 378). Trust ultimately leads to data disclosure and data exploitation without the awareness of online shoppers.

Perception requires learning in order to know the environment and make sound judgements (Rabinoff 2018: 56). The user gratification theory (UGT) induced by perception can help explain motives for e-consumer engagements (Irshad, Ahmad and Malik 2020: 2). Reynolds-Pearson and Hyman (2020: 16) argue that the data-driven digital economy is full of manifestations of widespread data sharing engagements. Furthermore, user-generated content (UGC) on the digital platforms involving conversations, referrals, sarcasm, complaints and criticisms that moderate perceived trust adds to free data resources provided by online retailers (Singh and

Chakrabarti 2020: 42). The TRA supports models leading to perceived trust in UGC content exploited by e-retailers to make predictions (Irshad, Ahmad and Malik 2020: 3). Therefore, perceived trust is interpreted as accepting vulnerability to free data resource exploitation due to self-disclosure by downplaying perceived risk. So, online engagements in turn propel free data resource exploitation on digital platforms. The online manifestations are exploited by e-retailers without e-consumer knowledge.

Individual motivation to mitigate online shopping risks of data disclosure is rooted in the protection motivation theory (PMT) related to avoiding vulnerability to the severity of data disclosure consequences (Adhikari and Panda 2018: 97). As much as perception is essential for the human soul’s rational judgement on what to avoid and what to pursue, individuals end up in pursuit of what is desirable but not what is good (Rabinoff 2018: 104). As a result, Gokcek, Carikcioglu and Yuksel (2019: 20) add that the cognitive dissonance theory (CDT) developed by Leon Festingers arose due to the discrepancies of individual beliefs compared to the outcomes of online shopping. Notably, these theories may assist in establishing how self-disclosure patterns allow data sharing behaviour (Ferreyra, Kroll, Aimeur, Stieglitz and Heisel 2020: 4). Individuals continuously search for information online, which is inevitable to bypass evaluating accuracy, leading to the exploitation of behavioural browsing data, enabling free data exposure and exploitation without the knowledge of e-consumers.

Ha (2020: 2029) affirms that TAM, originally developed by Davis in 1985 as a reinforcement of TRA, is useful in contrasting technological influences and behavioural control. E-retailers use technology to control online shoppers depending on internet connectivity with interactive technology, which renders e-consumers helpless by heeding to self-disclosure in order to accomplish online shopping goals (Riegger, Klein, Merfeld and Henkel 2021: 141). Digital technologies have enabled retailers to shift from offline infrastructure to create new opportunities with the online concept, allowing for more possibilities to make e-consumers plausible based on data self-disclosure, aiding the exploitation of innovative digital management (Jafari-Sadeghi, Garcia-Perez, Candelo and Couturier 2021: 101). The willingness to disclose data that is exploited by e-retailers is motivated by e-consumers to achieve online shopping goals (Aiello, Donvito, Acuti, Grazzini, Mazzoli, Vannucci and Viglia 2020: 491). Therefore, a vast amount of free e-consumer data is distributed on the internet for online retailers to exploit. Technology, along with behavioural control, boosts decisions, leading to self-disclosure and e-consumer free data resource exploitation.

Big Data Analytics (BDA) harvests e-consumer structured and unstructured data, letting e-retailers upgrade capabilities and ensure flexible decision-making by decoding data for organisational performance (Rialti, Marzi, Caputo and Mayah 2020: 1587). Due to the distance between e-retailers and e-consumers, issues surrounded by perceived trust online may arise (Oghazi Karlsson, Hellstrom, Mostaghel and Sattari 2020: 2). Farman, Camello and Edwards (2020: 304) have conclusive evidence that behavioural targeting is the rationale for e-retailers free data resource exploitation. Massive connectivity with the digital diaspora spreading across the globe allows for real-time data sharing (Singh *et al.* 2020: 5). Seemingly, technology and behavioural factors have an influence on free data resource exploitation without e-consumer awareness. The discourse of perception is discussed in the next section.

3:3 PERCEPTION ON FREE DATA RESOURCE EXPLOITATION

Today's data-driven economy considers e-consumer personal information to be the most valuable new asset category a firm can exploit to accumulate revenue in the highly competitive digital environment (Brandao and Rezende 2020: 1). Humans sometimes act contrary to their choices due to partial ignorance and a failure to develop perceptive intellect, thereby becoming vulnerable to exploitation (Rabinoff 2018: 109). Adapa, Fazal-e-Hasan, Makam, Azeem and Mortimer (2020: 1) consider real-time online interactions between e-consumers and e-retailers using smart technology to be the major source of free data resources that e-retailers exploit for business growth. As noted in Chapter 2 of this study, algorithms learn and collect human behavioural online patterns without e-consumer awareness (Lorenz-Spreen, Lewandowsky, Sunstein and Hertwig 2020: 1102). Perception requires thinking in order to evaluate alternative accounts of different situations (Rabinoff 2018: 56). This chapter of the study illuminates e-consumer awareness of free data resource exploitation in relation to the influence of perception on e-consumer data disclosure.

Worldwide, online retail companies are storing enormous amounts of e-consumer browsing history to moderate behaviour in consideration of habits to stream automated product recommendations during online shopping (Pelau, Niculescu and Stanescu 2020: 829). Product ratings, reviews, complaints, and conversations are part of the free online consumer data resources that are exploited by e-retailers to make valuable decisions (Singh and Chakrabarti 2020: 42). E-consumers who generate this valuable content, referred to as data resources, are unaware that retailers are freely benefiting from e-consumer data accumulation on digital platforms. Aristotle, an ancient Greek philosopher refers to the human race as animals with god-like capacities to think and reason out encounters with the environment to develop habits characterised by indeterminacy amidst multiple possibilities (Rabinoff 2018: 57). As a result, online consumers continue to be vulnerable to free data resource exploitation, especially during the indispensable-multiple information search for the purpose of useful online shopping (Wang and Wang 2020:252). No research has directly focused on e-consumer awareness of free data resource exploitation to recommend remediation strategies by recognising e-consumer valuable data input.

There is evidence that the irritating pop-up ads during internet surfing are caused by e-retailers who exploit e-consumer data resources for free (Akter, Us-Salehin, Azad and Soheli 2020: 37). For example, the content-based algorithm filters individual preferences and employs collaborative hybrid approaches to modify product attributes that fit with the grouped user-generated online content (Banker and Khetani 2019: 500). Perception can therefore be altered by virtue of deeper influence on the intellectual soul by employing qualitative individual thoughts in society (Rabinoff 2018: 65). Literature about digital marketing focuses on harvesting e-consumer data for profitable targeting without considering e-consumer awareness of online retailers' free exploitation of e-consumer data input. The owners of this data input that creates value ought to be recognised in order to develop appropriate remediation mechanisms to reward the usage in a bid to strengthen e-retailer-e-consumer relationships. As a result, the recognition of e-consumer data input may re-boot e-consumer power in the dynamic digital environment, embracing the concept of digital consumerism.

E-retailers use technology-driven approaches to match a combination of online users' data resources with customised product offerings (Riegger *et al.* 2021: 142). Also, online retailers use collaborative filtering by matching previous e-consumer behavioural data with the present behaviour, guiding online shoppers by suggestion and coercing them based on previously exploited e-consumer data (Virdi, Kalro and Sharma 2020: 557). Notably, perception varies from individual to individual depending on the numerous cues of importance of the situation faced by a person during online shopping (Rabinoff 2018: 65). Despite the ubiquitous digital technology used by e-retailers to exploit e-consumer data resources for free, no research has centred on e-consumer awareness of free data resource exploitation in relation to the influence of perception.

On the flipside, there is unlimited e-tailing use of automated decision-making executions that are processed in a very short time and are supported by tracking and monitoring management systems dedicated to exploiting free e-consumer data resources (Nagel, Corea and Delfmann 2020:1). The notion that the customer is king is fading away with diminishing e-consumer power and control due to the growing digital power of online retailers to exploit unsuspecting e-consumers who are submissive to free data resource exploitation (Gupta, Gupta and Dhir 2020: 207). Rabinoff (2018: 77) subscribes to the view that perception is structured by intellect to assist the individual in seeking a solution for the present phenomenon while downplaying the ultimate consequences. The manipulation of human choices through free data exploitation by e-retailers ignores the fact that e-consumers are shoppers and at the same time, citizens who deserve recognition for their data input contributing to the exponential growth of electronic commerce.

On the other hand, the internet has subverted the traditional consumer power, where the e-consumer digital footprint is exploited without the awareness of the consumer as large amounts of digital behavioural data are utilised to energise predictive models (Nuccio and Guerzoni 2019: 313). In the data-driven digital economy, e-consumer autonomy is undermined by mandatory data disclosure, where online shoppers have no option but to give up control over personal data in order to complete the online transaction (Busch 2019: 310). Bandara, Fernando and Akter (2020: 1) articulate that e-consumer data resources are a vital category of new asset that generates revenue for the growth of e-commerce. In order for online retailers to accelerate online shopping frequency, managers have put up exploitative systems that are primarily dedicated to harvesting free e-consumer data resources, focusing on short-term earnings and ignoring long-term e-consumer relationships (Reynolds-Pearson and

Hyman 2020:15). Albeit online users are aware that digital channels can influence their decisions, many e-consumers are unaware that their behavioural data resources are being exploited by e-retailers.

Certainly, perception is in most cases reflective of the present desire for something, where something painful may be perceived as desirable depending on the relative short-term benefits (Rabinoff 2018: 96). Therefore, it can be argued that e-consumers are unaware of free data resource exploitation, which might negatively affect e-retailer and e-consumer long-term relationships in the digital economy. In the developing digital economy, e-tailing firms manoeuvre through massive e-consumer data resources by uncovering trends that establish behavioural patterns, which are exploited to build decisions linked to organisational performance (Rialti *et al.* 2020: 1586). Thinking is holistically involving the soul and the body in decision-making after evaluating the consequences of a particular action (Rabinoff 2018: 77). Online retailers can exploit e-consumer data to tailor need satisfaction; however, the owners of the data resource input deserve to be aware of the mutual benefits of the recognition of the net input made by e-consumers.

Flexible organisational innovativeness of retailers is achieved by applying digital technology to extract e-consumer data resources that guide the ambidexterity of retailers to compete favourably in the digital environment (Jafari-Sadeghi *et al.* 2021: 108). The free exploitation of e-consumer data can be assimilated to the Marxist concept of exploitation in such a way that e-consumers arduously create unpaid online content that generates web-clicks used for decision-making (Gjerde 2020:425). Aiello *et al.* (2020: 491) caution that sceptical e-consumers are getting overwhelmed by e-tailing requests for personal data to enable the completion of online transactions. E-consumers instinctively, in turn, provide their data resources to complete the transaction, which permits the retailer to harvest and exploit the free data for future targeting decisions. The existing literature indicates that e-consumers are unaware that their data resources are exploited by online retailers to generate e-commerce revenue. Retailers do not pay for the use of e-consumer data input that accumulates revenue; instead, consumers are promised tailored offers, which come at a cost.

It is worth noting that imagination is initiated by perception, which extends human thinking to the body that activates decisions (Rabinoff 2018: 78). In the growing digital era, retailers are getting obsessed with capturing e-consumer imagination to achieve profitable e-commerce objectives by reshaping the digital competitive logic towards the dynamic e-consumer trends (Grosso *et al.* 2020: 524). Additionally, in the dynamic digital market, online retailers are faced with the difficulty of ascertaining whether e-consumers are still potential or have silently defected by unveiling the probabilities based on data exploitation to make predictions (Reutterer, Platzer and Schroder 2021: 194). Digital marketers can then detect that, occasionally, intellect is not always necessary for perception in some individuals who have acquired knowledge of the environment and later perceive without using intellectual capacity. E-consumers, as the providers of valuable data resources, ought to be aware of their contribution to online retailers' e-commerce success in order to reward their input.

Riegger *et al.* (2021: 146) view e-retailers as opportunistic traders taking advantage of e-consumers' low level of awareness of free data resource exploitation, thereby benefiting from a lack of transparency by limiting personalised offers and intentionally curving online shoppers' path on the browser towards slow-moving products. The free exploitation of e-consumer data resources using behavioural artificial intelligence data mining operations enshrines great empowerment for e-retailers to feature in hyper-nudges with ads that modify pre-existing individual online shopping goals (Pusztahelyi 2020: 15). Online retailers aim to increase visibility on the digital platforms by exploiting e-consumer behavioural data to facilitate targeted ads based on search behaviour during online shopping activities (Nuccio and Guerzoni 2019: 314). Bandara, Fernando and Akter (2020: 4) assert that when e-retailers track and profile e-consumers first-hand data, it is possible to exploit e-consumer secondary behavioural data. Without e-consumer knowledge, the secondary online browsing behavioural data is exploited by online retailers for retargeting based on hidden patterns.

Digitalised retail firms can identify the smart devices e-consumers used during the online shopping activities to uncover salient past online behaviour and online registration details, thereby prompting an interoperability drive to click on similar products (Busch 2019: 316). The hidden patterns reveal vital insights that humans do not hold to be particularly accurate (Rabinoff 2018: 95), with rational judgements moderated by perceptions regarding what is pleasurable as opposed to what is consequential during online shopping. Therefore, free data exploitation is considered the organisation's ambidexterity to uncover hidden e-consumer data patterns to successfully co-ordinate profitable company objectives (Rialti *et al.* 2020: 1586). Ultimately, since the exploiter needs the exploited, the exploiter gives the exploited some power to click agree on the terms and conditions during online shopping, which permits data collection for exploitation (Gjerde 2020: 426). Although the human soul is obedient to reasoning, sometimes individuals ignore perceptions and act irrationally (Rabinoff 2018: 96). Online shoppers become susceptible to exploitation while fulfilling their online shopping needs and downplay any possibilities of free data resource exploitation.

To compete favourably in the data-driven economy, digital marketers are now working with data scientists who are solely dedicated to unveiling the hidden patterns of online shoppers to improve their digital marketing programmes (Pelau, Niculescu and Stanescu 2020: 830). Reutterer, Platzer and Schroder (2021: 5) state that during the first online purchase, e-consumers are born; however, to retain e-consumers' recurring survival, e-retailers deliberately exploit the available e-consumer data resources. Ultimately, e-consumer data is exploited to develop predictive models intended for perpetual repurchase intentions. Hence, the discourse of perception on free data resource exploitation ends up taking on three facets, which include digital Recommenders, digital self-efficacy, and digital self-disclosure, discussed in the next sections.

3:3:1 Digital Recommenders

Online retailer websites are embedded with recommender systems that seek to eliminate overburdening e-consumers; for example, Amazon assimilates online shoppers and recommends extra products based on browser movements (Lorenz-Spreen *et al.* 2020: 1104). Digital Recommenders use algorithms that monitor and exploit e-consumer data input depending on product searches, thereby overwriting consumer intuitions where, in certain instances, they recommend inferior but expensive products that e-retailers prioritise replenishing (Banker and Khetani 2019:

501). As online retailers exploit free e-consumer data resources to induce their preferred product recommendations, online shoppers are unaware of the exploitative systems embedded in retailers' websites.

Virdi, Kalro and Sharma (2020: 557) argue that e-tailing firms exploit free online consumer data resources to create a hybrid recommender that allows simultaneous suggestions of alternative products out of the infinite online products. Additionally, digitalised retailers with on-site brick-and-mortar settings use track-by-monitoring technology to store unique addresses of e-consumers searching for products and recommend their brick-and-mortar store for collection (Cervantes and Franco 2020:357). Busch (2019: 316) contends that the tracking of e-consumer free data resources unveils hidden consumer needs; for example, e-consumers searching for antenatal products may receive recommendations for nutritional supplements, baby unscented lotions, and hand sanitisers. Online retailer digital recommender systems exert cognitive control over individual choices, which distracts e-consumers from achieving their intended goals based on their norms and capabilities to perform online shopping with less e-tailing control (Bandara, Fernando and Akter 2020: 5). Research for the awareness of e-consumer free data resource exploitation propelled by Recommenders is still in its infancy based on the current literature.

Baker and Khetani (2019: 500) are of the view that automated recommendations filter e-consumer data and make suggestions in consideration of e-consumer preferences, but the overdependence on digital Recommenders limits consumer welfare while propagating biases that favour exploitative e-retailers. Therefore, e-consumer choices are controlled by decision aids where the digital Recommenders' suggestions track some clues from e-consumer data and squeeze in alternative products based on stock availability (Virdi, Kalro and Sharma 2020: 560). Lorenz-Spreen *et al.* (2020: 1104) allude to the fact that digital Recommenders can ease e-consumers' product search tasks to access products quickly. However, e-consumers are unaware that Recommenders are based on e-retailers' recommended product variety on the website, removing e-consumers' control of their choices. There is no research solely focused on raising awareness of free e-consumer data exploitation and highlighting digital Recommenders. Also, a few studies of data exploitation in relation to digital self-efficacy can be identified in the existing literature covered in the next section, but more should be studied on digital self-efficacy in relation to e-consumer awareness of free data exploitation.

3:3:2 Digital self-efficacy

In the digital economy, e-consumer digital self-efficacy depends on the ability to avoid being vulnerable to exploitation on the digital platform while transacting online (Adhikari and Panda 2018: 99). By the same token, e-consumers with low digital self-efficacy are hindered by the successful execution of online transactions and normally end up entering personal data online depending on how they perceive online shopping (Adapa *et al.* 2020: 4). But perception is based on the significance of the situation, which may differ from individual to individual in the same environment (Rabinoff 2018: 29). Normally, digital self-efficacy enables online shoppers to engage online, thereby attracting e-retailers to exploit data.

The high level of information search during online shopping entails some degree of digital self-efficacy as e-consumers continue to browse for better product specifications, resulting in a trail of free browsing data (Ramesh and Vidhya 2020: 66). Adapa *et al.* (2020: 3) state that the complexity of digital technology coupled with the low level of e-consumers' innovativeness to switch among retailers' websites limits the extent of e-consumer data that can be exploited due to low online engagement. Human perception requires thinking aided by retailers' website features, which bring memories that transform individual decisions (Rabinoff 2018: 79). Digital self-efficacy may favourably or unfavourably contribute to e-consumer free data resource exploitation, which is a precursor to digital self-disclosure. In the next sub-section, digital self-disclosure is discussed.

3:3:3 Digital self-disclosure

Digital self-disclosure refers to the tendency of e-consumers to voluntarily disclose their data resources on digital platforms (Aiello *et al*. 2020: 491). Digital self-disclosure is somehow related to digital self-efficacy because the individual disclosing data must have the ability to use digital technology wilfully (Jafari-Sadeghi *et al.* 2021: 102). Ferreyra *et al.* (2020: 3) affirm that emotions, quick judgement and reduced digital complexity have enabled e-consumer digital self-disclosure. Depending on subjective perception, individuals shopping online are voluntarily exposing their valuable data resources on the digital platform in proportions hard to comprehend (Brandao and Rezende 2020:4). Certainly, Aristotle's evaluative position concerning perception of the good or bad scenario motivates action to feel pleasure or avoid a situation with subjective judgement, where some situations may be neither pleasant nor painful or may not be noticed at all (Rabinoff 2018: 132). Grosso *et al.'s* (2020: 526) findings indicate greater willingness for e-consumer digital self-disclosure of personal data depending on whether e-retailers have brick-and-mortar stores, which can ease likely tensions. Inadvertent self-disclosures facilitate free data resource exploitation by e-retailers.

Furthermore, Busch's (2019: 311) study illuminates how online shoppers ignore lengthy personal data disclosure notices, which has resulted in e-consumers inadvertently disclosing their data resources for free during the e-consumer purchase journey. In a study conducted by Pelau, Niculescu and Stanescu (2020: 833), it was found that women are more open to disclosing personal data on digital platforms than men. Research linking digital self-disclosure to awareness of e-consumer free data resource exploitation is particularly scarce. Scholars have dedicated limited attention on the influential factors of free e-consumer data exploitation awareness and the establishment of remediation mechanisms for e-consumer data input. More research on e-consumer awareness is crucial.

Grosso *et al.* (2020: 525) articulate that once online shoppers are confronted with e-tailing data disclosure requests, they unwittingly conform or decline the request depending on the expectations and consequences perceived without considering data exploitation. Albeit online retailers' websites are embedded with ex-ante disclosure typification, the standardised disclosure typification guidelines are pre-digital and seem more like a very distant echo to e-consumers (Busch 2019: 313). Additionally, Aiello *et al.* (2020: 492), on the other hand, consider gender and age to be critical in regard to the willingness to submit to digital self-disclosure; for example, youth and females are not concerned about their data. Digital self-disclosure of data resources is therefore inevitable whenever e-consumers engage online. Online shoppers unwittingly disclose their data while they are transacting, which attracts online retailers to exploit such free data for retargeting. But while transacting online, e-consumers have to adhere to numerous risks, which are discussed in the next section.

3:4 PERCEIVED RISK

The concept of perceived risk was initially introduced by Bauer in the early 1960s, when consumer behaviour was gaining enormous traction in consumer studies among professional scholars (Carstens, Ungerer and Human 2019: 7). In the digital economy, perceived risk is defined as e-consumer uncertainty during the entire process of online shopping and all the interactions on the digital platform (Alshahrani 2020: 477). There is a contradiction in the idea that perception is based on intellectual judgement, when in some instances, perception is simply based on the pleasant outcome of the situation, irrespective of the risks involved (Rabinoff 2018: 133). Rehman, Baharun and Salleh (2019: 75) refer to perceived risk in e-consumer behavioural studies as the negative consequences of purchasing products and services online. While Ariffin, Yajid and Azam (2020: 1145) define perceived risk as a subjective belief of loss that e-consumers fail to foresee in pursuit of online purchases and digital engagements. Dabrynin and Zhang (2019: 17) delineate perceived risk as the estimated probability of undesirable magnitude relating to the repercussions resulting from transacting online. E-consumers unwittingly disclose their data after taking risks online, thereby allowing online retailers to harvest their digital footprint.

Puri and Mohan (2020: 1144) describe perceived risk as consumer concerns bordering on the invasive activities deliberately conducted by e-retailers encroaching on behavioural data during online shopping. The adverse outcomes of perceived risk greatly affect e-consumer attitudes (Samarasinghe, Samarasiri and Mataraarachchige 2020: 4) to transact online, which limits the extent of free data exploitation by retailers. Alshahrani (2020: 477) argues that the expected loss as a result of transacting online discourages e-consumers from using the digital platforms, thereby reducing the chances of vulnerability to free data resource exploitation. However, risks are often assessed on an individual-by-individual basis depending on cognitive capacity where conscious people associate uncertainty with online transactions, while others may not equate online activities with risk (Ferreyra *et al.* 2020: 1). Based on the current literature, data exploitation in relation to perceived risk has not been sufficiently addressed. Against this backdrop, this section of the study seeks to investigate the influence of perceived risk on e-consumer awareness of free data resource exploitation.

Perceived pleasure or pain is influenced by what is beneficial or harmful, but what is good is not necessarily pleasant, and what is bad may be pleasant to others under pressure by habituated experience accumulated over time (Rabinoff 2018: 137). Nevertheless e-consumers connect online shopping with risk, which impacts online shoppers' willingness to transact online, thereby reducing the amount of free data resources exploited on digital platforms (Balogh and Meszaros 2020: 15). Perceived risk forces e-consumers to constantly search for a variety of information during online shopping, which has resulted in e-consumers to unwittingly leaving tremendous traces of browser behavioural data exploited by retailers (Manikandan 2020: 135). Similarly, Guru, Nenavani, Patel and Bhatt (2020: 139) conceptualise perceived risk as a formidable influence on e-consumer buying behaviour mediated by the degree of uncertainty of the outcome of online shopping. Notably, while the current literature concentrates on the influence of perceived risk on online shopping, virtually no research specifically relates e-consumer awareness of free data resource exploitation in relation to perceived risk.

Perceived risk has the potential of igniting positive or negative attitudes in that, if the risk is intense, e-consumers will not transact online, whereas a low risk attracts online engagement, leading to free data resource exploitation (Sahin and Gelmez 2020: 2294). Despite of risks associated with e-commerce, online shopping is growing exponentially, which has led to enormous amounts of digital footprint being scattered online, ready for exploitation (Sharma 2019: 1162). E-consumers are therefore simply interested in achieving their online shopping goals rather than the exploitation of data, which has put online users in the vulnerable position of being victims of free data resource exploitation. People can take pleasure even when they think what they are doing is bad, which calls for the separation of bad from good through the application of intellectually based perceptions as mere abstracts (Rabinoff 2018: 138). E-consumers are therefore unaware of free data resource exploitation propelled by perceived risk based on the current literature.

Perceived risk is a multi-dimensional concept that encompasses psychological, social and global risks that influence e-consumer decisions to engage on digital platforms (Bach, da Silva, Souza, Kudlawicz-Franco and da Veiga 2020: 3). E-consumers have the potential to evaluate risks in order to make online shopping decisions by demonstrating judgement built from the gains and consequences of engaging on digital platforms using cognitive probabilistic beliefs (Li, Sha, Song, Yang, Zhao, Fiang and Zhang 2020: 77). In fact, perception helps the individual discriminate between extreme cases by invoking awareness to engage in understandable actions in the environment (Rabinoff 2018: 135). Notably, the existing e-consumer studies differ from this study in such a way that previous studies are silent about the influence of perceived risk on e-consumer awareness of free data resource exploitation.

The major issue that attracts a high level of perceived risk is that e-consumers have to disclose personal data related to contact details, electronic payment data, and delivery address in order to complete online purchases resulting in free data resource exploitation (Alshahrani 2020: 478). In some instances, perceived risk is stringent on website content due to the fact that online shoppers have a positive perceived risk of a well-organised display attracting free data disclosure and exploitation (Tran 2020: 222). The high level of risk on the digital platforms hinders firms that have adopted a purely online model, which has resulted in the establishment of conventional brick-and-mortar settings alongside e-tailing in South Africa (Carstens, Ungerer and Human 2019: 2). On this note, e-consumer confidence is enhanced by the physical store presence, thereby motivating online shopping and enabling data disclosure, leading to free data resource exploitation without e-consumer knowledge.

Online shoppers merely depend on product images, text and video content posted on retailers' websites to make shopping decisions, which are considered riskier than offline brick-and-mortar settings. Mwencha and Muathe (2019: 170) are of the view that e-consumers refrain from transacting online due to the prevalence of high levels of risk associated with online retailers, limiting the extent of free data resources online. South Africa has intensified digital marketing on the Gumtree website, allowing consumers to compare prices and products, but most of the retailers do not have physical stores, which raises risks (Carstens, Ungerer and Human 2019:3). In relation to demographics, particularly gender, males have greater concerns pertaining to the severity of perceived risk due to negative consequences; however, studies indicate that females downplay risks (Puri and Mohan 2020: 1145). Therefore, males are less likely to engage on the digital platform, putting them at a lower risk of being vulnerable to free data resource exploitation by online retailers.

Ha (2020: 2031) describes perceived behavioural control as an individual judgement of the unfavourable and favourable analyses of shopping online amidst the cloud of risks, which can encourage or discourage consumers from transacting online. E-consumer free data resource exploitation can be overlooked in circumstances where online shopping's perceived benefits and goals outweigh the perceived risk (Puri and Mohan 2020: 1145). Considering the numerous studies conducted by various scholars, no researcher has devoted adequate effort to studying the influence of perceived risk on e-consumer awareness of free data exploitation. Perceived risk influences e-consumers to shop online, ultimately exposing browsing data that is exploited by e-retailers. In the next section of the study, a comparison of the various facets of perceived risk in relation to free data resource exploitation is discussed.

3:5 FACETS OF PERCEIVED RISK

Samarasinghe, Samarasiri and Mataraarachchige (2020: 5) articulate that the magnitude of risk depends on the type of risk that shapes the e-consumer's attitude towards online shopping. The fact that e-consumers are dealing with an unknown online seller whose identity is unspecified may lead to reluctance to purchase goods and services online, consequently limiting the amount of free data to exploit online (Alshahrani 2020: 478). Individual perception of digital platforms legitimacy is deemed adequate to compromise the risks perceived in disclosing free data resources for e-retailers to exploit (Ferreyra *et al.* 2020: 2). Not only is the threat of financial loss a deterrent to online shopping, but the absence of physical trials and personal contact also poses a high risk of online shopping decision, which in turn affects the possibility of free e-consumer data exploitation (Balogh and Meszaros 2020: 15). It is not perception that is of concern, but what perception can lead to in terms of decision-making that can be contextualised as eventualities of perception (Rabinoff 2018: 130), like free data resource exploitation. Therefore, perceived risks online, prompt e-consumers to accept vulnerability, which includes innocently falling prey to free data exploitation.

Perceived risk also depends on perceived certainty that a negative consequence might occur during or after online shopping, which is the main deciding factor in transacting online (Manikandan 2020: 135). The feeling of uncertainty happens when there is no assurance that the e-consumer will accomplish his or her goals with the online purchase (Guru *et al.* 2020: 138). Perceived risk is a reason for e-consumers expansion of search opportunities in a bid to unveil favourable and less risky online shopping websites, which results in e-consumers inadvertently littering off free data resources in the form of browsing footprints exploited by e-retailers (Sharma 2019: 1164). Although it is impossible to evaluate all the information, rational e-consumers systematically search for products vigorously to minimise risk, which eventually leads to retailer monitoring of browsing behavioural history for exploitation (Bach *et al.* 2020: 2). E-consumers weigh the risks of transacting online and make decisions that can lead to data disclosures and free data resource exploitation.

Sahin and Gelmez (2020: 2294) and Mwencha and Muathe (2020: 171) view performance risk, financial risk and communication risk as the main facets (dimensions) of perceived risk that influence e-consumers' decisions. While Carstens, Ungerer and Human (2019: 8) consider security risk, time risk and physical risk, inter alia, to be the major facets of perceived risk, Alshahrani (2020: 478) is consistent with Sahin and Gelmez (2020: 2294) about the facets of perceived risk but adds delivery risk as well as terms and conditions risk to the risks cited earlier. The dimensions of perceived risk are a recipe for undesirable outcomes resulting e-consumers refraining from online shopping, thereby limiting free data resource exploitation (Rehman, Baharun and Salleh 2019: 75). Therefore, e-consumer awareness of the exploitation of free data resources generated by online activity is hindered by the facets of perceived risk online. The major perceived risk dimensions or facets are security risk, product risk, delivery risk and psychological risk. These facets are explained in the next sub-sections.

3:5:1 Security risk

E-tailing activities necessitate consumer data to function competitively in today's data-driven economy, and therefore, e-consumers face a risk of data usage security. However, the assurance of security, motivates data disclosure, leading to exploitation (Dabrynin and Zhang 2019: 17). Tran (2020: 223) argues that e-consumer data is plausible for online retailers, which renders online shoppers in an insecure position preoccupied with the risk related to the possibility of data manipulation, which demotivates online engagements; hence, reducing the volume of free user data online. E-consumers face the security risk of becoming victims of extreme targeted advertising, which leads to negative feelings and a sense of loss of power after disclosing their data to retailers during online shopping. As a result, e-consumers end up not transacting online, thereby limiting free data exploitation. However, not all e-consumers are aware of security risks, and therefore, some online consumers ignore the security risks and disclose their data during online shopping.

On the flip side, online shopping that is secure, safe, and highly confidential guarantees e-consumers' data resources are being disclosed for free, awaiting e-tailing exploitation through precise targeting without the e-consumers' awareness of (Bhatti and Rehman 2020: 38). E-consumers are concerned about the security risk where the storage of their data, such as home address, mobile contacts and payment details, might subsequently be reused, which deters online shopping and thereby affects free data resource exploitation (Alshahrani 2020: 478). Nevertheless, the average e-consumer has difficulty estimating security risks in the online environment (Ferreyra *et al.* 2020: 2). As a result, online shoppers are becoming victims of free data exploitation as they unwittingly disclose personal data during online shopping without considering security risks.

In a study aligned to online security risks conducted by Sharma (2019: 1163), the conclusive remarks indicate that e-consumers feel uncomfortable providing personal and financial data to internet technology-based retailers, citing data security. E-consumers feel a sense of betrayal when retailer websites store online behaviour, undermining online shoppers' safety from security risks alongside temptations to surrender data resources for free during the shopping journey (Carstens, Ungerer

Human 2019: 9). As a result, e-consumers feeling security risk concerns desist from online shopping all together, leading to unintentional avoidance of free data resource exploitation. Researchers are less focused on investigating the influence of security risks on e-consumer awareness of free data exploitation, according to the studies.

Furthermore, Mwencha and Muathe (2019: 171) caution that e-consumers feel threatened about behind-the-scenes data collection while they are navigating retailer websites with a sense of insecurity relating to loss of control over personal data. This sense of insecurity reduces online engagement and free data resource exploitation, which affects e-retailers decision-making capabilities based on e-consumer data input. Online shoppers are concerned about the supervision of the flow of data for the purpose of evaluating behavioural targeting (Dabrynin and Zhang 2019: 18). Perceived severity and vulnerability to a security risk discourage e-consumers from engaging in any activity that is likely to lead to personal data disclosure, like online shopping that facilitates data exploitation (Adhikari and Panda 2018:97). Consequently, the protective security measures of e-consumer free data resource assurances are fundamental motivators of online shopping, leading to e-consumer self-disclosure without realising subsequent free data exploitation by e-retailers.

Security risk concerns discouraging online shopping also include e-consumers being targets of spam emails with unreliable inappropriate advertisements and inferior product targeting induced by online shopper tracking (Carstens, Ungerer and Human 2019: 9). Likewise, security risks concerns are noticed with insufficient online retailers' information relating to their location and incomplete disclosures of e-consumer rights, which reduce online shopping decisions, leading to the backfiring of free data resource exploitation (Alshahrani 2020: 478). Ferreyra *et al.* (2020: 3) caution that the security risk paradox that manifests when online shoppers are promised data resource protection, which is a recipe for revealing and leading to free data resource exploitation. The comprehensive digital security framework ensuring the safety of e-consumer data resources is an illusion of low security risk in the digital environment that fortuitously assists victims of free data resource exploitation to wilfully disclose data (Balogh and Meszaros 2020: 15). Perceived security risks influence e-consumers awareness of free data resources to some degree, but more studies are necessary to qualify this argument.

Puri and Mohan (2020: 1145) contend that e-consumers are unintentionally doing little to secure their data resources because they are unaware at what point to share data, making them overlook warnings of free data exploitation. Security risks that involve phishing, vishing (unknown phone calls), and unknown SMS special offers often discourage online shoppers from data disclosure (Brandao and Rezende 2020: 3). Gupta, Gupta and Dhir (2020: 211) add that the suspicion of e-tail phishing and spam emailing is a deterrent to online shopping, eventually limiting the incidence of free data resource exploitation. E-consumers security risks are also about personalised commercials generated by previous online shopping activities, as some consider them creepy, triggering negative reactions due to persuasions and the stigma of being monitored (Puri and Mohan 2020: 1144). Notably, some e-consumers focus on security risks and are unnerved by free data resource exploitation. provided that the online retailers assure them of security.

On the other hand, e-consumers feel the threat of security risk of negotiating the terms and conditions because the clickwrap online sales agreement disappears on clicking agree, which permits free data exploitation clauses that are not downloadable (Alshahrani 2020: 479). Some retailer websites are embedded with preventative nudges that guide online shoppers with safer cybersecurity practices that assure user security and enhance confidence, leading e-consumers to unwittingly disclose data read for free exploitation (Ferreyra *et al.* 2020: 399). E-consumers are rational human beings who carefully evaluate the consequences of risk and make online purchase decisions based on fear of disappointment as a result of unforeseen security risks that reduce online shopping decisions limiting free data exploitation (Bach *et al.* 2020: 3). However, once the online risks are minimised by online retailers, e-consumers tend to be willing to engage in self-disclosure activities online, which increases exposure to free data resource exploitation.

Other issues that make e-consumers feel insecure entail constant reminders of similar products that are listed on e-consumer browsing history, which are met with discomfort, thereby discouraging online shopping due to data security (Pelau, Niculescu and Stanescu 2020: 834). In fact, not all e-consumers are unaware of free data exploitation, as some have resorted to the defensive behaviour of falsifying the data disclosed on the digital platforms due to the security risks of being victims of free data exploitation (Bandara, Fernando and Akter 2020: 2). Additionally, online shoppers feel insecure about e-tailing's constant requests for personal data during the e-consumer's purchase journey leaving them vulnerable to inadvertently disclose their data resources awaiting exploitation (Aiello *et al.* 2020: 491). Once the security risk is eased, e-consumers unwittingly disclose their data resources to online retailers, becoming victims of data exploitation. Another facet of perceived risk that is discussed in the next sub-section is product risk.

3:5:2 Product risk

In e-commerce, product risk refers to the possibility that the product purchased online might not meet the merchantable standards or the expected level of performance, which calls for vigorous searching that leaves free data online (Alshahrani 2020: 478). Product risk affects e-consumers' decisions to purchase goods and services online, especially if there is a high possibility that the product might not satisfy the e-consumers' goals leading to lesser online sales and free data disclosure (Dabrynin and Zhang 2019: 18). The most compelling argument of Aristotle is that the human soul depends on images to think in order to make rational decisions (Rabinoff 2018: 82). E-consumers face the risk of shopping for products online without prior observation of the physical features of the products, depriving inspection and judgement, which exposes free e-consumer search data for product alternatives that are exploited for targeting (Ahmad, Fauzi, Ditta, Idris, Purwanto and Asbari 2020:4). With the threat of product risk, e-consumers unwittingly leave a large chunk of free behavioural browsing history, which forms part of the data input, providing clues of preferences that are exploited for future targeting and predictions. Less attention is specifically centred on the influence of product risk on e-consumer awareness of free data resource exploitation.

Depending on the category of online products, some products like medical supplies require a lot of search information, which provides enormous free browsing data resources to exploit compared to apparel and books, which require a single click (Ariffin, Yajid and Azam 2020: 1144). Individuals purchasing embarrassing products that create cognitive discomfort in a physical store unknowingly expose personal data for exploitation by opting for confidential online shopping (Sharma 2019: 1169). Tran

(2020: 222) adds that online retailers with a return policy for products that fail to function positively influence online shopping, leading e-consumers to unwittingly disclose personal data resources that e-retailers exploit for future targeting. E-consumers are confronted with the fear that the product purchased online might be defective, requiring replacement or repairs, or inadequate, compromising their online shopping desires, thereby limiting free online data (Balogh and Meszros 2020: 17). Therefore, based on the existing studies, perceived product risk has an influence on e-consumer awareness of free data resource exploitation as online shoppers strive to minimise product risk.

The failure of the product to perform implies a potential loss to e-consumers, which result in a loss of confidence in online shopping, eventually limiting the availability of online consumer behavioural data for exploitation (Guru *et al.* 2020: 140). The complex and expensive products pose a high level of product risk, forcing e-consumers to conduct extensive interactive online searches with e-retailers, making e-consumers inadvertently disclose free data and guiding e-tailers to target according to preference (Bach *et al.* 2020: 2). Generally, product risk arises when e-consumers fail to predict the actual features of the product in comparison to the advertised features, which compels online shoppers to desist from online purchases (Sahin and Gelmez 2020: 2294). As e-consumers are met with various brands on the retailer's websites, they struggle to evaluate the originality of the genuine brand that will meet their expectations (Li *et al.* 2020: 77). Thus, online shoppers' curiosity about online products inevitably results in free data disclosure and exploitation due to unrelenting web searches.

Due to the high prevalence of product risks, e-consumers participate in pre-purchase interactions with e-retailers unaware of free data disclosure and exposure to data exploitation as e-retailers track preferences for future targeting (Aiello *et al.* 2020: 496). Product risk is threatening, especially when e-consumers perceive online products to be sub-standard and susceptible to malfunctioning, scaring online order placements, which unintentionally influence e-consumer free data exploitation due to reduced online data exposure (Carstens, Ungerer and Human 2019: 8). Online shoppers are unable to evaluate the advertised online products in a virtual store without touching or feeling the product, discouraging online shopping, which unwittingly affects e-consumer exposure to free data exploitation (Ahmad *et al.* 2020: 4). Studies indicate a low perceived product risk may influence e-consumers to inadvertently become vulnerable to free data resource exploitation. However, apart from product risk, delivery risks discussed in the next sub-section may also contribute to the influence of e-consumer awareness of free data exploitation by e-retailers.

3:5:3 Delivery risk

The possibility of non-delivery or delivery to the wrong address is a deterrent to online shopping, which requires the consigned shipment to be delivered to the given address at a later date, which indirectly influences e-consumer free data disclosure and exploitation (Alshahrani 2020: 478). Also, the likelihood of non-delivery of associated goods in the case of products requiring accessories may prevent shoppers from placing online orders, indirectly reducing the flow of e-consumer data for exploitation (Ahmad *et al.* 2020: 4). By the same token, e-consumers assured of timely delivery, a guaranteed return policy, and exchange delivery of mal-functioning orders will inadvertently risk disclosure of personal data resources and ignore the consequences of free data exploitation (Mwencha and Muathe 2019: 168). Samarasinghe, Samarasiri and Mataraarachchige (2020: 5) also affirm that a reliable online return policy attracts e-consumer confidence, leading the online shopper to unknowingly disclose data resources for free exploitation during the purchase journey. E-consumers inevitably have to be delivered online orders at a disclosed address with a requirement for delivery information, which retailers capture for exploitative re-purchase targeting without e-consumer knowledge.

Contrastingly, e-consumers are faced with a risk of inadequate deliveries, long delivery times, and damages during delivery, all of which dissuade e-consumers from online shopping, and indirectly limit the incidence of free data exploitation (Balogh and Meszaros 2020: 17). Online retailers with discreet deliveries provide a comfortable scenario, which inadvertently lures e-consumers into perpetual online shopping decisions that facilitate free data resource exploitation (Sharma 2019: 1169). E-consumers also face the risk of having to wait for online order deliveries, which may affect the decision to purchase products using offline real-time access to the goods, which counteracts online purchases associated with personal data exploitation

(Ahmad *et al.* 2020: 13). Online retailers with superior delivery services, packaging, and timely deliveries invoke swift online shopping decisions (Alshahrani 2020: 478). The delivery services eventually propel e-consumers to unwittingly provide valuable data resources for free, leading to data exploitation.

Tran (2020: 223) affirms that retailers' websites that assure e-consumers protection of shoppers' delivery data enhance e-consumer confidence in support of online shopping, leading to delivery data disclosure, which helps e-tailing future targeting. Balogh and Meszaros' (2020: 119) argument is consistent with Tran's (2020:223) that e-consumers are worried about exposing their delivery data, which includes their addresses and telephone numbers, which may be exploited for unwanted re-targeting. So, some e-consumers are influenced by delivery risks for the awareness of free data resource exploitation because the completion of the online purchase journey is sealed by the unavoidable disclosure of delivery details. In general, psychological risks explained in the next sub-section, are the major facets of perceived risk influencing e-consumer awareness of data resource exploitation.

3:5:4 Psychological risks

Psychological risks encompass the overall emotional feeling of different risk facets that encircle, inter alia, possible data interruption, over-spending, product performance stress, rip-offs, and maintenance and refund issues (Alshahrani 2020: 478). Emotional worries restrict e-consumers from transacting online due to the psychological risks analogous to digital platforms, thereby decreasing the possibilities of free data resource exploitation. The emotional feeling of financial loss coupled with the difficulty of withstanding financial loss and hidden costs like shipping or insurance affect online shopping, which indirectly restricts e-consumer free data resource exploitation without the e-consumers' knowledge (Dabrynin and Zhang 2019: 18). Furthermore, e-consumers are distressed by disclosing the required online shopping personal financial data, which forces buyers to seek alternative conventional offline shopping, thereby indirectly restricting free online consumer data resources for exploitation (Samarasinghe, Samarasiriand Mataraarachchige 2020: 4). Due to the high number of psychological risks on digital platforms, e-consumers reveal less data owing to their fears of possible consequences, even if they might not be aware of free data resource exploitation, in particular.

On the other hand, tensions arise when sceptical e-consumers perceive the possibility of e-retailer's inconsistencies about warranties and web information between pre-purchase searching and order execution limiting online purchase decisions that facilitate free data (Guru *et al.* 2020: 140). Psychological risks are basically related to the emotional hazards of stressful anxiety associated with making poor and disappointing online decisions, where the e-tailing motivation to feel comfortable with online choices lures continued online shopping (Bach *et al.* 2020: 3). Typically, there is a psychological tendency among e-consumers to assume that online shopping compels to reveal personal data during the purchase journey, which is met with scepticism, resulting in online purchase disregard, thereby limiting free data exploitation (Li *et al.* 2020: 90). A few studies have examined the influence of psychological risks on online shopping behaviour, while no studies have pushed further to relate psychological risks to e-consumer awareness of free data resource exploitation apart from this study.

The ego losses as well as the severity of the repercussions of perceived risk create a feeling that online shopping will not fulfil personal goals, which unintentionally restricts online decisions that facilitate free data exploitation (Manikandan 2020: 135). On the flip side, the possibility that e-consumers will receive telemarketing calls due to prior free data resource exploitation during previous online transactions emotionally demoralises online shopping decisions, leading to the loss of free e-consumer data to exploit (Alshahrani 2020: 480). The high prevalence of psychological risks has made it necessary for e-consumers to ease tensions by increasing their information searches (Dabrynin and Zhang 2019: 17). Excessive online searches result in cyber-scattering of valuable behavioural data awaiting exploitation.

E-consumers are highly motivated to minimise psychological risks rather than maximise utility with a cognitive tendency to not withstand after-sales disappointments, which negatively influence online decisions, inadvertently limiting free data resource exploitation (Balogh and Meszaros 2020: 16). Psychological risks are exacerbated by the fact that e-consumers do not physically contact the online retailer to evaluate body language, which decreases their chances of pursuing online shopping (Guru *et al.* 2020: 140). Online shoppers usually downplay the online shopping risks, which hinder them from transacting online and thereby engaging online, which exposes them to free data resource exploitation without noticing. The psychological risks that influence e-consumer awareness of free data exploitation are therefore shaped by motivation, belief and attitude towards online shopping, resulting in perceived risk relievers discussed in the next section.

3:6 PERCEIVED RISK RELIEVERS

Perception, which relates to the individual perspective of how people interpret the environment and make decisions based on norms, and cognition can be altered by relievers that modify attitude (Akter *et al.* 2020: 29). Attitude is a subjective behavioural aspect that relates to the extent to which an individual favour or disfavours a particular scenario with respect to familiar norms (Ha 2020: 2031). Perceived risk relievers refer to actions implemented by online firms or e-consumers to mitigate the incidence of negative consequences (Manikandan 2020: 136). Therefore, in any environment, the absence of caring perception renders the capacity of another party to act irrationally to secure self-preservation rather than intellectual perception of empathy (Rabinoff 2018: 130). During the process of online shopping, e-consumers as well as online retailers strive to minimise the possibility of risky situations, which saves e-consumers frustration while at the same time leading to increased data exploitation that benefits retailers.

Online retailers are introducing hybrid operators, instilling a high level of confidence in e-consumers with the concept of a physical store alongside e-commerce with online trial incentives (Carstens, Ungerer and Human 2019: 3). The introduction of clickwrap, permitting e-consumers to accept or reject terms and conditions of online sales, opens the escape route for cart abandonment to avoid risky transactions while at the same time guiding shoppers to unknowingly consent to free data collection leading to data exploitation (Alshahrani 2020: 479). On the other hand, the risk facets are often downplayed by e-consumer innovativeness towards online shopping, which values breaking habitual routines by being open to new digital options, which inadvertently lands them in the free data exploitation trap (Adapa *et al.* 2020: 4). Little is known about perceived risk relievers influence on e-consumer awareness of free data resource exploitation by e-retailers. The uniqueness of this section of this study is that it seeks to illuminate the influence of perceived risk reducers on e-consumer awareness of free data resource exploitation.

Additionally, retailer websites are now embedded with accredited third-party payment systems that restrict the storage of financial data, relieving security risks but leaving e-retailers behavioural data open to free exploitation without the awareness of the consumer (Tran 2020: 222). The absence of face-to-face salesmanship raises product risk issues, which have been alleviated by websites embedded with interactive decision aids that advise on products deemed fit for their intended purpose, which unwittingly invoke e-consumers to disclose free data exploitation (Virdi, Kalro and Sharma 2020: 556). Additionally, e-retailers have introduced robust return policies, replacement facilities, and speedy automatic refund guarantees to counteract possible risks and encourage online shopping, leading to free data exploitation (Samarasinghe, Samarasiri and Mataraarachchige 2020: 5). Tran (2020: 222) shares the same view that product risk can be mitigated by a reliable return policy, which unwittingly influences e-consumers to reveal data, which is eventually exploited by e-retailers for free. Therefore, perceived risk relievers have an influence on e-consumer awareness of free data resource exploitation.

Puri and Mohan (2020: 1151) warn online retailers against using advanced digital technology to track and exploit e-consumer data to develop positive perceptions towards e-consumers and suppress concerns about free data resource exploitation. For example, e-tailing controls like product trials can reduce problematic risks concerning product performance and influence online purchases that lead to the divulgence of personal data that e-retailers exploit for precise targeting (Bhatti and Rehman 2020: 37). (Samarasinghe, Samarasiri and Mataraarachchige 2020: 11) affirm that a reduction in all facets of risks moderates the negative perceived risk, thereby increasing online purchase decisions that propel free data resource exploitation. Furthermore, as e-consumers search products on multiple websites, they face a problem of time loss and information overload, which is mitigated by high-speed digital technology that quickly categorises products, thereby encouraging a gratified interface leading to data disclosure and exploitation (Guru *et al*. 2020: 142). E-consumers themselves try as much as possible to avoid risks by indulging in information searches to minimise losses, resulting in the unintended spread of free data and attracting exploitation.

Albeit e-consumer re-purchase online may positively reduce perceived risk, each time e-consumers make an online purchase, it is a unique event that comes with risks that should be minimised by e-retailers to encourage online shopping, facilitating free data exploitation (Bach *et al.* 2020: 2). Nonetheless, the immensity of e-consumer innovation, especially among the youth, influences individual attitudes towards shopping with a low-risk perception by accepting digitalisation, which eventually leads to data disclosure and data exploitation (Sahin and Gelmez 2020: 2296). However, most e-consumers apply intuitive risk evaluation to quickly judge hazardous online activities by transacting online with smart decisions, unaware of the trap for free data resource exploitation (Li *et al.* 2020: 77). Adapa *et al.* (2020: 8) contend that e-consumers who are innovative eliminate the inferiority complex of having to be left out of digital technology by seeking to benefit from online shopping value, leading unforeseen to free data resource exploitation. E-consumers with a high rate of certainty relating to online shopping eventualities are prone to being submissive to self-disclosure, thereby unwittingly becoming victims of free data resource exploitation.

Online retailers are tasked with providing sufficient information on the website in order to eliminate perceived risk issues, resulting in online sales maximisation meeting e-consumer high-level approval ratings, leading to data disclosure and eventual personalised exploitation (Virdi, Kalro and Sharma 2020: 561). In pursuing pleasure, there is a tendency to object to perceptions by following the soul rather than reasoning intellectually, which render individuals prone to downplaying long-term consequences (Rabinoff 2018: 99). The degree to which e-consumers become familiar with the digital environment reduces the magnitude of perceived risk by eliminating uncertainties, assisted by the ubiquitous internet, which facilitates free data resource exploitation (Carstens, Ungerer and Human 2019: 10). Once the online risks are eliminated, e-consumers innocently disclose their data on the digital platform without noticing the eventual exploitation by trusted online retailers.

Risk is a major determinant of behavioural attitude and with the growing popularity of e-commerce as a new norm, e-retailers are required to ensure safety, which has facilitated free data resource exploitation without e-consumer awareness (Alshahrani 2020: 477). Therefore, without the awareness of e-consumers, perceived risk relievers influence free data resource exploitation due to increased certainty leading to enhanced digital self-disclosure. However, Mwencha and Muathe (2019: 169) have a different argument, insisting that rather than focusing on reducing perceived risk, it is imperative to build perceived trust in the data-driven economy. Risk relievers can instil trust, which can help exploit e-consumer data profitably without e-consumer knowledge. Perceived trust is discussed in the next section in detail.

3:7 DISCOURSE OF PERCEIVED TRUST

In the current study, trust is viewed as a multi-facet indicator of confidence resulting in the declaration of behavioural data on digital platforms, which attracts e-consumer free data resource exploitation by online retailers (Nghia, Olsen and Trang 2020: 546). The multi-facets of trust depend on technology, brand, company, product strategy, and security, which are crucial in influencing online purchase decisions that lead to free data resource exploitation (Bugshan and Attar 2020: 1). The anonymity typical of e-tailing introduces vulnerability issues due to the uncertainty of the authenticity of e-retailers, raising trust concerns among online strangers that may result in loss (Martin 2019: 21). Pistor (2020: 103) cautions that e-consumers are unknowingly turning themselves into unpaid data producing agents as they make online transactions by engaging on digital platforms using their android smart devices. The influence of trust on e-consumer awareness of free data resource exploitation has received no substantial research by scholars.

Contemporary capitalism requires online retailers to be data-driven by accumulating e-consumer free data to boost profitable innovation in the competitive digital economy (Sadowski 2019: 1). Nevertheless, what is good may not be perceived as desirable by another party influenced by habits (Rabinoff 2018: 97) as well as the conditions. To achieve free data exploitation, e-retailers build trust through technological advancement aimed at rebooting value perceptions (Singh *et al.* 2020: 7). Trust is the individual determination to consider others to be honest and compassionate with online dealings (Chetioui, Lebdaoui and Chetioui 2020: 3). Additionally, in the digital data-driven economy, the general public is unaware that technology is modifying e-consumer behaviour in the fast-moving digital society obsessed with free data resource exploitation in the competitive digital environment (Ikhsan, Islam, Khamis and Sunjay 2020: 293). E-consumer trust in technology may unintentionally result in self-disclosures and free data resource exploitation. Based on available research, no studies have investigated the influence of trust on e-consumer awareness of free data resource exploitation.

On this note, the nature of online trust differs from offline conventional trust because the conceptualisation of human trust in the online setting reveals e-consumers' blind-folded faith in accepting that invisible e-retailers live up to their promises (Harwood and Garry 2017: 445). The subjective wellbeing of an individual in the digital environment persuading e-consumers to live a quality life has inevitably resulted in online users trust in online retailers, which has led to the prevalence of free data resource exploitation (Nghia, Olsen and Trang 2020: 547). Online shoppers and sellers are not on equal footing in favour of sellers enriched with the predictive power of shopper's data collected at zero marginal cost from trusting data producers (shoppers) who are kept in the dark (Pistor 2020: 104). Therefore, e-consumers are unaware that the more they trust online firms, the more they become victims of free data resource exploitation. E-consumers are unaware that they are data producers who feel better off trusting online retailers in order to access online services and shopping, which facilitate data harvest intended for future exploitation for precise prediction.

Online shoppers with tough choices face the dilemma of trust issues by seeking enormous amounts of choice related information by searching several digital platforms for better decisions, leading to unintended self-disclosure and data exploitation (Kumar, Rajan, Venkalesan and Lecinski 2019: 140). There is a need for e-retailers to build e-consumer trust by developing attractive online portals that unwittingly influence online shopping, which facilitates free e-consumer data exploitation (Singh et al. 2020: 9). Risk and trust conflict in such a way that the riskier the activity, the less trust is vested in the activity (Kaur and Arora 2020: 2). Therefore, trust leads to attitude, which is defined as the individual's evaluation of a situation, which may be positive or negative in influencing beliefs (Chetioui, Lebdaoui and Chetioui 2020: 3). The digital economy has liberalised community beliefs that have positively influenced trust, luring anyone to transact on the digital platforms resulting in a changing lifestyle of social patterns permitting free data resource exploitation (Ikhsan *et al.* 2020: 293). This data extraction activity is enabled by the growing trust, as e-consumers are unaware that retailers are exploiting consumer data resources due to positive trust in self-disclosure.

E-retailers extract free data from data producers (e-consumers) to build data bases with high bargaining power to pre-ordained behavioural algorithms that are one-sided in favour of predictive control with no accountability for data harvest and exploitation (Pistor 2020: 104). Trust develops the individual's psychological intention to accept the responsibilities brought about by the vulnerability of being transparent on digital platforms based on the promises of the trustee (e-retailer), which lure self-disclosure fuelling free data resource exploitation (Sharma and Klein 2020: 5). The trust element signals e-consumer commitment built on the reputable integrity of e-retailers faith, which leads to free data exploitation during online shopping from trusted e-retailers' websites (Oghazi *et al.* 2020: 2). Therefore, online trust overrides e-consumer uncertainty beliefs, which downplay the threats of possible discontinuity of online purchase decisions that boost free data resource exploitation without the awareness of the e-consumers.

E-consumer trust in unmet expectations is motivated by the desire to achieve a particular goal irrespective of any consequences of online shopping activity that is a source of free data resource exploitation (Irshad, Ahmad and Malik 2020: 2). Free data that is produced by e-consumers and entrusted to e-retailers is metaphorically labelled as the new oil, which generates huge returns due to the predictive power it possesses (Pistor 2020: 106). Marketing activities, as asserted by Geric and Dobrinic (2020: 340), provide compelling, relevant content that alters e-consumer online purchase evaluation towards trust without e-consumer awareness of eventual free data resource exploitation by online retailers. Due to the fact that the value of e-consumers is realised after aggregating individual data points, the influence of trust cannot be based on individual cognition to have an impact on e-consumer awareness of free data resource exploitation (Nghia, Olsen and Trang 2020: 548; Pistor 2020:

108). Trust goes along with information sharing to influence socially supportive online shopping decisions that lead to free data resource exploitation without the awareness of e-consumers.

Applying the flipside, e-consumers not only have to trust online retailers but also the interface of the predictive smart machines that encrypt behavioural data, functional security, and whether the machines will adhere to e-retailers promises during online shopping (Harwood and Garry 2017: 447). Upon gaining trust, the massive data harvested from e-consumers has no value, but the analytical capacity of the data and control exerted on e-consumers can be interpreted as free data resource exploitation (Pistor 2020: 112). Trust is also built by online retailers' App, which are checked for certain standards and validated to assure safety, which render e-consumers to disclose behavioural data that is later exploited without the e-consumers' knowledge (Martin 2019: 22). For example, HealthifyMe App is designed with the interactive capacity of nutritionists who improve e-consumer trust by offering suggestions of habits ideal for a healthy lifestyle (Kumar *et al.* 2019: 137). The importance of the marketing content lures e-consumers to unwittingly reveal behavioural data due to trust leading to future data exploitation.

Albeit it is complicated to evaluate trust as an outcome or antecedent of perceived risk, trust acts as a mental guarantee of risk-free online shopping accomplishment (Kaur and Arora 2020: 12), which leads to self-disclosure and free data resource exploitation. Online shoppers' actions are centred on the expectation that online retailers will perform their part in e-commerce with due diligence, which shapes individual attitudes towards online shopping that facilitates free data resource exploitation (Chetioui, Lebdaoui and Chetioui 2020: 5). Online trust throws open e-consumer data resources towards online retailers who use trust as a lubricant to online shopping decisions that allow self-disclosure and exploitation without e-consumer awareness (Oghazi *et al.* 2020: 1). The individual is impaired by passion, which renders e-consumers vulnerable to free data resource exploitation without their awareness (Rabinoff 2018: 107). E-consumers as data producers trust online retailers with behavioural data, which is exploited without pay, and by the same token, e-consumers suffer the loss of power and control as victims of manipulation.

The empowerment of e-consumers in the digital environment calls for urgent attention, but scholars have put little attention on digital consumerism involving free e-consumer data exploitation, which puts e-consumer-e-retailer relationships at stake. Irshad, Ahmad and Malik (2020: 4) are of the view that trust boosts online shopping and e-consumer targeting, which is usually facilitated by free data resource exploitation. Martin (2019: 21) contends that trust is built over time as e-consumers gradually evaluate the trustworthiness of online firms as they gather online information searches that guide them to execute online purchase decisions that lead to free data resource exploitation. Furthermore, trust, as affirmed by Harwood and Garry (2017: 444), is becoming a fundamental component in the data-driven economy due to the ubiquity of technologies that allow numerous interactions. The interactions attract behavioural responses on digital platforms, which influence e-consumers to reveal data that is later exploited. Therefore, the next section of the current study focuses on the influence of perceived trust on e-consumer awareness of free data resource exploitation.

3:8 PERCEIVED TRUST

Perceived trust is the probability that e-consumers assume that online retailers are honest, allowing online users to become vulnerable to e-tailing exploitation due to a grounded feeling of confidence (Carstens, Ungerer and Human 2019: 5). Rabinoff (2018: 110) states that trust usually originates from the habituation of passion, which causes individuals to ignore perceptions, ultimately leading to exposure to free data resource exploitation. Improved shopping value through customised services and satisfactory online offers increases perceived trust over time, which attracts repeat business subjected to data tracking towards predictive marketing strategies (Bahari, Azmi, Kamal, Zainol, Marat and Abudullah 2020: 208). Perceived trust, as articulated by Ariffin, Yajid and Azam (2020: 1147), has to do with the expectation that e-retailers are not behaving opportunistically in fulfilling their commitments to e-commerce-appropriate principles. The feeling of pleasure e-consumers enjoy on the online platform enhances trust and self-disclosures that lead innocent shoppers to be exposed to free data resource exploitation.

E-consumers are faced with the dilemma of developing perceived trust towards e-retailers by revealing behavioural data during online shopping activities, which is secretly exploited for e-tailing re-targeting (Samarasinghe, Samarasiri and Mataraarachchinge 2020: 4). In addition, e-consumer belief in the benefits of shopping online propels perceived trust, which triggers data disclosure acting as a precursor to free data resource exploitation without e-consumer awareness (Bhatti and Rehman 2020: 35). In the data-driven digital environment, credibility fetches a high volume of online engagement, leading to e-consumers self-disclosure, which is a recipe for free data resource exploitation without e-consumer awareness (Bach *et al.* 2020: 2). Perceived trust is a psychological aspect that motivates beliefs through learning and determines attitudes towards making online purchase decisions that facilitate free data resource exploitation without e-consumer knowledge (Sharma 2019: 1163). Therefore, individual intention to accept vulnerability on account of perceived trust happens when e-consumers consider online retailers to be morally upright, which results in self-disclosure and free data exploitation.

The perception that e-retailers have nothing to benefit from being dishonest is a temptation to make online purchase decisions that lead to free data resource exploitation without e-consumers' notice (Carstens, Ungerer and Human 2019: 5). The actions of the online retailers may be perceived to be infringements on e-consumers if management fails to identify critical impediments to fair e-commerce for long-term survival (Samarasinghe, Samarasiri and Mataraarachchinge 2020: 3). On the other hand, loyal e-consumers spend more time expanding into new product categories on e-retailer websites, which increases the incidence of browsing behavioural data related to preferences that are exploited for product improvement (Sharma 2019: 1163). Perception of the object (Rabinoff 2018: 29) differs from perception of the incident depending on the attitude or expression of others, such as e-retailers. However, e-consumer psychological consolidation of the ubiquitous e-commerce uncertainties fails to reconcile them with unforeseen consequences (Bach *et al.* 2020: 3). The uncertainties sometimes result in negative perceived trust in online purchase decisions, negatively impacting exposure to free data resource exploitation.

Perceived trust, as affirmed by Ariffin, Yajid and Azam (2020: 1147), takes the belief that e-retailers stick to their promises by behaving in a socially ethical manner, which increases online engagements that boost free e-consumer data resources to exploit. On the flipside, e-consumers have lost trust in e-tailing because of the inherent nature of behavioural tracking, which is considered an infringement on online shoppers, rendering e-consumers powerless, resulting in negative perceived trust limiting online engagements and free data resources to exploit (Puri and Mohan 2020: 1144). However, the belief that e-tailing websites have adequate built-in security interfaces intensify online shopping decisions (Carstens, Ungerer and Human 2019: 5) that consequently lead to free data resource exploitation without the awareness of e-consumers. Also, Bhatti and Rehman (2020: 38) hold the same view that the security of e-consumers' behavioural data positively affects perceived trust in online shopping, which indirectly facilitates e-consumer free data resource exploitation. Although the awareness of e-consumer free data resource exploitation by online retailers is unclear, the assurance of website security boosts perceived trust online, unwittingly leading to data disclosures and exploitation.

The study conducted by Bach *et al.* (2020:10) concluded that benefits expected result in perceived trust in online purchases, which inevitably leads to online self-disclosure that fosters free data resource exploitation without e-consumers' knowledge. The positive expectations noted by Nghia, Olsen and Trang (2020: 545) of online shopping with subjective well-being have recently increased e-consumers' perceived trust in e-commerce, which indirectly favours free data resource exploitation. E-consumers' perceived trust is enhanced by the belief that the interactions with e-retailers are typical of a particular business with no intent to track data and no disguise whatsoever, leading to voluntary self-disclosure and data exploitation (Carstens, Ungerer and Human 2019: 5). Online shoppers struggle to believe that user profiles will not be exploited behind the scenes during the online purchase journey (Sharma 2019: 1166). Sources from all the identified studies faintly focus on the influence of perceived trust on e-consumer data exploitation and no studies are particularly expanding research on the awareness of e-consumer free data resource exploitation by online retailers apart from this study.

Furthermore, the interlinking of social platforms with e-tailing websites is propelling effective data sharing that boosts online shopping's perceived trust, which carelessly results in e-consumers revealing free behavioural data that is exploited by e-retailers without the e-consumer's knowledge (Bugshan and Attar 2020: 1). E-consumers engage on digital platforms in calculative commitments in structural bonds with online retailers linked to social platforms, which builds a reasonable measure of perceived trust leading to self-disclosure and behavioural data exploitation (Harwood and Garry 2017: 444). Additionally, social influence, as emphasised by Kaur and Arora (2020: 8), adds external pressure from colleagues, superiors, and family members, which influence perceived trust from consultants, consequently sugar-coating individual trust, leading to data disclosure and exploitation by recommended e-retailers. Thus, in the mist of the complexity of perceived trust, e-consumers seek to identify alternative signs of trust by observing online vendors points of strength that can attract online purchase decisions associated with free data resource exploitation.

E-consumers are slowly moving away from traditional to liberalised digital beliefs to transact without meeting the retailer, changing the medium of exchange from cash to online payments, calling on inevitable perceived trust and exposing e-consumers to free data exploitation (Ikhsan *et al.* 2020: 291). Martin (2019: 21) affirms that the cyber trust seals with notices on e-tailing websites are designed to strengthen the perceived trust of online strangers advertising as traders, thereby luring e-consumers to reveal behavioural data, which is eventually exploited without e-consumer awareness. Personalisation due to e-consumer data resource exploitation solidifies the bond between e-consumers and online retailers, refining attitudes towards perceived trust in e-commerce, resulting in an unnoticed recurring cycle of free data resource exploitation (Kumar *et al.* 2019: 136). Studies in South Africa by Carstens, Ungerer and Human (2019: 6) indicate that individual interpretation related to the disposition of perceived trust differs in propensity. So, some online purchase decisions due to perceived trust facilitate enormous free data resource exploitation in the absence of e-consumer awareness.

On the other hand, scholars like Singh *et al.* (2020: 1) view education as a very strong determinant of perceived trust in online shopping, resulting in loyalty, which unexpectedly invokes data disclosure and exploitation by e-retailers. Chetioui, Lebdaoui and Chetioui (2020: 4) consider the relative advantage of online shopping to be more superior than conventional brick-and-mortar stores, which increase the possibility of online purchase decisions. Online shopping decisions due to perceived trust unwittingly expose e-consumers to free data resource exploitation. Perceived trust can be conceptualised in four different dimensions that include digital reviews, credible portals, shopping value and brand popularity, which are discussed in the subsequent sub-sections.

3:8:1 Digital reviews

Perceived trust, as articulated by Martin (2019: 22), can be enhanced by the general postings on the digital platforms that allow e-consumers to discuss events with comments, which motivate online shoppers' decisions, leading to free data exploitation. Online retailers use unsupervised collaborative filtering of recommendations, product reviews and product usage (Kumar *et al.* 2019: 138) to match offerings that can increase cognitive trust, which attracts more disclosures of hidden behavioural patterns that are exploited for re-targeting. Unlike positive digital reviews, Lis and Fischer (2020: 637) warn that negative reviews are pre-occupied with harmful consequential implications, which decrease perceived trust, resulting in the abandonment of online shopping decisions, leading to free data resource exploitation. Positive digital reviews strengthen e-consumer trust, which motivates online shoppers to engage online, leading to data disclosure and free data resource exploitation.

Any potential positive or negative statement made by e-consumers on the digital platforms can influence perceived trust, which affects online purchase decisions unintentionally associated with free data resource exploitation by e-tailing (Chetioui, Lebdaoui and Chetioui 2020: 5). The content of digital reviews is important for e-consumers to make guided purchase decisions based on perceived trust, which exposes online shoppers to the hidden tools harvesting free data for exploitation by e-retailers (Roy, Datta and Mukherjee 2019: 662). In reality, e-consumers faced with favourable or unfavourable digital reviews continue to navigate through similar reviews to ascertain credibility (Lis and Fischer 2020: 639). During this time, e-retailers are monitoring and exploiting the digital path that re-boots online shopping decisions. E-consumers are unaware that free data resource exploitation is influenced by digital reviews in some instances.

Although the browsing of reviews is an added time cost to online shopping, the useful tips about online retailers emotionally trigger an effect on perceived trust (Li 2019: 1).

Bugshan and Attar (2020: 1) consider e-consumer digital ratings, referrals, and recommendations to be very strong digital reviews that attract online retailers to exploit for product modification based on preferences. Certainly, e-consumers are identified with the online shopping groups' decisions boosting perceived trust towards products that appeal to online groups rendering confidence to reveal behavioural data open to e-tailing exploitation (Sharma and Klein 2020: 5). When e-consumers generate positive feedback about the product, they develop motivational empowerment due to peer-to-peer perceived trust, which translates into purchase decisions associated with free data resource exploitation by e-tailing behavioural tracking (Irshad, Ahmad and Malik 2020: 10). Perceived trust due to useful tips sometimes indirectly influences self-disclosure and exposure to free data resource exploitation.

In a study overseen by Lis and Fischer (2020: 640), it is evident that e-consumers perceive high trust in digital reviews from actual victims of online shopping experiences, which determine online purchase decisions, facilitating free data resource exploitation. The establishment of digital group platforms like Groupon has facilitated a herd mentality of alerting group members of upcoming deals with partnerships, eliminating price uncertainties and busting discounted co-operative e-commerce (Sharma and Klein 2020: 2). Using the TripAdvisor website, e-consumers receive and post reviews of previous e-tailing treatments, intuitively revealing the negative and positive experiences that shape perceived trust and data disclosures exploited by e-retailers without the e-consumers' knowledge (Martin 2019: 23). Social pressure from opinions posted by trusted superiors, exalted family members and distinguished colleagues may enhance perceived trust in e-commerce, which attracts free data resource exploitation for predictions (Kaur and Arora 2020: 8). Therefore, the online groups' views enhance perceived trust, leading to data self-disclosure and free data resource exploitation.

Studies by Arya, Sethi and Paul (2019: 145) emphasise that e-consumers create digital DNA by sharing blogs, posts, bookmarks, ratings and links that cement perceived trust. Chetioui, Lebdaoui and Chetioui (2020: 2) contend that e-retailers are investing heavily in establishing a societal digital presence to monitor and refine digital reviews from unsuspecting credible e-consumer sources in a bid to strengthen perceived trust, which leads to a cycle of free data resource exploitation. By the same token, Arya, Sethi and Paul (2019: 144) add that community members on the digital platforms unknowingly communicate their trusted preferences, which form part of the digital footprint that is exploited by e-retailers matching offers based on community likes. Notably, e-retailers try as much as possible to track and disperse the negative digital reviews by counter-posting motivating positive reviews to moderate perceived trust in online shopping leading to further free data resource exploitation for predictions (Roy, Datta and Mukherjee 2019: 663). Ultimately the postings attract online engagements that lead to free data resource exploitation without e-consumer awareness.

Irshad, Ahmad and Malik (2020: 5) characterise digital platforms as the major source of reviews that positively link e-consumer motivation to online product purchase and free data resource exploitation during online shopping navigation. Digital platforms are saturated with views, ideas, and beliefs secretly exploited by e-retailers to enhance perceived trust, which later results in online purchase decisions with free data resource exploitation (Geric and Dobrinic 2020: 339). In a study conducted by Chetioui, Lebdaoui and Chetioui (2020: 339), it was discovered that females are more susceptible to the influence of perceived trust due to digital reviews than males, which makes females more vulnerable to online free data resource exploitation. Since individual emotions of digital reviews are subjective, the usefulness of perceived trust due to these reviews varies, which renders some e-consumers unable to improve evaluation by engaging in more curiosity-based browsing searches (Li 2019: 1). The searches unknowingly render e-consumers to disclose browsing behavioural data and to become prey to free data exploitation.

Upon accepting digital reviews to enhance perceived trust, e-consumers make evaluations regarding the consistency of the content without simply accepting digital reviews with a humorous tone of malice by referring to multiple digital platforms, leaving a trail of free browsing data that is exploited (Roy, Datta and Mukharjee 2019: 664). Similarly, digital reviews with identical emotional outcomes with content that is consistent, poses valuable opinions that can build perceived trust in e-commerce, which paves the way for free data resource exploitation due to digital self-disclosures. E-tailing digital marketing incorporating socialisation motives where online users receive empowering incentives for commenting, liking and sharing digital reviews interplays among e-consumers, leading to self-disclosure and data exploitation due to perceived trust (Irshan, Ahmad and Malik 2020: 11). The careful monitoring and harvesting of the peer recommendations noted in this section of the study are exploited without the awareness of e-consumers to improve strategies.

When new digital reviews surface on digital platforms, e-consumers immediately start to revise their online shopping judgements, reflecting on the magnitude of the content affecting perceived trust linked to e-consumer free data exploitation (Lis and Fischer 2020: 639). Online user-generated content therefore motivates perceived trust, increasing the decisiveness of e-consumers to shop online, unaware of behind-the-scenes free data resource exploitation (Gupta, Gupta and Dhir 2020: 211). Pelau, Niculescu and Stanescu (2020: 831) argue that e-retailers initiate seductive content that triggers conversations about the brand to attract the exchange of digital interactions in a bid to instil perceived trust, which is followed by self-disclosures and data exploitation without the e-consumer's awareness. Although e-consumers are likely to post falsified digital reviews, there is a high rate of valuable factual self-disclosure on the digital platforms (Grosso *et al.* 2020: 530). The reviews posted, moderate perceived trust and self-disclosure, leading retailers to exploit free data resources on the platforms without the e-consumers' awareness.

However, e-consumers' comprehensive evaluation of user-generated content in the form of digital reviews posted by third parties is perceived to be more compelling to enhance perceived trust than e-retailers reviews, which are inclined towards harvesting free data for exploitation (Singh and Chakrabarti 2020: 42). Digital reviews assist e-consumers faced with the anonymity of information related to the intended online purchase by searching for product ratings that support perceived trust (Virdi, Kalro and Sharma 2020: 558). As more digital reviews are updated, e-consumers retrieve prior reviews and conduct diagnostic evaluations of the content using multiple digital platforms simultaneously to defend or discard perceived trust (Lis and Fischer 2020: 639). E-consumer evaluation of digital reviews unintentionally generates free data to exploit. The searches subsequently result in retailers' free data exploitation of e-consumer product searches to trigger precise targeting. Perceived trust can therefore be considered influential in raising awareness of free data resource exploitation. Another dimension of perceived trust is discussed in the next sub-section, relating to the credibility of e-tailing web portals.

3:8:2 Creditable portals

Portals that clearly indicate services, warranties, and user control captivate perceived trust, inclining to reveal behavioural data that is later exploited for personalised marketing strategies (Sharma and Klein 2020: 5). Vivid portals have a lasting impression, instilling perceived trust based on constant memories of the spectacular animation of colour contrast narrative presentations that positively influence attitude imagery simulation of the actual product, luring data disclosure and exploitation (Yeo, Tam, Lim, Leong and Leong 2020: 97). Unlike the brick-and-mortar concept, online retailers depend on web portals to display offers and engage in interactive transactions; for example, the hospitality portals used for online bookings before travel must be designed with quality that attracts perceived trust to reveal data for exploitation (Irshad, Ahmad and Malik 2020: 5). Also, hotel portals are designed with service descriptions, fascinating visuals, and a complete location address (Bahari *et al.* 2020: 203). Credible portals motivate perceived trust by luring unintended voluntary self-disclosure, facilitating free data resource exploitation by re-targeting.

Sharma (2019: 1167) states that intrusive portal advertisements with automated recommendations that miss-match between the supplied search terms and the results from webpages negatively affect perceived trust in online shopping, reducing exposure to free data resource exploitation. Credible portals claim high perceived trust as they do not compel e-consumers to accept cookies but are embedded with hidden JavaScript software, which backups browsing history (Arya, Sethi and Paul 2019: 145). Normally, the first encounter with the portal may not arouse perceived trust, but algorithms track the initial encounter in the web page category (Li, Abbasi, Cheema and Abraham 2020: 133). But subsequent encounters are streamlined based on the free behavioural browsing data history exploited without e-consumers knowledge. Bornschein, Schmidt and Maier (2020: 139) hold the same view that credible portals provide visible cookie notices collecting data with agree or refuse options. However, e-consumers normally agree due to perceived trust in order to accomplish their online shopping goals, leading to data disclosure and free data exploitation.

Pelau, Niculescu and Stanescu (2020: 831) subscribe to the view that portals guiding online shoppers about the terms of collection of browsing behavioural history with a straightforward option allowing the abandonment or continuation of data collection for exploitation are perceived as credible. In e-commerce, perceived trust is a double-edged sword that cuts through e-retailers trust and web portal trust connected to machines with volition to protect online shoppers' data (Harwood and Garry 2017: 446). Therefore, credible portals lure e-consumers to reveal behavioural data, which is later exploited by e-retailers without potential online shoppers' knowledge. Furthermore, Sharma (2019: 1165) cautions that e-consumers are very sceptical of e-tailing portals that have a high propensity of not returning to the site, especially if the website is in the lower ranks on the internet, affecting perceived trust and free data to exploit. The belief that the digital environment is circumspect leverages e- retailers to exploit potential spill overs of e-consumer free data resources (Yeo *et al.* 2020: 96). Moreover, the guarantees added to the website content can unwittingly expose e-consumers to unintended self-disclosures, leading to free data resource exploitation.

E-consumers possess strong perceived trust in credible portals interlinked with Twitter, Facebook, Skype, WhatsApp and Instagram, which allow interactions like rating testimonials and shaping purchase decisions associated with free data resource exploitation (Ramesh and Vidhya 2020: 61). Human thinking depends on images as the individual develops assertions to pursue pleasant scenarios by avoiding bad experiences (Rabinoff 2018: 80). The straightforward display of items on the web portal allows e-consumers to easily click and order with corresponding e- mail notices that build confidence and a positive perception of credibility (Li 2019: 1). In fact, portal features with a visual appeal that is capable of retaining visitors to the end of the online purchase journey command high perceived trust, especially among females, who unknowingly reveal behavioural data that is later exploited (Carstens, Ungerer and Human 2019: 11). Sharma and Klein (2020: 5) concur that interactive quality e-tailing portals allure perceived trust. The quality of credible portals renders e-consumers susceptible to free, self-motivated data disclosure and exploitation for predictions. Thus, online shoppers end up trapped in the free flow of behavioural data exploited for re-orders without their knowledge.

Portals with a combination of text, video, and photo contents stimulate e-consumers' sense of imagination when viewing the quality presentations that replicate individual feelings, resulting in self-disclosure (Yeo *et al.* 2020: 96). Also, the portal speed, quality information, reliable content and entertainment features instil credibility with perceived trust, leading to online purchase decisions easing free data exploitation (Sharma 2020: 1163). The design of the portal layout, graphics and overall visual atmosphere create the perception of credibility, inducing successive browsing, which unintendedly exposes e-consumers to free data resource exploitation (Rodrigo, Wijesekara, Bandara, Akurugoda, Munasinghe and Weerarathne 2020: 117). Web portals that incorporate functionality, benevolence and entertainment tend to motivate perceived trust (Arya, Sethi and Paul 2019: 146). Benevolence invokes online shopping decisions that encourage free data resource exploitation without the e-consumer noticing it. The emotional feelings of online shoppers increase online engagements that are exploited without e-consumer knowledge.

Online retailer web portals are designed in consideration of winning e-consumer perceived trust with security mitigating measures like encryption seals that drive confidence in online shopping with data disclosures and exploitation (Carstens, Ungerer and Human 2019: 9). Gupta, Gupta and Dhir (2020: 210) argue that portals containing no monetary risks, with isolated assortments segregated to various departments, and fast-loading pages enhance perceived trust in online purchases, leading to free data exploitation. Due to e-consumer interest in a hassle-free lifestyle, prospective online shoppers develop perceived trust if the web portal is user-friendly (Ahmad *et al.* 2020: 4). Bhatti and Rehman (2020: 36) agree that simple portals offering a wide variety of products with a user-focused window display command high credibility, enhancing perceived trust. Ultimately, the simple, credible portals lure users to dig deeper into the browser, thereby unwittingly leaving behind free browsing behavioural data that is exploited by e-retailers. Therefore, user-friendly, credible portals attract a relentless, enjoyable browsing habit that leaves a trail of free data exploited without e-consumer awareness.

Therefore, perceived trust in credible portals is adequate to trigger an online shopping spree without considering the concerns of behavioural data exploitation (Carstens, Ungerer and Human 2019: 7). The early exit resulting in cart abandonment of unconverted web sessions indicate negative perceived trust in the credibility of the portal, alerting e-retailers to track e-consumer browsing behaviour to determine the causes of abandonment, which e-retailers exploit to seek remediation (Li *et al.* 2020: 134). It can be deduced that no closer studies have investigated the influence of credible portals as a dimension of perceived trust on e-consumer awareness of free data resource exploitation. In the next sub-section, shopping value as another perceived trust dimension is examined.

3:8:3 Shopping value

Online shopping value is associated with trust perceptions; for example, novel products are perceived to be of high shopping value, requiring rigorous online information searches that attract free exploitation of browsing behaviour for targeting potential consumers (Adapa *et al.* 2020: 4). Perceived trust due to shopping value activates the shopping propensity-linked self-disclosure depending on whether the shopping involves expensive luxuries or cheap home apparel of low shopping value, attracting free data disclosure and exploitation (Grosso *et al.* 2020: 525). Therefore, the quality (Gupta, Gupta and Dhir 2020: 209) of online goods and services determines perceived trust, which triggers the online purchase decisions associated with self-disclosure and data resource exploitation. E-consumers perceive online products to be innovative with a superior, relative advantage compared to products in the local store (Chetioui, Lebdaoui and Chetioui 2020: 4). The superior products online positively influence online shopping linked to self-disclosure and free data resource exploitation by online retailers.

Furthermore, innovative products valued for their pleasurable feelings, arouse curiosity rather than functional ability (Zhang *et al.* 2020: 4). Innovative products result in a high rate of online engagements that produce a huge amount of browsing history exploited by online retailers without e-consumers knowledge. Li *et al.* (2020: 129) allege that purpose-oriented online shopping is steered by shopping value, which necessitates a distinct online information-seeking browsing behaviour in a goal-oriented direction, which inadvertently renders e-consumers to litter data all over digital platforms awaiting free exploitation. Nghia, Olsen and Trang (2020: 547) add that online shopping value is centred on hedonic and utilitarian motives, where utilitarianism is inclined towards cognitive benefits while hedonism is an aesthetic, emotional feeling of affection fond of online social engagements that are exploited without the e-consumer’s knowledge. Online products of utilitarian value necessitate multiple evaluative online searches to develop perceived trust due to their shopping value (Adapa *et al.* 2020: 4). During the online searches, the shopping value inadvertently propels online shoppers to scatter browsing behavioural data ready for e-tailing exploitation without shoppers’ knowledge.

Agreeably, utilitarian shopping value is normally a product-centric evaluation that requires abundant information on product attributes considered in developing perceived trust, necessitating a wider scope of searches that are exploited to predict demand (Irshad and Ahmad 2019: 93). Li *et al.* (2020: 131) argue that the shopping value of utilitarian products is motivated by well-defined searchable attributes requiring minimal page browsing to develop perceived trust, inadvertently limiting exposure to free behavioural browsing data exploitation. The value-attitude-behaviour preposition is central to perceived trust to transact online for hedonic products whose value is based on emotional pleasure forcing e-consumers to downplay perceived trust (Nghia, Olsen and Trang 2020: 546). Due to the value of the product, e-consumers end up revealing free data without noticing the resultant exploitation. Perceived trust based on shopping value favours the free flow of e-consumer data resources to e-retailers, especially when the product is sophisticated, calling for online searching scrutiny, leading to the exploitation of behavioural browsing data.

Therefore, products of high value command intensive performance in indexed online information searches, rendering e-consumers to unknowingly disclose behavioural data exploited for product recommendations (Gupta and Gupta and Dhir 2020: 210). With some online products, the intrinsic entertainment motivation and fantasy depicting the product arouse the shopping value of the appealing features that posit perceived trust, resulting in self-disclosure and data exploitation (Irshad and Ahmad 2019: 94). Li *et al.* (2020: 132) affirm that portals with hedonic shopping value implication are characterised by leisurely page viewing across multiple digital platforms, exposing e-consumers to a wide scope of free data resource exploitation. Extraverted e-consumers develop a shopping value attitude inclined more toward critical searching with a strong presence on the online brand community platforms

(Nghia, Olsen and Trang 2020: 548). So, e-consumer presence on the digital platform propels e-retailers to harvest browsing behavioural data that is exploited to make precise predictions.

Also, products of hedonic value like toys lure e-consumers to often engage on social platforms compared to utilitarian shopping value products, allowing a low level of purposeful straightforward online engagement, hence leading hedonic product shoppers to be more in the spotlight of free data resource exploitation (Li *et al.* 2020: 139). Shopping value relates to product quality commanding high perceived trust to unintentionally influence self-disclosure during the online purchase journey, paving the way for free data resource exploitation (Yeo *et al*. 2020: 98). Farman Camello and Edwards 2020: 301) state that e-retailers monitor and exploit unsuspecting e-consumer shopping value insights to direct personalised ads based on the desired values, which develop perceived trust resulting in a repetitive exercise of free data exploitation. Contrary, products with low shopping value like groceries render e-consumers to ignore issues of perceived trust, compared to high shopping value products requiring consultative online searches revealing behavioural data for e-tailing exploitation.

Consequently, the shopping value preposition is remarkably associated with subsequent commitment to the e-retailer, creating a bond of perceived trust leading to eventual data disclosure and exploitation (Harwood and Garry 2020: 444). Albeit human evaluation is capable of rational cognitive limitations, e-consumers weigh shopping value against costs, which requires enormous information searches that enhance perceived trust and purchase decisions that fuel free data resource exploitation (Rajani and Nakhat 2019: 3). Shopping value acts as a mental guarantee to enhance trust elevated by associated online services that motivate online shoppers to reveal behavioural data exploited in turn without e-consumers' knowledge (Kaur and Arora 2020: 2). Kuchta (2020: 37) argues that accessible, easy-to-use online support services improve perceived trust, leading to recurring purchase decisions, along with free data resource exploitation for personalised services. The quality of personalised services linked to online shopping certainly enhances perceived trust (Bahari *et al.* 2020: 206). So, the personalised services motivate confidence in revealing data awaiting e-tailing exploitation for precise targeting.

The quality features of online products or services moderate perceived trust, motivating a positive attitude towards online shopping and facilitating free data resource exploitation behind the backs of e-consumers (Chetioui, Lebdaoui and Chetioui 2020: 2). Once e-retailers monitor the shopping value insights, they re-target offers based on individual value perception, which improves perceived trust, resulting in repeat e-commerce and further data exploitation tendencies (Farman, Camello and Edwards 2020: 298). Therefore, online retailers build shopping value consciousness through content that portrays value attracting e-commerce leading to data self-disclosures aiding free data resource exploitation, unnoticed by e-consumers (Geric and Dobrinic 2020: 340). Depending on the extent of individual perceived shopping value, e-consumers search carefully for information from numerous sources. allowing behind-the-scenes e-tailing monitoring towards the purchase destination, which is facilitated by free data resource exploitation.

Yeo *et al.* (2020: 95) warn that e-consumers are unable to determine how e-retailers utilise online shopping behavioural data, doubting whether the firm is focused on their best interests, rendering e-consumers more reluctant to be interactive online. E-consumers are ignorantly willing to succumb to vulnerability in consideration of positive expectations by facing the actions of the trustee (e-retailer) focused on maximising revenue through free data resource exploitation. Although several studies have researched shopping value in relation to online shopping behaviour, no studies have illuminated the influence of shopping value as a dimension of perceived trust on e-consumer awareness of free data resource exploitation. In the next sub-section, brand popularity as another element of perceived trust is discussed in relation to free data resource exploitation.

3:8:4 Brand popularity

Arya, Sethi and Paul (2019: 144) emphasise that deeper relations with popular brands motivate perceived trust with emotional connectivity and pride in being identified by the popular brand, prompting self-disclosure and free data resource exploitation. Yeo *et al.* (2020: 97) articulate that the total cognitive connotation e-consumers accumulate about the brand preserves recurring memories, augmenting perceived trust in online shopping, resulting in unintended exposure to free data resource exploitation by e-retailers. Consumer-Based Brand Equity (CBBE), which explains the influence of brand attributes, is used in this study to guide the determination of perceived trust on e-consumer awareness of free data resource exploitation (Manikandan 2020: 134). Bahari *et al.* (2020: 208) affirm that a well-managed, symbolic, functional brand ranking on top of the digital platforms upgrades perceived trust. Popular brands that assure e-consumers of secure, quality service ultimately motivate trust, leading to online self-disclosures that facilitate free data resource exploitation by innocent brand followers.

The reputation of the brand reflects an ex-ante belief in reliable exchange, promoting perceived trust due to lower levels of uncertainty, encouraging online shopping, linked with unintended free data resource exploitation by e-retailers (Oghazi *et al.* 2020:2). Due to the digital marketing activities yoked to trending content on the digital platforms, brands become popular and translate to successful online shopping decisions, along with e-consumers' unforeseen free data resource exploitation by e-retailers (Geric and Dobrinic 2020: 340). Brand popularity on digital platforms is an intangible that renders the product unique, intensifying excessive e-consumer self-indulgence, leaving a clutter of free data resources secretly exploited by e-retailers (Arya, Sethi and Paul 2019: 142). E-consumers are likely to disclose data for as long as the brand is popular (Singh 2020: 5). The popularity of the brand unwittingly lures e-consumers to generate real-time engagements with confidence, leading to exposure to free data resource exploitation.

Perceived trust in popular brands, as articulated by Harwood and Garry (2017: 448), builds e-consumer belief with the illusion that the prospective e-retailer is honest, morally upright, and fair, with the promises, that individual data will not be exploited without prior notice. Yeo *et al.* (2020: 98) report that e-consumers evaluate the brand depending on online information to develop perceived trust based on the product attributes' inclination toward value, which attracts online purchase decisions linked to free data resource exploitation. Brand popularity is normally decisive in improving e-consumer perceived trust even before the onset of online shopping, indirectly evolving into free data resource exploitation (Bahari *et al.* 2020: 206). E-consumers invest enormous time surfing for the features of popular brands online, aiming to match any attributes to individual needs (Arya, Sethi and Paul 2019: 144). The continuous searches result in a trail of behavioural browsing data exploited without e-consumers knowledge. Brand popularity along with digital reviews motivate e-consumers to confidently reveal behavioural data due to perceived trust, leading to free data resource exploitation.

Online retailers build brand popularity to address issues (Oghazi *et al.* 2020: 1) of uncertainty as well as opportunism associated with e-commerce in order to strengthen perceive trust facilitating data exploitation for predictions. As a result, Geric and Dobrinic (2020: 341) add that the popular brands yield a corporate emotional connection, which symbolises status breeding a herd of loyal e-consumers who comfortably reveal behavioural data exploited by e-retailers to improve targeting. Subsequently, the popular brand App compatible with mobile smart devices are redirected to e-consumers with the aim of tracking behaviour for personalised targeting based on the popular brand App footprint (Arya, Sethi and Paul 2019: 143). E-consumers install popular brand App unaware of e-tailing monitoring for free data resource exploitation to render personalised services that generate massive corporate revenue.

Bornschein, Schmidt and Mairer (2020: 139) are consistent with Singh *et al.* (2020: 5) argument that the positive perceived trust due to brand popularity lures e-consumers to deliberately accept monitoring cookies, unaware of eventual free data exploitation. Purchase and Volery (2020: 775) assert that brand innovation increases visibility, credibility and novelty, enhancing brand popularity with curiosity-driven information searches for the upgrades, which inadvertently expose e-consumers to free data exploitation. However, the popularity of the brand can be affected by destructive emotional criticism related to functional product performance, which can cripple perceived trust as an enabler of free data resource exploitation (Lis and Fischer 2020: 637). Brand design aesthetics along with advanced functional technology associated with the popular brand inevitably lure e-consumers to search deeper online (Arya, Sethi and Paul 2019: 146). Online shoppers ultimately leave enormous and valuable digital traces when browsing which are exploited by e-retailers for free.

Consequently, e-consumers develop loyalty as the brand becomes popular on the digital platforms, boosting brand affiliation and moderating perceived trust, which invokes online purchase decisions linked to free data resource exploitation (Singh *et al.* 2020: 5). E-retailers use social digital platforms to build virtual brand communities instilling beliefs of quality, integrity, and goodwill in a bid to develop brand popularity, resulting in perceived trust in online shopping linked to free data resource exploitation (Geric and Dobrinic 2020: 342). Therefore, online interaction with popular brands creates a bond that quickly evolves into perceived trust, espousing e-consumers to execute online shopping commitments without realising the hidden e-tailing data harvest and exploitation. On this note, it is evident that past studies have not conducted in-depth research on the influence of brand popularity as a facet of perceived trust in relation to e-consumer awareness of free data resource exploitation in a bid to establish remediation strategies.

3:9 CONCLUSION

This chapter aimed to discuss free data resource exploitation from a broad perspective before focusing on the South African context. Specific issues discussed in the chapter include perceived risk and perceived trust. It emerged that perceived risk and perceived trust have an influence on e-consumers in South Africa. Based on available studies, free data resource exploitation is not a well-researched phenomenon widely spreading within online transactions between e-consumers and e-retailers. Perception is viewed as a major factor influencing self-disclosure on digital platforms, resulting in free data resource exploitation without the knowledge of the consumer. This chapter related perceived risk and trust in online shopping as the main influences on e-consumer awareness of free data resource exploitation. But all in all, the lower the perceived risk, the higher the perceived trust in most scenarios however, in some instances, e-consumers ignore the risks of free data disclosure, leading to free data resource exploitation in a bid to meet online shopping goals. Apart from perceived risk and perceived trust, shopping experience and purchase intention, discussed in the next chapter, may have a substantial influence on e-consumer awareness of free data resource exploitation.

CHAPTER: 4. REMEDIATION OF FREE DATA EXPLOITATION

4:1 INTRODUCTION

In Chapter 3, perceived risk and perceived trust were found to be related to influencing e-consumer awareness of free data resource exploitation. This chapter discusses literature focusing on the remediation of free data exploitation. The purpose of this discussion is to lay a solid foundation for the study by clarifying the context of the specific components of purchase intention and shopping experience. The chapter is divided into seven sections. This chapter commences with an introduction in Section 4.1, a review of the theoretical background in Section 4.2, free data exploitation remediation discourse in Section 4.3, and conceptualisation of purchase intention and shopping experience in Sections 4.4 and 4.5, respectively. The remediation strategies in Section 4.6 are followed by the conclusion in Section 4.7. Therefore, this chapter focuses on providing a broad understanding of the remediation of free data exploitation with a focus on the influence of purchase intention and shopping experience on e-consumers.

4:2 THEORETICAL BACKGROUND

The theory of planned behaviour (TPB) has been used by several researchers to predict complex individual behavioural intentions (Lim and Weissmann 2021: 3). Certainly, the TPB is in most cases used in conjunction with the TAM when investigating the mediators of online purchase intention and online shopping experience (Baeshen 2021: 100). Smart technology, which facilitates e-consumer online task completion, has influenced online behavioural intentions due to the shopping experience associated with digital innovation (Riegger *et al.* 2021: 141). The digital technology has exposed online shoppers to free data exploitation due to online engagements linked to purchase intention due to the shopping experience.

Lim and Weissmann (2021: 2) reiterate that volitional control turns behavioural control towards reasoning actions that trigger behavioural intentions, and therefore the TRA is also helpful in investigating purchase intention. The TRA, TPB, and TAM shape attitudes towards the intentions to purchase online, especially if online shoppers positively perceive the usefulness and ease of online technology (Choi and Park 2020: 4). Perceived usefulness and perceived ease of technology (Harrigan, Feddema, Wang, Harrigan and Diot 2021: 4) influence online shoppers to reject or accept online shopping, which determines exposure to free data exploitation online. Shopping experience is also a psychological aspect that reflects subjective, holistic, hedonic, aesthetic, and utilitarian memories that control the emotions of online shoppers who later become loyal (Hamouda 2021: 2). Then online consumer loyalty innocently prompts online engagements associated with self-disclosure and free data exploitation.

The privacy calculus theory (PCT) is also used to guide this study with reference to how e-consumers weigh the benefits of online shopping in relation to the issues of self-disclosure online, where the benefit of online shopping motivates data disclosure (Khoa 2021: 587). However, behavioural control is self-efficacy moderated by the beliefs and subjective norms that influence e-consumer intention to purchase goods and services online, which increase exposure to free data exploitation (Choi and Park 2020: 5). Consequently, online purchase intention is normally followed by purchase action, which may lead to satisfaction and repurchase intentions, which form a recurring wave of free data exploitation without the awareness of online shoppers who are constantly targeted (Cachero-Martinez and Vazquez-Casielle 2021: 1). In the next section, the remediation discourse of e-consumer awareness of free data exploitation is discussed along with suggested remediation strategies.

4:3 FREE DATA EXPLOITATION REMEDIATION DISCOURSE

Lee (2019: 24) is of the view that the wealth generated by the enormous free e-consumer data resources has led to online firms prioritising the most relevant data for exploitation without the awareness of online shoppers. However, with the growing e-consumer awareness, online companies are endeavouring to remediate free data exploitation by acknowledging that customer value carries a higher bar than retailer value (Nam and Kannan 2020:31). Fuchs (2020:2) argues that humans are particularly concerned about their autonomy in relation to the hidden harvesting of everyday traces of online activity. Individual awareness of free data exploitation may aggregate with time, resulting in undesirable ramifications of unrest and defection from online engagements that enable e-commerce. Therefore, remediation action is paramount in the exponentially developing data-driven digital economy.

Moreover, the exploitation of e-consumers through digital labour, where online firms are harvesting valuable online user data production using opaque algorithms, has to be addressed with urgency (Cochoy, Licoppe, Mcintyre and Sorum 2020: 2). Companies are constantly zooming in and extracting the traceability as well as the granularity of e-consumer behavioural data with free access, which might eventually enrage data producers (e-consumers) in the long run (Airoldi 2021: 101). Presently, free e-consumer data is a raw material used as a building block to generate revenue for the capitalists, as neo-Marxist scholars critique the technological glorification, which has created inequalities between digital capitalists and society (Mutsvairo, Ragnedda and Orgeret 2021: 297). Notably, e-consumer awareness of free data exploitation requires attention in a bid to establish remediation strategies that will prevent online shoppers from defecting or getting involved in altercations, which may worsen customer relations.

Furthermore, it has become popular in the digital economy that data is treated as the new oil organisations might use to trade-off the benefits and costs of free data resource exploitation in order to strengthen declining e-consumer relations (Krafft, Kumar, Harmelin, Singh, Zhu, Chen, Duncan, Fortin and Rosa 2021: 133). The trade-off of data is eminently sparked off by the growing awareness of free data exploitation, calling for individual control of data disclosures (Mican, Sitar-Taut and Moisescu 2020: 1). Nevertheless, algorithmic e-consumer data sorting, filtering, and exploitation are allegedly done to make members of society live an easy life experience, but such unnoticeable operations are met with discomfort due to the issues of digital identity (Lomborg and Kapsch 2020: 746). Moreover, digitalised firms command excessive control of the e-consumer shopping experience by monitoring the browsing habits that are exploited to vitalise purchase intentions (Moran 2020: 891). E-consumer awareness of free data exploitation can be necessary in seeking remediation strategies in the data-driven digital economy.

Additionally, Concilio, Pucci, Raes and Mareels (2021: 42) indicate that citizens' data is both individual and collective resources that are usually exploited in aggregate in order to constitute value. So, online firms can easily match sociodemographic data with individual data reflections to activate mass-customisation strategies (Bidler, Zimmermann, Schumann and Widjaja 2020: 507). Online companies assume that individuals exert the necessary controls to restrict the flow of personal data but permit certain data spill overs deemed to be insensitive to encourage self-disclosure through self-regulation (Feher 2021: 193). Nonetheless, online companies are increasingly becoming powerful in guiding the e-consumer purchase journey using invisible data monitoring tools (Villanova, Bodapati, Puccinelli, Tsiros, Goodstein, Kushwaha, Suri, Ho, Brandon and Hatfield 2021: 117). Certainly, e-consumers awareness of free data exploitation is still not thoroughly known.

On the other hand, online companies are seeking consumer-centric remediation action by initiating requests to accept the harvesting to gain access to the web content, which indeed is a crude strategy requiring unintended initial registration, jeopardising purchase intention (Gomez-Barroso 2021: 539). This strategy makes e- consumers unknowingly disclose free data suspecting the invisible data monitoring algorithms. Therefore, a remediation mechanism is essential to establish common ground between online firms and e-consumers in a bid to recognise e-consumer data input in consideration of the net mutual benefits. The exploitation of free raw material consumer-generated data is darkening the digital dream of development by the deliberate undermining of individual autonomy by glitches that grandiose humans into inadvertently disclosing their personal information. (Lupton 2021: 4). E-consumers are seemingly unaware that while they transact online, their data is being harvested by online retailers. The remediation discourse of free data exploitation can further be illuminated based on the present digital culture discussed in the next sub-section.

4:3:1 Digital culture

With the current dynamic data-driven digital economy, the epistemological genesis of free e-consumer data exploitation is embedded in the present digital culture settings with the notion that data is socially constructed, where any piece of dataset is subject to ongoing usage without contesting ownership (Pangrazio and Selwyn 2019: 420). The society is intertwined by the internet, which grants digital citizenship where participation is impossible without data sharing (Lutz, Hoffman and Ranzini 2020:

1169). While e-consumers are contesting the pervasiveness of data monitoring in the contemporary data-sharing digital economy, they subscribe to the view that surveillance is indispensable (Draper and Turow 2019: 1825). Lupton (2021: 4) adds that the idea of data universalism covers the way in which individual data is harvested and digested for targeting using automated recommender systems to lure purchase intention. Notably, e-consumers are becoming aware of free data exploitation due to its intensity in the data-driven economy.

Against this backdrop, the ontological perspective of e-consumer-focused logic of memorable experiences derived from precise targeting through free data exploitation considers e-consumer data resources as a community asset for collective ownership (Concilio *et al.* 2021: 42). So, online retailers interact with e-consumers in the large digital eco-system in search of sociocultural insights and consumer preferences that determine purchase intention (Nam and Kannan 2020: 28). Strong cultural norms, values, and previous online shopping experiences are tracked by profiling algorithms that propel purchase intention (Lupton 2021: 6). Therefore, the advent of current sophisticated technology has penetrated cultural settings to unwittingly encourage individual participation on digital platforms, thereby creating a large reservoir of free data exploited by online firms (Yeo 2020: 589). Online shoppers are eventually lured into online disclosures to cope with the digital culture, which opens the way for free data exploitation without the knowledge to the consumer.

Moreover, the current valuable global resource is no longer oil. Oil has been replaced by data as a new commodity that is raising concerns of free exploitation (Fuchs 2020:12). The widely acquired digital devices have led to the emergence of a new digital culture that has elevated consumption norms, ethical intimacy, self-publishing, self-discovery, and a shift of power from e-consumers to online capitalists (Cochoy *et al.* 2020: 2). The digital culture is shaped by the TAM depending on the norms, values, and attitudes of society members (Fernandes, Venkatesh, Panda, Shi 2021: 2). E-consumers hardly realise that large troves of data are harvested for the purpose of customisation to improve purchase intentions (Moran 2020: 892). The digital culture has expanded algorithms with oppressive black box classifiers of the human soul (Lomborg and Kapsch 2020: 753). Also, the digital culture permeates the aesthetic e-consumer judgements allowing, an abundant flow of digital traces to companies that monetise behavioural harvests for micro-targeting (Airoldi 2021: 97). But still remediation action is important to address this phenomenon of free data resource exploitation, which requires e-consumer awareness.

Numerous valuable firms are building around a profit-driven framework of data tracking, which encourages community data exploitation for innovation (Yablonsky 2020:8). The digital revolution is now extending to Africa, where the technological renaissance glorification is biting with materialism, unmasking beliefs and behavioural and personality traits used by online firms' innovation towards the shopping experience (Mutsvairo, Ragnedda and Orgeret 2021: 297). Similarity social norms can be tracked using collaborative filtering while browsing to enable recommender systems that can persuade in referring products (Liao and Sundar 2021: 2). Although they are sometimes biased towards providing quality to marginalised societies, recommender systems automate e-consumer needs based on data harvesting algorithms (Lupton 2021: 4). Jin, Ma and Ye (2020: 85) posit that data exploitation is a necessary evil that adds value to the e-consumer experience in the form of personalised products and services; however, there is no assurance that there will not be any future conflicts over data ownership and usage. E-consumers will not forever remain in the dark with regard to free data exploitation, which necessitates urgency in establishing a remediation strategy.

E-consumers often disclose data voluntarily, where the granularity of this behavioural data allows online firms to target various segments with personalised services, which attracts purchase intention (Krafft *et al.* 2021: 136). Additionally, as the COVID-19 variants intensify, e-consumers are relying on online shopping, which requires an expanded form of matching personalised services to individual preferences, which can easily be facilitated by e-consumer data monitoring (Bonnet and Westerman 2021: 84). E-consumers seem to be unaware of data harvests, but privacy concerns have awakened their consciousness of data exploitation (Mican, Sitar-Taut and Moisescue 2020: 2). Therefore, e-consumers are compelled to succumb to free data exploitation as they develop purchase intentions mediated by numerous factors, as indicated in the next section.

4:4 PURCHASE INTENTION

Harrigan *et al.* (2020: 5) define online purchase intention as the willingness to buy goods and services on online platforms where the usefulness of the platform is important for behavioural intention. On the other hand, Hamouda (2021: 5) considers purchase intention as a measure of the possibility of the customer taking a purchase action after evaluating alternatives. Behavioural intention to purchase goods and services online is determined by positive or negative assessment of the online firm, leading to the development of attitude (Pena-Garcia, Gil-Saura, Rodriguez-Orejuela and Siqueira-Junior 2020: 3). So, online shoppers searching for products are simultaneously intercepted by invisible algorithms that create superficial mental short cuts, prompting purchase intention based on browsing behaviour tracking (Liao and Sundar 2021: 2). While they are searching for products online, e-consumers are unaware that they are leaving large volumes of valuable data, which is exploited by online retailers.

The purpose of conducting an information search prior to actual purchase is to develop trust by gaining confidence to wilfully accept vulnerability to the eventualities of online purchase intentions, and once trust is assured, e-consumers data is then exploited further during online engagements (Harrigan *et al.* 2021: 2). E-consumers constantly seek information from ads on the search engines without having to travel long distances to the retail outlet, which motivates purchase intention related to online self-disclosures and data exploitation (Gauri, Jindal, Ratchford, Fox, Bhatnagar, Pandey, Navallo, Fogarty, Carr and Howerton 2021: 44). As e-consumers develop intentions, they inadvertently demonstrate trackable behaviour online without explicit e-retailers' request, who passively observe online shoppers' intentions for precise targeting (Krafft *et al.* 2021: 134). To date, there is a dearth of research on purchase intention as an influential factor in online shopping, but no research has linked purchase intention to e-consumer awareness of free data resource exploitation in a bid to recommend remediation strategies.

As e-consumers develop purchase intention during the online purchase journey, online firms view the insights of intention exposed on the online website and shape the insights towards attracting actual purchases, thereby enabling targets for the right shopper (Villanova *et al.* 2021: 117). Choi and Park (2021: 4) state that TAM along with TPB enable subjective reasoning to transact online, which later exposes shoppers to free data exploitation. While developing purchase intention, online shoppers engage in purposive searching to obtain sufficient information about the product, which unintentionally prompts e-consumers to leave a trail of free exploitable browsing behavioural data for predictions (Wang and Wang 2020: 252). In fact, individual desire and willingness to purchase goods and services online are monitored by following e-consumers' information search clues (Bulsara and Vaghela 2020: 48). Therefore, during this stage of purchase intention on the purchase journey, e-consumers are unaware that e-retailers are monitoring their purchase intentions, which are exploited to automate recommendations matching online shoppers browsing behavioural intentions.

Furthermore, e-consumers developing the intention to purchase goods and services online are looking for trustable companies that can support their confidence to purchase actions that put online shoppers in a vulnerable position towards free data resource exploitation (Harrigan *et al.* 2021: 2). Eventually, attitudinal and behavioural intentions are ultimately exploited for precise targeting (Riaz, Guang, Zafar, Shahzad, Shahbaz and Lateef 2021: 101). Hamouda (2021: 3) articulates that browsing online information sparks the stimuli of attitudinal intentions that are monitored and exploited to entice actual purchases. The task of online retailers is to extract data from e-consumer interactions on the website and then break down the meaning of the psychological, economic, and social factors related to individual purchase intentions (Baeshen 2021: 101). Against this backdrop, e-consumers hardly notice the invisible algorithms tracking behaviour in the process of developing purchase intention.

Qalati, Vela, Li, Ahmed, Dakhan, Thuy and Merani (2021: 5) affirm that purchase intention is controlled by how e-consumers perceive the risks of transacting online. So, a low online risk will attract purchase intention, leading to self-disclosure and free data exploitation. As noted in Chapter 2, e-consumers are fearful of regretting their online purchase decision due to the possibility of loss (Zhao, Wang and Jiang 2021: 4). If the risks are minimised, online shoppers unwittingly become victims of free data exploitation. To mitigate risks, e-consumers search for useful tips that may shape their attitude towards purchase intention (Qalati *et al.* 2021: 2). Ahmed, Samad and Khan

(2021: 32) agree that perceived usefulness of online information tips is very important determinant of purchase intention. Purchase intention leads to self-disclosure through online engagements, which are traced for targeting. Therefore, it may be fair to argue that e-consumers developing online purchase intentions are unaware that online companies are quietly monitoring their data for free exploitation to make economic predictions.

Moreover, even if there are risks involved in online purchase intentions, the proximity of the retail outlets may influence consumers to develop online purchase intentions irrespective of risk issues (Lee and Charles 2021: 1). Purchase intention is linked to consumer behaviour involving attitudinal perceptions that ultimately are associated with online self-disclosures and free e-consumer data exploitation (Dabrynin and Zanga 2019: 17). Draper and Turow (2019:1825) contend that online shoppers are now interested in the benefits of online shopping by downplaying risks related to online purchase intention, which exposes e-consumers to free data resource exploitation. Notably, no studies have attempted to relate e-consumer awareness of free data resource exploitation to purchase intention.

Additionally, online purchase intention is now weighed by privacy calculus in that, if the perceived benefits outweigh the consequences of data disclosure, e-consumers are trapped in the privacy paradox, prompting online self-disclosure in pursuit of benefits by overriding risks (Lutz, Hoffmann and Ranzini 2020: 1169). The privacy calculus theory (PCT) enables e-consumers to weigh the costs and benefits of online shopping in relation to issues of self-disclosure online, where the benefit attracts data disclosure (Khoa 2021: 587). The privacy paradox is a subjective factor influencing purchase intention due to the fact that e-consumers perceive data disclosures differently and act differently in controlling self-disclosure based on the benefits of online shopping (Gomez-Barroso 2021: 537). While online shoppers are downplaying the consequences of data disclosure, they inadvertently disclose data online, which is eventually exploited by online retailers.

Normally, purchase intention motivates e-consumers to interact online, but the pre-existing algorithms embedded in retailers' websites are not fully known by online shoppers (Lomborg and Kapsch 2020: 750). Nevertheless, a handful of online shoppers interviewed in the study of Draper and Turow (2019: 1826) believe that data exploitation cannot be avoided and have resorted to digital resignation by accepting that they have little control over their data. Individuals believe that they cannot refrain from data monitoring in consideration of the fact that it is no longer possible to participate online without exposing their data to free exploitation. There are numerous factors that mediate purchase intention, which may ultimately influence e-consumer awareness of free data resource exploitation by online firms. Some of these factors include personalisation, social influence, convenience, and ethical beliefs, which are deliberated on in the subsequent sub-sections.

4:4:1 Personalisation

Although there is no standard definition of personalisation, delivering the right content to the right customer and using the double-edged sword that incorporates e-consumer self-referencing is referred to as personalisation (Riegger *et al.* 2021: 141). Data analytics is used to assign codes to browsing consumers to target personalised advertising by incorporating individual data in the ad content, aiming at invoking purchase intention and luring data disclosures that facilitate free data exploitation (Zhu and Kanjanamekanant 2021: 1). Although there are a few studies linking personalisation to purchase intention, no studies have gone further to investigate the influence of purchase intention mediated my personalisation to uncover e-consumer awareness of free data exploitation. Online shoppers are innocently lured into data disclosures due to personalisation intended to attract purchase intentions.

Nevertheless, e-tailing platforms have unprecedented opportunities to harvest historical data and match it with real-time data to analyse behavioural patterns, which assist in providing personalised offers that spark off purchase intentions that eventually expose online shoppers to free data exploitation (Ren, Cao, Xu and Gong 2021: 1). Lomborg and Kapsch (2020: 752) believe that the personalising algorithms that shape purchase intention often go unnoticed by online shoppers because they are clean and hidden, but they become visible when they are persuasive, thereby alerting e-consumers to data tracking for free exploitation. Therefore, it can be argued that e-consumers are unaware of free data resource exploitation while they develop online purchase intentions mediated by personalisation.

Although there are several issues with harvesting e-consumer data online, firms argue that they use such data insights to personalise and recommend the right products based on behavioural history, thereby motivating purchase intention and exposing online shoppers to free data exploitation (Moran 2020: 892). Technological development used to harvest data from e-consumers is certainly used to target the same e-consumers through personalisation, but online shoppers are not aware that purchase intention mediated by personalisation has an influence on free data exploitation (Mican, Sitar-Taut and Moisescu 2020: 2). Gauri *et al.* (2021: 53) expound that personalised services along with recommender engines, strongly determine purchase intention, consequently leading to self-disclosures linked to free data resource exploitation. Personalisation allows e-consumers to develop purchase intentions, resulting in online product search clues that are exploited without the awareness of the consumer.

Moreover, personalisation requires the use of personal data, raising the issue of privacy paradox because e-consumers need personalised services but, by the same token, are concerned about privacy imbalance (Cloarec 2020:1). Tracking e-consumer data facilitates personalisation using hidden cookies enabled by mandatory authorisation to access the browser (Liao and Sundar 2021: 2). Furthermore, the cornerstone of contemporary reasons for algorithmic tracking is focused on offering tailor-made services based on ongoing monitoring of e-consumers to facilitate predictive targeting to lure e-consumer purchase intention (Kotras 2020: 3). For example, if a customer clicks on multiple websites that are related, relevant ads pop up to guide the user, who enjoys a personalised browsing experience that may trigger purchase intention. Therefore, there might be some degree of relationship between e-consumer awareness of free data exploitation and purchase intention mediated by personalisation. From the existing literature, it is possible to argue that e-consumers are unaware of free data resource exploitation.

Personalisation usually predicts purchase intention, especially when e-consumers prefer tailor-made products and services, which are filtered by algorithms tracking user content with collaborative filtering of like-minded e-consumers targeted as a bandwagon (Liao and Sundar 2021:1). Zeng, Ye, Li and Yang (2021: 668) share the same view that personalisation has an influence on purchase intention. Albeit personalisation may raise privacy issues as well as the risks linked to vulnerability, there is a greater likelihood of developing positive purchase intention due to the gratitude, delight and satisfaction derived from personalisation, which trigger self-disclosure and data exploitation (Riegger *et al.* 2021: 142). Based on the available studies, it is unlikely that e-consumers are unaware of free data exploitation due purchase intentions mediated by personalisation.

Moreover, content-based filtering matches e-consumer personal preferences with a particular product and then socially oriented collaborative filtering recommends endorsed products by shoppers with similar behaviour, driving mass personalisation and leading to purchase intentions linked to data exploitation (Liao and Sundar 2021:2). Kotras (2020: 2) cautions that personalisation algorithms split open granular individual behaviour, which assists online firms to anticipate demand and offer personalised services that attract purchase intention. The surveillance of human experience to facilitate personalisation leading to purchase intention that eventually generates revenue is done by exploiting the free raw material of e-consumer behavioural data (Cloarec 2021:5). Additionally, online personalised products intensify the actual willingness to purchase online without noticing free data exploitation, which increases e-consumer acceptance of personalised promotions that generate high revenue (Zeng *et al.* 2021: 670). So, personalised services and products propel e-consumers to wilfully leave a trail of data as they become interested in the benefits of personalisation.

In the study conducted by Riegger *et al.* (2021: 149), the findings reveal that e-consumers value personalisation but are against disclosing personal data, but once personalised services provide an emotional feeling of efficacy, online shoppers develop purchase intentions linked to free data exploitation. Personalisation is often criticised as cynical algorithmic manipulation, which strengthens the grip on human behavioural intentions to optimise profitable marketing strategies, giving firms unprecedented control over innocent online shoppers (Kotras 2020: 3). E-consumer awareness of free data exploitation due to purchase intention mediated by personalisation is not well known. This study is essential in investigating e-consumer awareness of free data exploitation in a bid to propose remediation strategies. In the next sub-section, social influence as another influence of purchase intention is discussed.

4:4:2 Social influence

Social influence is defined by Dewi, Mohaidin and Murshid (2021: 286) as the opinions of people affecting the perception of an individual, which externally motivate the stimulus to purchase intention, exposing online shoppers to free data exploitation. Based on the theory of socialisation, members of society learn from each other to develop behavioural norms (Harrigan *et al.* 2021: 4) that shape purchase intentions, leading to self-disclosures exploited for targeting. Riaz *et al.* (2021: 99) propound that social influence in the digital environment mediates purchase intention through social networks that spark online engagements, unwittingly exposing e-consumers to free data resource exploitation. Albeit there are a few studies about purchase intention in relation to social influence, no research has gone forward to link their relationship to e-consumer awareness of free data exploitation.

Furthermore, electronic word-of-mouth (eWOM) from social networks shapes attitudes towards purchase intentions, which encourages interactive data exchanges exploited by online firms for targeting (Siddiqui, Siddiqui, Khan, Alkandi, Saxena and Siddiqui 2021: 1008). Qalati *et al.* (2021: 3) comment about how community influence on purchase intention can be related to implied online engagement that seeks to strengthen the intentions leading to free data exploitation. Online firms are getting involved in posting positive product ratings on social networks, which attract purchase intentions, luring e-consumers to engage online by disclosing data, which is ultimately exploited without shopper awareness (Meilatinova 2021:1). Based on previous studies, e-consumers are unaware of free data exploitation due to purchase intentions mediated by social influence.

Social shopping platforms influence e-consumers to purchase products and services on social networks with live e-commerce tools embedded with monitoring capabilities to enable behavioural targeting, which triggers recurring purchase intentions (Chen and Yang 2021:1). Harrigan *et al.* (2021: 4) argue that perceived ease and perceived usefulness of technology attract consumers to engage online, which results in exposure to free e-consumer data exploitation. In contrast, the ubiquity of negative online reviews affect e-consumer intentions to participate in e-commerce, thus reducing the vulnerability to free data resource exploitation, but e-retailers chip in to restore the damage to reinforce purchase intentions (Zhao, Jiang and Su 2020: 45). However, against this backdrop, the quality of information on social networks with favourable comments still holds substantial influence on purchase intention mediated by social influence, which inadvertently sparks off online self-disclosure and free data resource exploitation.

Certainly, individuals in society have the capability to observe behaviour, compare thoughts, feelings and personalities when evaluating content on social platforms with relevant information that can influence purchase decisions linked to self-disclosure and free data exploitation (Zhao, Wang, Tang and Zhang 2020:2). Normally, e-consumers tend to read online reviews before making online purchase decisions because comments assist in moderating uncertainties towards purchase intentions, leading to free data exploitation through precise targeting (Tran 2020:1). The absence of purchase intention or willingness to purchase goods and services online can severely affect e-commerce, which is a source of free e-consumer data disclosures for exploitation (Pena-Garcia *et al.* 2020: 2). Notably, e-consumers are unaware that while they develop online purchase intentions mediated by social influence, online firms are busy monitoring and exploiting their data resources.

Moreover, Krafft *et al.* (2021: 137) allude to the fact that e-consumers express their experiences on digital platforms, which helps their fellow members of society modify purchase intentions linked to free data resource exploitation. However, online companies tend to exaggerate the capabilities of social influence on purchase intention, which calls for closer monitoring of social platforms to link targets to specific purchase intention structures (Lupton 2021: 8). This is usually due to the interconnectedness of mediatised society, which has forced online firms to exert control over relevant data layers of digital identities on social platforms in the surveillance of cultural boundaries to target social settings based on purchase intentions in the media (Feher 2021: 193). Consumers are innocently influenced by society to engage online in order to accomplish purchase intentions, which leads to free data disclosures and exploitation.

Furthermore, the abundant data on social platforms influences online shoppers' intentions, which invokes free data exploitation and continuous targeting based on real-time social media updates (Lang, Xia and Lui 2021: 225). In fact, social settings encourage e-consumers to communicate with each other, where the shared information can motivate or demotivate online shoppers purchase intentions linked to free data resource exploitation (Dewi, Mohaidin and Murshid 2021: 286). Interpersonal interactions about the shopping experience boost the purchase intention and gradually enable e-retailers to exploit touch points of purchase intention using invisible tracking (Wang, Sun and Hou 2021: 467). Although negative reviews from social platforms undermine purchase intentions, credible positive reviews, which are not initiated by online firms, often lure online shoppers into purchase intentions, leading to free data exploitation (Fernandes *et al.* 2021: 4). When consumers appreciate the positive reviews, they develop purchase intentions, which ultimately lead to online engagements that are exploited.

Social influence normally arises from online shoppers' complaints about the capabilities of online companies, which may positively influence purchase intention, unwittingly trapping e-consumers in free data resource exploitation (Zhao, Jiang and Su 2020: 46). In most cases, social influence is effective in e-consumer social networking relationships, where shoppers cannot make individual choices without listening to the centrality of concerns, hence affecting purchase intention on a social scale (Chen and Yang 2021:3). With a high penetration of social platform usage, online firms monitor and identify factors influencing purchase intention without the awareness of e-consumers (Meilatinova 2021: 2). E-consumer awareness of free data resource exploitation in consideration of the influence of purchase intention, focusing on social influences, remains the unique section of this study.

Furthermore, Siddiqui *et al.* (2021: 1009) argue that e-retailers are now advertising through social media platforms by placing rewarding and positive assertions from customers rewarding positive views, which improve new customer purchase intentions and exposes them to free data exploitation. Reviews, ratings and recommendations posted on social platforms are sufficient to build trust, leading to self-disclosure and free data resource exploitation without the awareness of the consumer (Riaz *et al.* 2021: 101). With reference to the existing literature, no study has addressed the mediating factor of social influence on purchase intention to investigate e-consumer awareness of free data exploitation. In the next sub-section, purchase convenience is explained as another predictor of purchase intention.

4:4:3 Purchase convenience

E-consumers perceive online shopping to be an enjoyable activity where shoppers simply scroll their smart devices to view various online retailers' offerings in the comfort of their homes. They are unaware that e-retailers are monitoring shoppers online navigation (Gauri *et al.* 2021: 23). Convenience increases the possibility of self-disclosure as e-consumers become intimate, thereby developing trust and freely registering in preparation for actual purchases, which exposes them to free data resource exploitation without realising it (Zeng *et al.* 2021: 669). Ultimately, the hidden algorithms connect to recommender systems that filter the browsing behaviour to match products to e-consumers' preferences, giving a sense of convenience to the shopper with a high level of willingness to disclose data for free exploitation (Liao and Sundar 2021: 2). As long as the purchase process is convenient, online shoppers unintentionally subscribe online, which offers online retailers free browsing data to exploit.

Furthermore, purchase convenience is shaped by TAM in view of the ease of technology alongside its usefulness to facilitate online purchase activity, where the easier or more useful the technology, the greater the willingness to opt for online purchase, leading to data exploitation (Baeshen 2021: 100). So, the simplicity, product variety and swift price comparability due to online purchase convenience attract purchase intention, followed by e-retailer browsing behaviour monitoring of prospective shoppers to target (Ahmed, Samad and Khan 2021: 33). Koncar, Grubor, Vucenovic and Maric (2021: 3) acknowledge that online purchase convenience mediates purchase intention due to the fact that shopping online does not require travelling to the store, which increases the willingness to disclose personal data online, resulting in free data exploitation without the awareness of e-consumers. Several studies found a positive relationship between purchase intention and purchase convenience; however, no study has tested e-consumer awareness of free data exploitation, citing purchase convenience as a mediator of purchase intention.

Additionally, in recent years, Amazon has added voice assistant technology, helping e-consumers interface with the voice assistant during browsing with enhanced ease, which shapes purchase intention, leading to free data resource exploitation for targeting (Gauri *et al.* 2021: 57). Real-time communication increases the willingness and confidence of online shoppers to develop purchase intentions, where e-consumers unwittingly fall prey to e-retailers who monitor behavioural intentions online for targeting (Grewal, Gauri, Roggeveen and Sethuraman 2021: 7). When e-consumers enjoy smart efficiency with the sensation of online purchase convenience, tracking algorithms often go unnoticed due to the pleasure of the online purchase leading to re-purchase intention (Lomborg and Kapsch 2020: 752). Purchase convenience predicting purchase intention may later lead to the actual purchase, rendering online firms unprecedented free access to e-consumer data resources, innocently stripping online shopper data control (Moran 2020: 890). Therefore, e-consumers are unaware that purchase intentions due to convenience influence free data exploitation.

Several studies reveal that e-consumers often disclose personal data without explicit request by taking voluntary steps due to online purchase convenience, making online shoppers innocently vulnerable to free data exploitation (Krafft *et al.* 2021: 136). However, in the European Union, e-consumers are progressively becoming aware of data monitoring and profiling, citing the loss of individual control, which has escalated concerns about free data resource exploitation (Mican, Sitar-Taut and Moisescu 2020: 1). Due to the fact that e-consumers have limited time to visit physical outlets, the convenience of online shopping, where products are delivered after a simple button click, entices e-retailers to tag prospective shoppers for the purpose of exploiting their data for prediction (Baeshen 2021: 101). Due to convenience, online shoppers may not realise that they are leaving a trail of browsing data ready to be exploited by online firms.

Convenience is presently a major predictor of purchase intention online due to the new normal of avoiding human contact using contactless exchange with electronic payments, exposing online shoppers to free data exploitation for future targeting (Baeshen 2021: 99). Certainly, Gauri *et al.* (2021: 44) demonstrate that the cost of searching for the products online is much lower than travelling around window shopping with higher such costs, which leads e-consumers to choose click-streams associated with free data exploitation. So, innovative digitalisation has revolutionised e-consumer browsing by allowing users to easily compare offerings and online information from multiple channels across the global market, facilitating purchase convenience with purchase intention, leading to free data exploitation for prediction (Nam and Kannan 2020: 28). The increased usage of smart devices even in remote villages easily makes purchasing online convenient orders by clicking on retailers' websites, which increases the incidence of exposure to free data resources without online shoppers' knowledge.

Purchase convenience online that includes a variety of price discounts, packages, and product choices allows the customer to develop purchase intention and increases the prospects of web browsing being exploited to persuade e-consumers into actual purchases (Ahmad *et al.* 2020: 3). The internet is like a shopping mall, which does not shut down with full access during the day and night providing e-consumers the opportunity to buy any type of product that could otherwise not be conveniently accessed offline, resulting in inevitable data disclosures online, triggering free data exploitation (Baeshen 2021: 102). This current study is unique because it relates purchase intention mediated by convenience to e-consumer awareness of free data resource exploitation.

Moreover, Bhatti and Rehman (2020: 35) establish that the easy life the internet offers with quick searches in seconds encourages e-consumers purchase intentions. Based on the technology acceptance model TAM, perceived ease of online shopping prompts consumers to transact online (Choi and Park 2020: 4). Notably, the convenience of online shoppers allows e-consumers to compare and evaluate a wide range of brands, which motivates online purchase intention, propelling shoppers to dig deep while leaving free, useful data exploited by e-retailers for re-targeting (Bhatti and Rehman 2021: 36). Consequently, the cognitive situation of e-consumers motivated by internet speed, easy access, interconnectedness, smartly designed user-friendly websites, and visual appeal makes navigation addictive to the extent of attracting online purchase intention linked to data exploitation (Jaiswal and Singh 2020: 43). Furthermore, the possibility for e-consumers to switch from one online company to another with a simple click motivates purchase intention (Bhat and Darzi

2021: 1). Online retailers are then braced with a trail of historical browsing paths left by unsuspecting shoppers, thus, opening the chances for online retailers to exploit all the behavioural search data to recommend products.

Indeed, nowadays, daily habits are inseparable from the self-tracking smart devices that influence e-consumers' psychology due to the feeling of pleasure during online shopping linked to free data exploitation (Ahmad *et al.* 2020: 4). The collaborative power of recommender systems tracks the preferences of browsing online shoppers and filters searchable products with a high prediction accuracy that is convenient enough to attract purchase intention (Lupton 2021: 5). The excitement of online shoppers' due-purchase convenience prompts consumers to bear with any consequences of online shopping. Unlike this current study, previous studies have not investigated the mediating role of convenience on purchase intention as an influence on e-consumer awareness of free data resource exploitation. The other predictor of purchase intention, referred to as ethical beliefs, is discussed in the next sub-section.

4:4:4 Ethical beliefs

Beliefs shape behavioural intentions to purchase goods and services, whether in an offline or online store (Dewi, Mohaidin and Murshid 2020:284). Baeshen (2021: 101) believes that risk aversion depends on individual psychosocial factors to initiate purchase intentions. In fact, the assurance of the safety of personal data instils a belief that the online company is trustworthy, which prompts online shoppers to develop purchase intentions, which inadvertently expose e-consumers to free data exploitation through online behavioural intentions (Bhat and Darzi 2021: 5). In the data-driven digital economy, online shoppers are willing to disclose data even when it is not requested or rational because they are influenced by complex factors mediated by cognitive biases without considering free data resource exploitation (Gomez-Barroso 2021: 538). Behavioural intentions surely depend on attitude, perceptions, and subjective norms as online shoppers weigh the risks against the benefits of disclosing data during the purchase journey (Kushwaha, Singh and Tyagi 2021: 2). So, subjective low-risk assessments tempt e-consumer self-disclosures, leading to free data exploitation. The concept of ethical beliefs is fairly new and has not been widely investigated as a predictor of purchase intention. The current study uniquely investigates the role of ethical beliefs towards purchase intention in relation to e-consumer awareness of free data exploitation.

Furthermore, perceived reputation as to whether the online company is honest in executing promises, which consequently influence purchase intention, leads to online engagements due to reputation, thereby exposing online shoppers to free data resource exploitation (Qalati *et al.* 2021: 3). Online firms with a good reputation for order fulfilment, return policies, and cash on delivery payment options impart ethical beliefs that give online shoppers confidence in developing purchase intentions followed by self-disclosures associated with free data exploitation (Jain, Gajjar and Shah 2021: 1). The perception of justice among online retailers activates ethical beliefs of trust, enhancing purchase intention towards online engagements linked to free data resource exploitation (Zhao, Jiang and Su 2020:46). When e-consumers are developing purchase intentions, they use mental assumptions that stimulate curiosity about the authenticity of the online company, which prompt extensive information searches to ease ethical beliefs, which inadvertently lead to data disclosure and exploitation Therefore, e-consumers can be presumed to be unaware of the influence of purchase intention mediated by ethical beliefs on free data resource exploitation.

Moreover, the uncertainties of the eventualities related to individual data disclosure cause much anxiety due to the fear of the unknown consequences, causing online shoppers to desist from online purchase intentions (Dewi, Mohsen and Murshid 2020:286). However, the individual protective measures of online shoppers are associated with ethical beliefs, which are important predictors of purchase intention prompting self-disclosure (Kushwaha, Singh and Tyagi 2021: 3). Additionally, privacy protection coupled with incentives to disclose data positively affects the ethical beliefs of undecided e-consumers towards online purchase intention (Bidler *et al.* 2020:101). The data protection measures are making e-consumers aware that their data is somehow exploited resulting in some online shoppers sticking to ethical beliefs when developing online purchase intentions, which can sometimes save them from data exploitation in all forms (Mican, Sitar-Taut and Moisescu 2020: 2). Ultimately, the assurance of online protection attracts purchase intention with an ethical belief in authenticity, leading to self-disclosures and free data resource exploitation.

E-consumers are now applying logic by using privacy calculus related to risk-benefit analysis, if the benefits of online purchases outweigh the risks, subjective ethical beliefs are left to downplay the risks, thereby imparting purchase intentions (Feher 2021: 101). Nonetheless, the privacy calculus creates a situation of privacy paradox in which online shoppers decide to ignore privacy issues as benefits override risks, rendering e-consumers powerless as they ignore pre-existing ethical beliefs by continuing with the purchase intentions linked to data exploitation (Lutz, Hoffmann and Ranzini 2020:1170). As a result, online shoppers' trade-off online data, leading to digital resignation where e-consumers no longer desist from data exploitation due to their ethical beliefs compromising purchase intention (Draper and Turow 2019: 1825). Scores of e-consumers who are aware of online hidden surveillance denounce behavioural monitoring while they prefer cool online choices, which puts prospective online shoppers in a dilemma of ethical belief to develop purchase intention entailing them to wilfully disclose data eventually exploited (Lomborg and Kapsch 2020: 755). Therefore, many e-consumers seem to be unaware of free data exploitation due to their behavioural purchase intentions, which are predicted by ethical beliefs.

On the other hand, e-consumer expectations from online novel technology that reflects on prospective online shoppers' preferences due to algorithmic tracking motivate re-adjusting ethical beliefs towards online purchase intentions (Riegger *et al.* 2021: 142). Zeng *et al.* (2021: 667) agree that online shoppers often ignore their ethical concerns when developing purchase intentions, provided that the online company provides personalised services. Nevertheless, e-consumer ethical beliefs remain compromised for as long as the algorithms create mental shortcuts while browsing, thereby saving online shoppers from cumbersome product searches and making e-consumers re-consider ethical beliefs (Liao and Sundar 2021: 2). The precise targeting leads e-consumers to compromise ethical beliefs, leading to self-disclosure and free data resource exploitation.

Ethical beliefs are also influenced by perceived credibility, which is referred to as individual confidence in the excellent brand that makes prospective online shoppers comfortable due to the need for satisfying power that enhances reputation and purchase intention linked to free data exploitation (Khoa 2021: 589). Emotional attachment to credibility possesses persuasive power for online shoppers to downplay ethical issues by developing online purchase intentions associated with free data resource exploitation (Sanchez-Fernandez and Jimenez-Castillo 2021: 2). Although there is growing awareness that online traces are tracked and exploited by online retailers, e-consumers' ethical beliefs approximate a certain level of certainty that such consequences are unavoidable for online purchase intention. The creditability of retailers gives online shoppers a sense of comfort in overlooking ethical beliefs, rendering consumers more likely to trust credible firms with data. There is limited research on the influence of ethical beliefs on purchase intentions and there is virtually no research restricted to e-consumer awareness of free data resource exploitation citing purchase intention due to ethical beliefs.

Arguably, ethical beliefs are demonstrated when e-consumers assume perceived control over deciding what data to disclose, which instils confidence to develop purchase intention, leading to free data exploitation (Khoa 2021: 589). Trustworthiness, on the other hand, depends on ethical beliefs normally internalised by quality evidence or reality from influencers who compromise the normal ethical beliefs that could otherwise not support purchase intention linked to free data exploitation (Sanchez-Fernandez and Jimenez-Castillo 2021: 5). Moreover, established online companies have a good reputation, which is enough to negotiate individual ethical beliefs towards online purchase intention that make online shoppers voluntarily disclose personal data awaiting free exploitation by e-retailers (Lee and Charles 2021: 3). Corporate reputation alters ethical beliefs, prompting swift purchase intention without considering ethical standards, subjecting online shoppers to uncontested monitoring and free data exploitation behind the scenes (Burlea-Schiopoiu and Balan 2021: 1144). Large online retailers normally have the upper hand in luring consumers into unintended data disclosures that result in free data exploitation. E-consumer loyalty frequently modifies ethical beliefs alongside reputation, influencing potential online customers to overlook ethical flaws due to the emotional feeling of loyalty, leading to self- disclosure and free data exploitation.

In conjunction with reputation, ethical beliefs are often moderated by e-consumer loyalty influencing prospective online shoppers to overlook ethical flaws due to the emotional feeling of loyalty, leading to self-disclosure and free data exploitation (Aboul-Dahab, Agag and Abdelmoety 2021: 2). In fact, Alsaad (2021: 2) believes that what e-consumers regard as unethical from one perspective, may be ethical from another perspective, which largely contaminates individual standardised ethical beliefs towards purchase intention. However, the consequentialist approach involving ethical beliefs influence on purchase intention is principally based on the subjective desire to acquire goods out of the intended purchase, prompting the online shopper to trivialise ethics pursuit (Ahuja and Kumar 2021: 4). This results in unintended self-disclosures that trigger free data resource exploitation. This study is the first of its kind to factor in ethical beliefs as a predictor of purchase intention, influencing e-consumer awareness of free data resource exploitation.

E-consumers are progressively becoming aware of free data exploitation as they become dismissive of ethics on the premise that digitalisation automatically makes data disclosures, uncontrollable making the issue of ethics virtually irrelevant (Ahuja and Kumar 2021: 8). Since altered ethical beliefs affect behavioural prediction, predictable purchase intentions are not necessarily to be translated into behaviour due to the weak ethical standard (Lim and Weissmann 2021: 2). Against this backdrop, e-consumers may be unaware of free data resource exploitation due to purchase intentions mediated by personalisation, convenience, social influence, and ethical beliefs. Thus, online shoppers are innocently getting trapped into free data resource exploitation. In the next section, shopping experience is compared to purchase intention to investigate e-consumer awareness of free data exploitation in order to establish remediation strategies.

4:5 SHOPPING EXPERIENCE

Purchase intention, as discussed in the previous section, is either followed by the actual purchase or no purchase due to numerous factors explained in the preceding sub-sections. Once the online shopper starts loading the e-tailing website, complex algorithms automatically infer the salient shoppers' needs even before the completion of page loading, enabling user real-time bidding (Vernali 2021: 2). These complex algorithms are evidence of e-consumer monitoring to facilitate free resource exploitation unnoticed by online shoppers. Harrigan *et al.* (2021: 4) affirm that TAM, which encompasses the perceived ease and perceived usefulness of technology, is influenced by previous experience, which may attract or repel consumers from engaging online. The friendly interactions on retailers' websites offer a personalised enjoyable experience, attracting e-consumer satisfaction and the willingness to disclose data (Jaiswal and Singh 2020: 43). However, the experience of instantaneous algorithm services inadvertently lures online shoppers into full self-disclosure without realising the free exploitation of their data input used for economic predictions.

Furthermore, Hamouda (2021: 2) states that the shopping experience is the internal subjective response to online companies that is stimulated by standard quality products and services. The online shopping experience is the mental cognitive state of feeling in response to high-speed interactions, customisation, aesthetics, perceived control, perceived benefits, and interconnectedness (Jaiswal and Singh 2020: 43). Normally, e-consumers switch online companies due to previous bad experiences compelling them unwillingly disclose their data to such online firms that are typical of undesirable experiences (Gauri *et al.* 2021: 53). So, shopping experiences create bonds with the company that deserves e-consumer honour due to better services, which consequently build trust and the willingness to disclose data eventually exploited by the online company for prediction. Although there is a plethora of research about shopping experience in relation to purchase intention, there is a scarcity of studies mainly centred on the influence of online shopping experience on e-consumer awareness of free data resource exploitation.

Online companies monitor e-consumer complaints associated with a bad experience and de-escalate the situation by tracking the disgruntled using free e-consumer data available online (Zhao, Jiang and Su 2020: 2). The holistic experience of e-consumers and online companies is a recipe for favourable competition in e-commerce, which enhances online engagements associated with free data resource exploitation (Chen and Yang 2021: 2). The positive emotional experience, the digital intelligence experience, and the pragmatic experience give online shoppers a feeling of affection, attracting free data resource exploitation facilitated by online self-disclosures (Cachero-Martinez and Vazquez-Casielles 2021: 3). Once online shoppers enjoy a positive shopping experience, they overcome their pre-existing fears originating from perceived risk, consequently building trust to shop online, followed by data monitoring and exploitation for retargeting (Hemant, Kumar, Bulsara and Vaghela 2020: 50). Based on the available literature, e-consumers are unaware that their shopping expe- riences influence free data resource exploitation.

Moreover, the online shopping experience is influenced by technological advances like notifications while filling the shopping cart, which remind the shopper to add prod- ucts based on search criteria, but e-consumers hardly notice that these popups are enabled by free data exploitation (Zhao, Wang and Jiang 2021: 1). Also, online shop- ping experiences shape attitudes due to e-commerce pragmatic benefits influencing purchase behaviour linked to free e-consumer data exploitation (Pena-Gar- cia *et al.* 2020: 3). Furthermore, Cachero-Martinez and Vazquez-Casielles (2019: 596) allude to the fact that shopping experiences are based on hedonic and utilitarian ex- periences, where hedonism is all about enjoyment and utilitarianism is rooted in func- tional quality. Moreover, Bhattacharya and Srivastava (2020: 801) add that online shoppers enjoy an experience environment with aesthetic and hedonic consumption, which brings a pleasurable experience full of affection and emotional cognitive think- ing. The best experience eventually attracts unrelenting online shopping linked to free data exploitation. With a remarkable online shopping experience, online consumers are unknowingly entrenched in self-disclosure, leading to free data exploitation.

Unfortunately, the e-consumer's imaginary experience of algorithmic monitoring to facilitate free data resource exploitation is not clearly known (Lupton 2021: 8). Lomborg and Kapsch (2020: 752) articulate that individuals experience mood sensations due to the smart algorithmic tracking operations that are pleasant, clean, hidden, and unprovocative, which indicates that some online shoppers are aware of monitoring but not data exploitation. However, the TRA, TAM, and TPB allow consumers to reason out any decision to engage online based on a memorable experience. It is worth noting that the entire online purchase journey is amassed with experience, from information search to after-sales emotional feelings, which influence repeat online purchases and foster recurring free data resource exploitation (Villanova *et al.* 2021: 119). E-consumers’ self-initiated data disclosures due to shopping experiences attract online companies to carefully harvest the free data to improve profitability.

Furthermore, the experience of algorithms influences e-consumers by providing a memorable experience through algorithmic output involving real-time attendance to queries, which motivates continuous online engagements linked to free data exploitation (Lomborg and Kapsch 2020: 751). The subjective preferential experience invoked by interactions between the online firm and e-consumers is manifested (Park and Ha 2021: 5) by instrumental extrinsic value and utilitarian value, which rationalise cognitive provocation towards self-disclosures facilitating free data resource exploitation. On this note, it is evident that there is a dearth of studies seeking to establish the influence of the shopping experience on e-consumer awareness of free data resource exploitation.

Normally, the smart tracking algorithms create a very uncomfortable experience characterised by the irritating disturbance of retargeting met with resentment that limits online shopping (Ayodele and Chigbata 2021: 7). However, the customised shopping experience brought about by the positive algorithmic experience that predicts exactly what online shoppers desire is essential for repurchasing associated with recurring free data exploitation (Lang, Xia and Liu 2021: 3). E-consumer perception of value depends on the service experience throughout the complex purchase journey, where priorities are met with an online shopping experience that attracts repurchasing (Patti, Dessel and Hartley 2020: 2388). Nevertheless, online shoppers face a bad experience with targeted ads, which instils a feeling of anxiety due to personalised banners diluting the shopping experience, thereby reducing online participation and the incidence of free data resource exploitation (Ayodele and Chigbata 2021: 7). The compelling experience is a recipe for self-disclosure linked to free data resource exploitation without the awareness of the shopper.

Certainly, Jaiswal and Singh (2020: 322) comment that a positive shopping experience is gained from the ability of online retailers to tailor products depending on the searchable behaviour browsing history of online shoppers. Additionally, perceived usefulness due to the belief that the online shopping experience will automatically enhance satisfaction moderates people’s attitudes and the possibility of falling prey to free data resource exploitation (Bhat and Darzi 2021: 5). The cognitive component of affection is a mental activity that influences e-consumer memory with a long-term association prompts voluntary data disclosure and free data resource exploitation (Hamouda 2021: 2). Perceived usefulness is usually dependent on the previous shopping experience, attracting a continuous online shopping frenzy experience (Harrigan *et al.* 2021: 5). The usefulness of online shopping engagement results in the inadvertent self-disclosures exploited for future targeting. Research about e-consumer awareness of free data resource exploitation in relation to the shopping experience is still in its infancy.

The online shopping experience due to increased flexibility of e-consumer interactions powered by intelligent technology in the absence of human interaction is enabled by tracking free online shoppers' data to make profitable predictions (Ameen, Tarhini, Reppel and Anand 2021: 2). More studies are paramount to illuminate the influence of the shopping experience on e-consumer awareness of free data resource exploitation in order to establish lasting remediation strategies. Usually, what the consumer shopping experience entails is still unknown due to the multiplicity of new experiences along the purchase journey, which are dependent on subjective norms, speed of delivery, and quality, among other factors (Bhattacharya and Srivastaza 2020: 803). Park and Ha (2021: 3) are of the view that online self-regulated experiences allow online shoppers to think critically with a flexible mind of global processing by scrutinising online information without human interference, which has produced a trail of free data to exploit for prediction. Online shopping experiences influence self-disclosure, leading to free data exploitation.

Behavioural self-efficacy based on previous experience motivates online shoppers' level of engagement online (Choi and Park 2020: 5). E-consumers motivated by hedonic experiences while advocating for autonomy are caught up in the mix where they embrace accurate technology that predicts their needs while sacrificing data control for pleasure and convenience (Ameen *et al.* 2021: 3). The online shopping experience is enjoyable because it simply requires e-consumers to click on the website that gives immediate access to all sorts of products in real-time, which is a major influence on self-disclosure and leads to free data exploitation (Ayodele and Chigbata 2021: 3). Given that online shoppers accept technology, individual adoption behaviour opens doors to a unique online shopping experience based on free data resource exploitation for need-focused predictions (Fernandes *et al.* 2021: 3). Recent studies indicate that e-consumers seem unaware of the influence of their online shopping experience on free data exploitation. Service quality is discussed in the next subsections.

4:5:1 Service quality

E-consumers' perceived quality of online firms depends on the product and service fulfilment of online shoppers' expectations (Lang, Xia and Liu 2021: 227), and once online shoppers obtain value, there is a possibility of self-disclosure, leading to free e-consumer data exploitation. Service quality experience covers a wide range of activities, including delivery waiting time, return, and reimbursement policies, which enhance trust towards voluntary data disclosure and data exploitation (Patti, Dessel and Hartley 2020: 2388). Therefore, the quality of services determines e- consumers' willingness to criticise data harvesting that facilitates free e-consumer data exploitation (Cocq, Gelfgren, Samuelsson and Enborn 2020: 182). From the available studies, no study is particularly focused on the influence of the shopping experience mediated by service quality on e-consumer awareness of free data exploitation.

Furthermore, online service quality encompasses customised products, website friendliness, customer support, and security, which motivate consumer confidence with a high level of self-disclosures associated with e-consumer awareness of free data exploitation (Jaiswal and Singh 2020: 42). Since online shoppers lack visual experience due to the absence of physical contact, online companies try their best to present an enjoyable experience online, which includes a pleasant product assortment on websites and product acquisition speed based on prior browsing behavioural data (Gauri *et al.* 2021: 43). Online firms use this opportunity to harvest data and link it to previous experience, thereby creating new datasets about e-consumer behaviour and lifestyle (Cocq *et al.* 2020: 180). Once online shoppers are offered quality services, they are willing to engage in ongoing self-disclosures, leading to free data resource exploitation.

Also, the quality of the products with a comprehensive assortment gives the online shopper a memorable experience, motivating repurchases from the same online firm, which result in online engagements exploited for future targeting (Ahmed, Samad and Khan 2021: 33). Nevertheless, service quality related to standardisation, product variety, logistical support, cash on delivery, and billing accuracy encourage online shoppers to engage online with e-retailers, prompting free online customer data exploitation (Jain, Gajjar and Shah 2021: 1). In addition, the provision of entertaining gratuities and access to exclusive content alongside special offers depends on prior tracking of online shoppers' data and retargeting a specific archived e-consumer profile to boost sales (Krafft *et al.* 2021: 134). Service quality provides a valuable experience, with a positive attitude towards online deals that facilitate free data resource exploitation, making online shoppers victims of self-disclosures.

By encouraging online shoppers to engage on the online platform by offering gifts and then harvesting online engagements, e-retailers get an opportunity to target online shoppers based on the online engagements (Villanova *et al.* 2021: 127). Online companies also provide motivational gratification, attracting immediate enjoyment tailored towards attracting self-disclosures, leading to free data exploitation envisioned for profitable future predictions (Bidler *et al.* 2020: 508). Surely, gratification using targeted discount offers lures e-consumers to disclose data, which is later exploited to boost sales through retargeting (Lee and Charles 2021: 2). Most online companies focus on value-creating benefits like coupons to create behavioural loyalty; however, loyalty incentives may not necessarily pay back loyalty, but satisfaction ultimately motivates loyalty and repurchase (Mostafa and Kasamani 2021: 1037). Online repurchase due to service quality exposes e-consumers to free data resource exploitation.

Furthermore, technological customer services like chatbots that quickly respond to e-consumer service requests allow the service to handle an enormous caseload, which provides insights that are exploited in predicting demand (Guha, Grewal, Kopalle, Haenlein, Schneider, Jung, Moustafa, Hegde and Hawkins 2021: 29). Clearly, service quality in the digital economy is executed by algorithms that predict e-consumer needs through data monitoring and data exploitation to maximise sales (Ameen *et al.* 2021: 2). Also, the service interface in conjunction with the enjoyable online atmosphere influences the shopping experience, luring online shoppers into self-disclosures and resulting in free data exploitation (Bhattacharya and Srivastava 2020: 802). E-consumers may not be aware that such service offerings can trap them into data disclosure and free data exploitation.

Certainly, the power of algorithm-driven experiences with automated services due to complex tracking of online behaviour provides flexible interactions that assist e-retailers in amending the service quality for a pleasant and stronger brand relationship (Ameen *et al.* 2021: 2). Excellent service quality increases trust due to the outcomes of interactions that allow the stickiness of a single e-retailer to compromise self-disclosure and free data resource exploitation (Qalati *et al.* 2021: 3). Services that instil unforgettable memories with exceptional personal experience are made possible by data tracking and free data exploitation aimed at targeting online shoppers depending on their previous experience (Alfa, Addae, Inkumsah and Amponsah 2021: 4). Essentially, increased e-consumer confidence towards data disclosure depends on the excellence of service quality by matching the product and services to e-consumer needs (Khoa 2021: 589). Therefore, e-consumer awareness of free data exploitation due to the shopping experience mediated by service quality is plausible. Little is known about e-consumer awareness of free data exploitation due to the shopping experience predicted by service quality.

Additionally, the abundancy of browsing behavioural data online companies the ability to sift through data and exploit vital insights in order to operationalise micro-targeting after computational analysis of e-consumers' tastes, enhancing service quality to justify continuous free data exploitation (Airoldi 2021: 97). Service quality is also applied when e-retailers' App components are interconnected with the website, compelling e-consumers to dig for more on the browser, unintentionally falling prey to self-disclosure and data exploitation (Cachero-Martinez and Vazquez-Casielles 2021: 2). The recognition technologies provide a 24-hour service a day, allowing e-consumers curiosity and creativity to enquire and purchase goods and services online using algorithmic technology, retrieving tracked online shoppers' profiles (Anica-popa, Anica-popa, Radulescu and Vrincianu 2021: 122). Notably, in relation to service quality, the influence of shopping experience on e-consumer awareness of free data exploitation has received little attention based on previous studies.

Also, the inbound e-consumer requests are resolved by nudging technology, which deals directly with the online shopper while harvesting data to enact Recommenders that put forward the desired product in real-time, prompting full data disclosure and free data exploitation (Guha *et al.* 2021: 31). The exploitation of e-consumer data, however, enables online firms to identify solutions to improve service quality based on behavioural data as technologies harness direct interactions (Anica-popa *et al.* 2021: 122). The new e-tailing technologies are linked to behavioural tracking, which facilitates a unique and unrepeatable service quality experience enjoyed during each online activity prompting data disclosures and recurring data exploitation (Cachero-Martinez and Vazquez-Casielles 2021: 1). E-consumers seem to be unaware that such service offerings can trap them into data disclosure and free data exploitation.

Furthermore, website portals are so dynamic, with superior interfaces offering a great service quality experience, full of enjoyment with a visually appealing interface guiding navigation, which unwittingly lure e-consumers to disclose data, which is eventually exploited for retargeting (Jaiswal and Singh 2020: 43). It is worth noting that service quality makes online shoppers more comfortable by linking internet shopping to e-consumer free data resource exploitation (Bhat and Darzi 2021: 2). Little is known about whether service quality as a predictor of shopping experience has an influence on online free data exploitation. In the next subsection, behavioural royalty, another factor related to shopping experience, is discussed.

4:5:2 Behavioural loyalty

The TPB guides the prediction of behavioural outcomes that are moderated by attitude (Choi and Park 2020: 3). Behavioural loyalty refers to the activation of a behavioural attitude towards repeat purchases from a particular company, which increases exposure to free data exploitation (Kim, Wang and Roh 2021: 2). Repurchasing is normally due to loyalty behavioural control as a measure of commitment to favourite online retailers who take advantage of behavioural loyalty associated with wilful self-disclosure and free data exploitation (Meilatinova 2021: 3). However, e-consumers' state of loyalty will not remain permanently if the service quality deteriorates, which may limit exposure to free data exploitation (Mostafa and Kasamani 2021: 1038). The relationship between behavioural loyalty and shopping experience on e-consumer awareness of free data exploitation has not been investigated according to the existing literature related to this study.

In some cases, behavioural loyalty is associated with cultural identity when a particular online firm is reflective of cultural power consistent with societal norms, attracting online self-disclosure (Obiegbu, Larsen and Ellis 2020: 258). Moreover, Koncar *et al.* (2021: 2) allude to the fact that behavioural loyalty has to be monitored to analyse the insights reflected from previous experience in order to retain existing confidence rather than acquire new costly customers without prior behavioural loyalty experience. However, contradictory findings from the works of Lee and Charles (2021: 1) emphasise that e-tailing website loyalty does not necessarily mean that online shoppers are not sceptical of repurchasing from the same e-retailer, which may be true due to subjective factors. Normally e-consumers need a positive emotional experience during the purchase journey, invoking a strong bond due to ambient services linked to individual cognitive affection, leading to self-disclosure (Cachero-Martinez and Vazquez-Casielles 2021: 3). The extent of loyalty influences e-consumer awareness of free data resource exploitation, where a high level of loyalty leads e-consumers to ignore issues of data exploitation.

The proliferation of behavioural loyalty experiences is a stage where online shoppers seek greater authenticity, prompting e-consumers into self-disclosures, leading to free data resource exploitation (Obiegbu, Larsen and Ellis 2020: 255). Surely, behavioural loyalty is much more demonstrated once e-consumers have received the service quality they expected, thereby demonstrating disclosure behaviour, leading to free data resource exploitation (Meilatinova 2021: 4). Therefore, on the other hand, behavioural loyalty is mediated by service quality offered by online firms, which in turn provokes self-disclosure, leading to free data resource exploitation without the knowledge of the consumer. Online shoppers might be unaware that their shopping experience due to their loyalty to online companies, exposes them to free data exploitation.

The loyalty experience is maintained by multiple creative strategies that seek to impart value to online shoppers and motivate online shopping associated with free e-consumer data resource exploitation (Lang, Xia and Liu 2021: 226). Consequently, e-retailers observe online shoppers' journeys in a bid to detect and update strategies to reinstate dissatisfied e-consumers behavioural loyalty linked to repurchase and free e-consumer data exploitation (Patti, Dessel and Hartley 2020: 2393). The tracking of e-consumers' purchase journey informs e-retailers that online shoppers deserve loyalty incentives such as targeted discounts that lure e-consumers into free data exploitation (Krafft *et al.* 2021: 135). The survival of online shopping depends highly on behavioural loyalty experiences, which guarantee future use of the internet for shopping and are the source of free e-consumer data exploitation (Koncar *et al.* 2021: 1; Cachero-Martinez and Vazquez-Casielles 2021: 3). Online shoppers get blindfolded by loyalty due to the memorable experience and do not recognise ongoing data monitoring.

Loyal fans congregate on social platforms to express their passion, where the collective structures share experiences of admiration, which tempt online retailers to exploit the free e-consumer materially productive engagements used in targeting (Obiegbu, Larsen and Ellis 2020: 257). Narvanen, Kuusela, Paavola and Sirola (2020: 835) also agree that behavioural loyalty can originate from togetherness identity in a particular community where a familiar retailer identifies with a particular group willing to share data, which is exploited for profitable mass customisation. E-consumers are more interested in a symbolic, memorable shopping experience during the purchase journey than the tangible product, where the focus is on distinctive treats that trigger online shopping, ultimately leading to free data exploitation (Mostafa and Kasamani 2021: 1033). As a function of psychological non-random revisits to the online stores over time, the resultant commitment leads online shoppers to continuous data disclosures that are exploited for future targeting of new products (Sharma and Patra 2021: 131). Therefore, loyalty increases the level of trust, rendering consumers to be more receptive to the favourite online retailer, who harvests the free e-consumer data left online.

Although repurchase intention is usually determined by attitudinal loyalty, actual repurchase is a product of behavioural loyalty experiences linked to free e-consumer data exploitation due to unrelenting online engagements (Jain, Gajjar and Shah 2021: 4). Attitudinal loyalty is a psychological commitment that serves as a prerequisite for behavioural loyalty aimed at repeat patronage that constantly traps loyal online shoppers into free data resource exploitation due to regular online engagements (Obiegbu, Larsen and Ellis 2020: 254). Additionally, emotional attachment to a particular online company is normally due to satisfaction, but satisfaction does not automatically translate into behavioural loyalty. However, the emotional attachment attracts online shopping linked to free data exploitation (Ghorbanzadeh 2021: 2). As behavioural loyalty enhances trust, online shoppers develop strong long-term relationships that eliminate anxiety due to the uncertainties of online shopping, which motivates perpetual online engagements, leading to free data exploitation (Meilatinova 2021: 5). So, behavioural loyalty lures e-consumers to disclose data, which attract free data exploitation.

Behavioural loyalty measures the expression of liking that e-consumers use to recommend the online retailer to other e-consumers, attracting the online retailer to monitor preferences of emotional attachment that are exchanged on social platforms (Obiegbu, Larsen and Ellis 2020: 254). The passion due to behavioural loyalty is impulsive and tempting towards online shopping decisions, which provide access to free e-consumers' data exploited by online retailers (Mostafa and Kasamani 2021: 1038). The feeling of happiness, security, and comfort motivate a lasting relationship with a favourite online company due to behavioural loyalty, leads to online engagements that source free online consumer data resources exploited by e-retailers (Ghorbanzadeh 2021: 8). Behavioural loyalty, as an evaluative process that motivates attitude towards the propensity inclined to patronise a particular online store over time, is thereby developing trust, leading to data disclosure, facilitating free data exploitation (Sharma and Patra 2021: 131). The emotional attachment to a particular online firm overrides any possibility of e-consumer awareness of free data resource exploitation due to loyalty.

Additionally, loyalty intensifies commitment to persist in repurchasing from the same online company without defecting, which allows a free flow of e-consumer data to the favourite e-retailers, predicting future demand (Kim, Wang and Roh 2021: 4). Behavioural loyalty must include a positive attitude towards the online company with a deep commitment to patronise brand purchase consistency despite competitive efforts to switch, which drives cognitive repurchase action, leading to data exploitation (Ghorbanzadeh 2021: 4). Reasonably, shopping experience due to behavioural loyalty may have a relationship with e-consumer awareness of free data resource exploitation. Behavioural loyalty is a lock-in effect where e-consumers become dependent on a single online firm whether it is convenient or secure (Obiegbu, Larsen and Ellis 2020: 254). Mostafa and Kasamani (2021: 1038) argue that e-consumers self-connection to a particular online company is due to behavioural loyalty, which is tempting to the extent of self-disclosure, leading to free data exploitation. But whatever the rationale, the lock-in effect restricts the online shopper, rendering the preferred firm to exploit free e-consumer data.

The intimacy of e-consumers due to behavioural loyalty is sometimes taken for granted by online retailers who manipulate the dependent relation through tracking and free data exploitation for profitable targeting (Obiegbu, Larsen and Ellis 2020: 260). Certainly, while attitudinal loyalty (Ghorbanzadeh 2021: 5) emphasises commitment, behavioural loyalty focuses on online repurchase willingness, which leads to free e-consumer data exploitation. Behavioural loyalty is a reasoned action where e-consumers apply sensible choices by comparing alternatives to optimise satisfaction, where the entire process puts e-consumers in online searching mode, prompting the exploitation of browser data (Narvanen *et al.* 2020: 826). Online shoppers' propensity to resist competing offers due to long-term internal memory characterised by previous experience is capable of building behavioural loyalty (Narvanen *et al.* 2020: 827). Online retailers seek to differentiate themselves with unique experiences, which propel e-consumers towards behavioural loyalty (Sharma and Patra 2021: 131). Online shoppers may unintentionally downplay free data resource exploitation due to online firm equity.

The digitalisation of the e-consumer shopping experience has created value where online shoppers enjoy touchpoints supporting the purchase process while simultaneously harvesting free e-consumer data for future economic predictions (Tyrvainen, Karjaluoto and Saarijarvi 2020: 1). The devotion pertaining to loyalty can be so intense as to even survive scandals or performance issues, and perhaps the concerns of e-consumer awareness of free data resource exploitation (Obiegbu, Larsen and Ellis 2020: 260). Behavioural loyalty is purely emotional, with passion, affection and connection contributing to the manner in which e-consumers deal with e-retailers, often resulting in an imbalance of power favouring e-retailers towards free e-consumer data exploitation (Mostafa and Kasamani 2021: 1038). Certainly, a high degree of loyalty allows online engagements linked to free data exploitation.

Normally, e-consumers satisfaction is derived from the level of service quality fulfilment exceeding expectations, prompting repurchase and exposure to free online shoppers' data for exploitation (Kaurin and Boskonic 2020: 1631). Loyalty remains superficial until online shoppers shop from the same online firm repeatedly without changing, even when the larger corporations deploy marketing power putting e-consumers in a state of online self-disclosure (Obiegbu, Larsen and Ellis 2020: 255). Online shopping experiences are enjoyed from search, purchase and consumption, with greater emphasis on after-sales cognitive-emotional affection strengthening behavioural loyalty, followed by voluntary self-disclosures linked to free data exploitation (Tyrvainen, Karjaluoto and Saarijarvi 2020: 2). Loyalty corners the e-consumer into a vulnerable position of free data resource exploitation by the favourite firm engaging with loyal shoppers. Behavioural loyalty is to some degree related to satisfaction, as discussed in the next sub-section.

4:5:3 E-consumer satisfaction

Meilatinova (2021: 3) define satisfaction as a standard metric of success that indicates how goods and services perform in consideration of the e-consumer expectations. From this definition, it is evident that the level of service quality determines the level of satisfaction, which in turn develops loyalty. Customisation based on the exploitation of free e-consumer data is believed to be instrumental in boosting satisfaction and repeat online sales that increase revenue (Lang, Xia and Liu 2021: 226). Patti, Dessel and Hartley (2020: 2388) articulate that the critical task for online shoppers' value creation according to conventional wisdom relates to improved efficiency, self-service, friendly mobile App, and a linear value chain throughout the e-consumer's purchase journey associated with a trail of free browser data exploited by online firms. Furthermore, online shoppers can be very satisfied if the e-retailer's information is compatible with complete relevant accuracy, enabling online decision-making associated with free e-consumer data exploitation (Kaurin and Boskonic 2020: 1632). A successful shopping experience is associated with satisfaction, keeping e-consumers constantly online without realising the tracking and free data exploitation for targeting.

Online company websites that are carefully designed with the desire to eliminate uncertainties maintain e-consumer satisfaction with full support for self-disclosure linked to free e-consumer data exploitation (Vo, Chovancova and Tri 2021: 503). Also, Meilatinova (2021: 4) agrees that dissatisfaction posits consequences of the shopping experience affecting future online purchases and profitability due to loss of trust by disgruntled e-consumers who disengage from online shopping and exposure to free data exploitation. The website quality is the perceived physical appearance of the online store where the aesthetic features, visual presentation, content flow, and layout impart a warm welcome satisfaction experience that attracts a continuation of online engagements linked to free e-consumer data exploitation (Kaurin and Boskonic 2020: 1632). Against this backdrop, there is scanty research on shopping experiences mediated by satisfaction in relation to e-consumer awareness of free data exploitation.

Online retailers are optimising mobile and internet technology to link offline markets to online markets using mobile location monitoring by directing online shoppers to collect orders from the offline store, which improves trust and satisfaction, leading to self-disclosure (Kim, Wang and Roh 2021: 3). Vo, Chovancova and Tri (2020: 500) allude to the fact that website quality induces e-consumer satisfaction in the form of guiding information, interface, and interconnectivity, attracting online shoppers to search deeper, thereby leaving a trail of free data for exploitation to predict demand. Again, if the website is secure in protecting personal data, e-consumers become satisfied with the credibility of the authentic website protection, thereby encouraging online participation linked to free e-consumer data exploitation (Kaurin and Boskonic 2020: 1632). Reitsamer and Brunner-Sperdin (2021: 291) affirm that online retailers who fulfil their promises gain e-consumer confidence with an unforgettable satisfaction experience. Eventually, due to satisfaction, e-consumers are locked into a continuous cycle of online shopping, facilitating free data exploitation.

On the other hand, Vasic, Kilibarda andrejic and Jovic (2020: 2) argue that satisfaction starts with the availability of relevant information on the e-retailer’s website, the quality of the website, and the cost of shopping online, which predict subsequent satisfaction experiences and the possibility of further data disclosures facilitating free data exploitation. Online quality information guides online shoppers to avoid shopping unnecessarily due to useless feedback. Furthermore e-consumer satisfaction imparted by intrinsic quality information which attracts free e-consumer data exploitation for economic predictions prevents regrettable purchases (Kim, Wang and Roh 2021: 4). Easy navigation, flexibility, reliable responsiveness, and efficiency propel e-consumers to reveal massive browsing behavioural data trailed to make profitable company predictions (Kaurin and Boskonic 2020: 1631). Notably, it can be argued that satisfaction makes e-consumers downplay free data exploitation or that e-consumers are unaware that the shopping experiences mediated by satisfaction prompt them to self-disclosures linked to free data exploitation.

The functionality of the e-retailer website encourages page revisits that are monitored and exploited by e-retailers, who configure the revisit interactivities for retargeting based on preferences (Vo, Chovancova and Tri 2021: 502). Vasic *et al.* (2020: 2) articulate that practical logistical support and reliable communication positively impact e-consumer satisfaction, instilling loyalty, which increases the possibility of repurchas- ing due to prior satisfaction, leading to the online data exploitation of satisfied online shoppers for retargeting. E-consumers expect utilitarian or functional benefits related to efficiency with precision technology, which satisfies immediate needs, thereby attracting self-disclosure and free data exploitation (Riegger *et al.* 2021: 142). Additionally, a high level of convenience minimises the time spent on online shopping activities such as enquiry, order, payment, and delivery, which add value to the e-consumer satisfaction experience (Kim, Wang and Roh 2021: 4). Therefore, satisfaction experiences motivate the free flow of e-consumer data to e-retailers who exploit it for retargeting.

Product quality with accurate functionality is a major determinant of satisfaction in the shopping experience, allowing e-consumers to repurchase online, which can be compared with previous e-consumer data monitoring to predict demand (Vasic *et al.* 2020: 3). The reliability of e-retailers from order processing to actual delivery guarantees fulfilment, as does the willingness of e-consumer data disclosure, which inadvertently traps online shoppers into free e-consumer data exploitation (Kaurin and

Boskonic 2020: 1632). E-consumer satisfaction experiences ultimately tempt online shoppers to spread electronic word-of-mouth, requiring e-retailers to harvest vital insights that are used to match product offers to the needs of online shoppers (Meilatinova 2020: 2). E-consumer satisfaction experience is a subjective evaluation that encourages online shoppers to return or post comments recommending their favourite online company, which in turn exploits the online data trail to strengthen the marketing strategy (Vo, Chovancova and Tri 2021: 502). Thus, online shoppers' satisfaction is the positive evaluation of their shopping experience, which drives retention and emotional bonds that enhance trust, thereby exposing the satisfied to free data exploitation facilitated by recurring online engagements.

Consequently, the monitoring of online shoppers assists online firms in identifying dissatisfied e-consumers by detecting situations that require revising the present strategy using predictive technology (Anica-popa *et al.* 2020: 1631). Furthermore, there is greater e-consumer satisfaction evoked by e-retailers' innovation in creating self-association with products that match e-consumers' preferences provoking the repurchase decisions, resulting in free e-consumer data exploitation (Riegger *et al.* 2021: 142). The e-consumers' satisfaction experience is recognised with the speed, convenience and quality of the product, making online shoppers' regular customers, thereby increasing the possibility of free e-consumer data exploitation (Kaurin and Boskonic 2020: 1631). Therefore, the vital question of whether the shopping experiences mediated by satisfaction influence e-consumer awareness of free data resource exploitation is not fully answered based on available studies. It is necessary to discuss the influence of behavioural monitoring on e-consumers' awareness of free data exploitation in relation to the shopping experience. The behavioural monitoring factor is discussed in the next sub-section.

4:5:4 Behavioural monitoring experience

The shopping experience mediated by behavioural monitoring starts with pre-purchase product search and then continues up to the post-purchase stage enabling the online firm's ability to make sense of useful insights about the unsuspecting online shoppers in order to effect innovation (Nam and Kannan 2020: 28). The new online shopping experience referred to as the behavioural monitoring experience has surfaced due to the exponential growth of digital technology, where the monitoring of granular identities of online shoppers is suitable for recommending the right product and price (Guha *et al.* 2021: 33). The predictions of relevant product needs recommended by algorithms during online shopping present a pleasant behavioural monitoring experience (Mican, Sitar-Taut and Moisescu 2020: 2). The right product automatically endorsed during online shopping makes online shoppers inadvertently provide free data exploited for profitable predictions benefiting retailers. E-consumers might be aware that shopping experiences mediated by behavioural monitoring have an influence on free e-consumer data exploitation.

The matching of routine operations in line with adjusted autonomous cookies and configuring e-consumer profiles is assisted by behavioural monitoring experience, which facilitate the shopper's convenience (Cochoy *et al.* 2020: 5). Notably, the behavioural monitoring experience is enjoyable to the extent that online shoppers get good deals at lower prices (Moran 2020: 894). While evaluating alternatives during online information searches, e-retailers' algorithms distinguish utilitarian motives from hedonic motives, thereby reducing information overload by upscaling product choices based on the search criteria (Nam and Kannan 2020: 29). During behavioural monitoring experiences, decision support systems identify the preferences of online shoppers and give feedback with precision and accuracy that excites e-consumers (Mican, Sitar-Taut and Moisescu 2020: 3). Sometimes e-consumers continue shopping online without noticing the embedded free data exploitation for targeting.

Collecting data from shoppers, dates back to the 1800s, but the current behavioural monitoring experience crystallises the granularity of e-consumer behavioural data, which exposes the digital identity of searchable innocent e-consumers whose data is exploited for free for targeting (Krafft *et al.* 2021: 134). During the online shopping journey, e-consumers experience behavioural monitoring, which guides online shoppers in selecting choices proposed by tracking algorithms and saves them search costs (Guha *et al.* 2021: 34). However, when online shoppers notice that they are being monitored while executing online transactions, they tend to react negatively towards the behavioural monitoring experience, which may affect business relationships with e-consumers (Nam and Kannan 2020: 28). Thus, while shopping online, unsuspecting e-consumers are faced with behavioural monitoring technology that harvests consumer data exploited by online retailers for profitable predictions.

Behavioural monitoring experience considers the attitude of online shoppers towards data monitoring, which to some extent plays a role in perceived usefulness due to its personalised benefits (Mican, Sitar-Taut and Moisescu 2020: 3). Behavioural monitoring experience demarcates the pathway to optimise online shopping by perfectly matching prior behavioural monitoring experience to the present experience, directing online shoppers to the right product in a split second (Cochoy *et al.* 2020: 5). Consequently, behavioural monitoring experiences during the post-purchase stage provide useful interactions about consumption experiences through the posting of reviews, which help e-retailers to improve and motivate online shoppers (Nam and Kannan 2020: 29).

With the behavioural monitoring experience, online shoppers get trendy products, bestselling brands, and top-of-the range product popups, which are enabled by free e-consumer data exploitation without the awareness of the shopper (Mican, Sitar-Taut and Moisescu 2020: 3). The behavioural monitoring experience during pre-online purchase provides relevant and suitable content that reduces uncertainty by ensuring credibility, which builds trust to order and pay with confidence (Nam and Kannan 2020: 29). However, in the past, e-consumers were completely unaware of behavioural monitoring, but in recent years, online shoppers have raised concerns while others have appreciated the experience (Mican, Sitar-Taut and Moisescu 2020: 3). Therefore, from the existing studies, it can be inferred that no studies have dedicated full attention to the influence of shopping experiences mediated by behavioural monitoring on e-consumer awareness of free data resource exploitation.

As online shoppers familiarise themselves with the behavioural monitoring experience, they express concerns about discomfort of being watched and grouped into caricature-like profiles to anticipate their desires to drive a profitable consumption

force (Cochoy *et al.* 2020: 5). Even if online shoppers are becoming aware of the behavioural monitoring experience, to some extent, e-retailer monitoring activity is providing online shoppers the opportunity to enjoy the monitoring experience without realising their free data resources are being exploited for marketing purposes (Krafft *et al.* 2021: 138). The behavioural monitoring experience is enjoyable when online shoppers get the right product in real-time; however, behavioural monitoring is discriminatory based on browsing habits, thereby promoting inequality (Moran 2020: 893). Behavioural monitoring experience is so powerful to an extent that it can change the shopping context of online shoppers as they become exposed to a variety of unknown products matched to their browsing habits without the e-consumers' knowledge (Moran 2020: 891). Certainly, a shopping experience mediated by behavioural monitoring is a recipe to exploit innocent e-consumers using algorithms that discriminate on the basis of search criteria, controlling e-consumers towards specific purchases.

High-technology inherently involved in e-tailing is embedded in shopping websites with the ability to monitor e-consumers while conducting online shopping, which has led to a new online shopping experience referred to as behavioural monitoring (Guha *et al.* 2021: 28). In other words, the behavioural monitoring experience is often embedded in hidden manipulative persuasion cues that pressure online shoppers to develop purchase decisions and stay permanently as patrons of the online firms (Moran 2020: 896). The behavioural monitoring experience is noticed as consumer preferences are automatically generated by algorithms, but from the available studies, e-consumer awareness of free data exploitation facilitated by browsing behavioural monitoring is unknown. In a nutshell, the digital culture encompasses e-consumer behavioural intentions and online experience. The remediation strategies based on e-consumer awareness of the effects of data exploitation influenced by risks, trust, intentions and experience are briefly expounded in the next section.

4:6 REMEDIATION STRATEGIES

The current study suggests two remediation strategies based on e-consumer digital culture, and these strategies include e-consumer empowerment and e-consumer data optimisation. Notably, e-consumer empowerment seeks to strengthen the relationship between online firms and e-consumers in a data-driven digital economy. Surely the ownership of data is the starting point to negotiate the terms of data exchange for those with an explicit mandate over the ownership, which is crucial for e-consumer empowerment (Krafft *et al.* 2021: 134). E-consumer data optimisation is suggested on the premise of full utilisation of e-consumer data to balance the benefits of online companies and online shoppers on e-consumer data usage. Therefore, the strategies are intended to build the balance of power between e-consumers and online firms in order to eliminate the phenomenon of free e-consumer data exploitation favouring online firms and establish long-term harmony by allowing valued self-disclosures and online firms profiting from disclosures. E-consumer empowerment is briefly explained in the next sub-section.

4:6:1 E-consumer empowerment

Online companies invest in generating e-consumer data, which entitles them to claim implied control (Pangrazio and Selwyn 2019: 421). In the current digital era, data is a very important asset with increasing value explosion requiring digital strategies to assign data ownership to its producers as quickly as possible (Jin, Ma and Ye 2020: 79). Online firms use an Application Programming Interface (API) capable of accessing online shoppers' data, leaving a deficit of e-consumers to catch up with the benefits of data disclosures (Pangrazio and Selwyn 2019: 422). Online firms deliberately use technology to mislead online shoppers by creating an illusion of control and ensuring e-consumer security (Draper and Turow 2019: 1830). The unprecedented control over unsuspecting online shoppers provides irresistible free access to e-consumer data exploited by online firms for financial advantage (Moran 2020: 891). Nevertheless, individuals whose actions accumulate this data reservoir always have little control and are unaware of the harvest of their data input for profitable predictions. Notably, no studies have illuminated e-consumer awareness of free data resource exploitation to suggest remediation strategies for future study.

The concept of digital citizenship states that individual ability to participate on the online platform requires digital citizens to be educated about the implications of digitalisation, where digital participation is not possible without data sharing (Lutz, Hoffmann and Ranzini 2020: 1169). The study conducted in America found that individuals are willing to share personal data provided that there is an economic benefit (Li, Liu and Motiwalla 2021: 396). Digital consumerism is compelling online shoppers to disclose data with a materiality belief of the benefits of online shopping, which has trapped shoppers into free data resource exploitation for profitable predictions through precise targeting (Lutz, Hoffmann and Ranzini 2020: 1172). Developing data literacies is becoming a popular public campaign to break the black box of e-consumer free data resource exploitation in the proliferation of the data-driven digital economy (Pangrazio and Selwyn 2019: 432). E-consumers deserve to be aware of the value of their data input in the development of e-commerce business relations with online firms in the digital world.

Lutz, Hoffmann and Ranzini (2020: 1169) argue that, as online shoppers are become aware of free data resource exploitation, they feel a sense of powerlessness, ultimately rendering them to digital resignation, which means giving up personal data control. The feeling of digital resignation is due to the perception that free data resource exploitation is unavoidable in the data-driven digital economy. For example, 58% of Americans accept that they have no control over their online data and contemplate a trade-off of their data for compensation (Draper and Turow 2019: 1826). The findings in a study conducted by Gomez-Barroso (2021: 538) indicate that individuals are willing to engage in full self-disclosures provided that they are assured of monetary compensation for their input. The return for e-consumer exchange of valuable data is an ongoing debate as the proponents of e-consumer empowerment advocate for e-consumer willingness to disclose data to be determined by economic value to barter with online firms (Krafft *et al.* 2021: 139). As online companies shift towards digital transformation in the data-driven economy, there is a need to balance optimising e-consumer data and empowering e-consumers as the producers of data, which facilitates profitable predictions.

Auctioning data requires specific ownership to guide the appropriate measure of value depending on self-disclosure willingness in exchange for compensation (Li, Liu, Motiwalla 2021: 394). The danger of collective anger with civic action due to free data resource exploitation is eminent in the foreseeable future, which calls for urgent remediation strategies of mutual benefit among e-consumers and online companies (Draper and Turow 2019: 1829). Additionally, the growing e-consumer awareness of free data exploitation can produce detrimental repercussions related to e-consumer defection and e-consumer terrorism through negative word-of-mouth (Krafft *et al.* 2021: 140). Monetary compensation for e-consumer data resources usage for predicting demand is ideal to even encourage full, authentic disclosure that can boost the predictive power to generate revenue.

It is clear that online firms use online shoppers' data value in a relatively more beneficial way to the company, but recent scholars are unsure whether there might be a conflict of data ownership in future (Jin, Ma and Ye 2020:85). As data has become a digital asset generating enormous revenue in the data-driven digital economy, the issue of empowering the producers of data as a raw material for prediction is becoming organisational priority (Yablonsky 2020:4). To settle the issues of data ownership, it is important to identify the actual origins of the data, which is generated individually, where collective data can complicate the commercial ontology of data exchange, calling for another logic of data commercialisation (Concilio *et al.* 2021: 42). Online retailers ought to be more transparent about e-consumer data harvesting conducted without the awareness of the data producers.

Monetary compensation, loyalty programmes and tangible rewards are viewed as having a substantial impact on the probability of e-consumers disclosing data rather than relying on the naiveté of e-consumers regarding free data exploitation (Krafft *et al.* 2021: 134). The economic value of e-consumer data has sparked a discussion about whether e-consumer data should be exchanged like a commodity due to the fact that data is now worth billions of dollars (Li, Liu and Motiwalla 2021: 394). Once individuals are able to critique free data resource exploitation, they are likely to act aggressively against the implications of monitoring and profiling to facilitate free data resource exploitation (Pangrazio and Selwyn 2019: 430). So, to avoid tension and e-consumer terrorism due to free data resource exploitation, e-consumers ought to be rewarded rather than using the frequently adopted crude strategy, which restricts web page access by requiring prior registrations that permit free data resource exploitation (Gomez-Barroso 2021: 539). Therefore, it is important to empower online shoppers in order to optimally utilise e-consumer data in consideration of mutual benefit without conflict. In the next sub-section, e-consumer data optimisation is discussed.

4:6:2 E-consumer data optimisation

Krafft *et al.* (2021: 134) warn that the free harvesting of data from online shoppers to facilitate profitable predictions through precise targeting not only poses a challenge of privacy issues but also a feeling of powerlessness among online shoppers, as noted in the previous sub-section. Online firms that embark on e-consumer data optimisation ensure that online shoppers accept the technology of algorithms enabling customer services by clearly informing shoppers of the benefits of behavioural monitoring (Ameen *et al.* 2021: 3). Concilio *et al.* (2021: 4) caution that interpreting the continuous flow of large amounts of e-consumer data in real-time requires a change in methodological approaches using non-human intervention like algorithms. A remediation action to optimise e-consumer data is paramount based on the level of e-consumer awareness of free data resource exploitation and going forward to create straight-forward awareness to negotiate compensation in exchange for data optimisation.

In the era of digital transformation, managers are emphasising digital prowess with end-to-end integration with e-retailer App on smart devices of e-consumers and advanced real-time analytics using click, collect, and analyse systems (Bonnet and Westerman 2021: 87). The digital interactions between online shoppers and the online firms are monitored using mobile App technology, which e-consumers find strange when e-retailer's websites activate online purchase wishes based on e-consumers' prior purchase intentions on the browser (Guha *et al.* 2021: 32). Online companies follow systematic strategies using organisational skills to create mutually beneficial relationships with online shoppers in order to gain access to valuable data insights for competitive advantage (Krafft *et al.* 2021: 140). In order to optimise e-consumer data, online companies are innovating numerous technical services that are highly valued by online shoppers, which prompt voluntary disclosures (Gauri *et al.* 2021: 42). Harvesting e-consumer data may be optimised by intensifying analytical skills with problem-solving decision capabilities based on the abundant granular data by separating relevant data from the massive chaff.

Online companies are tasked with proving that e-consumer data harvesting is beneficial to online shoppers navigating endless streams of web pages (Lomborg and Kapsch 2020: 753). Effective utilisation of technology for data analytics speeds up strategy cycles, which sustain fast e-consumer expectations and the potential for increased satisfaction in building customer relationships (Ameen *et al.* 2021: 1). On the other hand, quality products and services, enhancing the shopping experience are crucial in luring authentic self-disclosures that are useful in optimising and informing online shoppers how their data contributed to providing these quality products and services (Gauri *et al.* 2021: 50). To improve the shopping experience by reaching a more satisfying experience, online firms require collaboration with other online firms with similar e-consumers, like travel and hospitality companies, making it convenient for travellers to access discount hotels, which increases the willingness towards self-disclosure (Krafft *et al.* 2021: 141). Increased awareness about the value of data and its intended use can compromise e-consumers' willingness to provide relevant data for economic predictions

Once online shoppers are compensated for their data input, they tend to downplay data disclosure controls due to the belief that online companies have co-ownership rights to e-consumer data, rendering online firms strict when using data for only personalised services (Zhu and Kanjanamekanant 2021: 3). Due to the fact that online shoppers interact with unfamiliar online companies, e-consumer data optimisation can be achieved by ensuring a multitude of ethical standards relating to security, privacy, and fulfilment which motivate trust (Lee and Charles 2021: 1). Some online companies lure online shoppers to reveal data by offering electronic coupons that prompt redemptions that lead to data disclosures (Ren *et al.* 2021: 1). If online firms opt for monetary compensation to combat free data exploitation, efforts must be intensified to optimise e-consumer data in order to recoup the expenses (Krafft *et al.* 2021: 134). Based on the available literature, technology in the data-driven economy has made online shoppers searchable and identifiable, enabling online companies to optimise e-consumer data usage. E-consumer awareness is paramount in order to suggest mutually beneficial remediation strategies to mitigate free e-consumer data exploitation, as reflected in the subsequent section pertaining to the conclusion.

4:7 CONCLUSION

This chapter aimed to discuss the remediation of free data exploitation from a broad perspective before focusing on the South African context. Specific issues discussed in the chapter include purchase intention and the shopping experience. The chapter further indicated that there are still significant challenges besetting the remediation of free data exploitation. Purchase intention and shopping experience, among the main components of the digital culture, have some degree of influence on e-consumer awareness of free data resource exploitation. Based on previous research, online shoppers enjoying a memorable shopping experience are most likely to develop purchase intentions repetitively, thereby getting exposed to free data exploitation. It is worth noting that a consumer's behavioural intentions are used as a starting point in navigating the e-consumer purchase journey, which inadvertently involves product information searches, leaving a trail of free data to be exploited by online companies. The challenges include e-consumer empowerment and data optimisation. Having set the purchase intentions and shopping experience context, the next chapter focuses on discussing the research methodology to expand our knowledge of the phenomena.

CHAPTER 5. RESEARCH METHODOLOGY

5:1 INTRODUCTION

The preceding chapter of the study wrapped up the final part of the literature review concerning e-consumer awareness of free data resource exploitation. This chapter discusses the selection of a suitable research methodology for this study. A methodology, which is a major part of research is defined by McGregor (2019: 216) as the creation of knowledge using methods that include sampling, measuring instrument, data collection and analysis. The chapter has 12 sections. After the introduction in Section 5.1, the digital phenomenon pertaining to this study is discussed in Section 5.2 in order to account for the appropriate design in Section 5.3, which can be replicated. Then a detailed research design is discussed, starting with the logic of inquiry followed by the research paradigm. In Section 5.4, the mixed methods approach is subsequently elaborated in terms of typology, shortcomings and rationale. Also, the hypotheses are developed in Section 5.5 followed by the study population and the sample in Sections 5.6 and 5.7 respectively. Additionally, the online survey in Section 5.8 and interviews in Section 5.9 are discussed. Data analysis in Section 5.10 is followed by research ethics in Section 5.11 and Section 5.12 ends the chapter with the conclusion. In the next section, the digital phenomenon of the study is discussed.

5:2 DIGITAL PHENOMENON

In navigating websites to make a purchase, online retailers check through the search behaviour and collect free digital traces using Internet Protocol (IP) to target shoppers with personalised offers, which generate substantial revenue (Quinton and Reynolds 2018: 127). The aim of this study is to assess e-consumer awareness of free data resource exploitation in a bid to establish remediation strategies that may trade-off between e-consumer empowerment and e-consumer data optimisation. Therefore, the digital phenomenon of this study is about digital traces in the form of browsing behaviour that companies aggregate, filter and exploit (Rasmussen 2017:51) for profitable decision-making. Contemporary socio-technological aspects in the digital environment link technologies to social processes and act as agents for social transformation (Fielding 2018:12). The research design discussed in the next section is related to the digital phenomenon of this study.

5:3 RESEARCH DESIGN

The research design is an overarching plan of research depending on the aim of the study and involves sampling, measurement and data collection and analysis (Gray 2018: 132). A research design is a guide for the study supported by logic linked to the logistics of the research to enable the answering of the research questions based on approved methods that can generate data guided by a plan (McGregor 2019:211). A research design is about a careful and constructive connection between the purpose of the study and the appropriate strategies to implement the research project (Creamer 2018: 60). This study employed a mixed method approach. The mixed method research combines techniques, approaches and concepts into a single study, indicating the purpose of mixing at all levels of integration (Molina-Azorin 2019: 105). Morse, Cheek and Clark (2018: 21) allude to the fact that mixed method design must prove that two data sets combined add value to the study, and the conclusions must expand beyond one single approach.

For the quantitative strand in this mixed methods study, online surveys were used because they are becoming popular and less prone to social desirability common than face-to-face studies where the participants' responses are influenced by the appearance of the researcher (Gray 2018: 244). Also, probability sampling is not possible when using internet-mediated research (IMR) due to the lack of a central register for internet users from which to draw the sample frame (Hewson, 2017: 67). A sample of 400 online shoppers out of Durban's online shoppers' population was selected using convenience sampling depending on the population characteristics (Wagner and Gillespie 2019: 34). A five-point Likert scale is used for the quantitative data collection tool (Rosenberg and Silva 2018: 144).

While a method is a mode of inquiry according to techniques and procedures presented in a logical order, a methodology connotes the philosophy underpinning the research design as a plan before the creation of new knowledge (McGregor 2019: 209). Also, the measurement of reliability considers internal consistence, where the scale has to measure the same thing as ensured by Cronbach's acceptable alpha of

0.70 or greater (York 2020: 321). The factor analysis technique was used to ascertain the validity of the questionnaire by demonstrating that multi-item scales belong in one group and are different from other group scales (Dawson 2018: 32).

Brinkmann and Kvale (2018: 118) allude to the fact that qualitative research is often inductive since participants are approached without preconceived ideas, unlike quantitative deductive logic with testable hypotheses based on theory. Induction seeks to justify explanations depending on the accumulation of data on a particular situation, and deductive explanations seek to justify a general statement about the situation; therefore, both deduction and induction in the form of abduction were adopted in this mixed method study (Gibbs 2018: 6). In the qualitative strand, interviews were conducted with online retailers because retailing is the gateway to data exploitation. Phenomenological interview research with semi-structured open-ended questions provides thick descriptions of experience, although interviews are difficult to replicate (Gray 2018: 31).

Furthermore, this study is cross-sectional. Cross-sectional studies are observations at one point that represent a slice of a particular population, and once cross-sectional studies are repeated over time from the same target population and sample, the study becomes a longitudinal cohort (Wagner and Gillespie 2019: 6). Cross-sectional studies use a large sample to take a snapshot of data related to the subjects at a single point in time nlike longitudinal studies that gather data at different points in time, which is time-consuming and costly (Thomas 2017: 176). Cross-sectional research is not expensive, and the sample is easier to conduct, but the respondents differ over time (Wagner and Gillespie 2019:8).

In the quantitative strand, SPSS was used for the following procedures: reliability test, factor analysis, correlation coefficients, t-tests, ANOVA, regression and multivariate analysis of variance (Courtney 2018: 1582). Also, structural equation modelling (SEM) was used to confirm whether the data fits the hypothesised model. SEM path analysis allows for the testing of the direct and indirect effects of variables at the same time based on the causal relationship of the hypothesis unlike multiple regression analysis, which attends to one dependent variable at a time (Ma and Shek 2018: 1629).

NVivo selected for the qualitative strand is linked to the Qualitative Data Analysis Software (QDAS), which deals with nonnumerical data but integrates with quantitative software tools, making it ideal for a mixed methods approach (Davidson 2018: 1167). Smart PLS software is used in SEM analyses due to its superior graphical interface and ability to handle and deal with variables that cannot be directly measured (Ma and Shek 2018: 1626). However, since Amos is more advanced than Smart PLS, this study used Amos to test the proposed model (Tan-lei and Lin 2018: 83). In the next section, deductive and inductive reasoning is discussed.

5:3:1 Deductive and Inductive logic

Since the study used a mixed method approach, both deductive and inductive reasoning were important for this research project, with deduction being used in the quantitative strand and abduction by combining deductive and inductive reasoning in the qualitative strand. Abduction considers both deduction and induction in such a way that the researcher identifies the data that supports the theory and also recognises surprise data, which calls for modification of the pre-existing theory (Kennedy 2018: 52). Selecting a research paradigm can be linked to deductive or inductive reasoning. So, the research paradigms are discussed in the next section to strengthen the decision reached on the appropriate paradigm.

5:3:2 Research paradigms

A paradigm is the acceptable explanation of patterns of belief that assist individuals in understanding the world, irrespective of whether they are researchers or not (McGregor 2019: 27). Academically, a paradigm is a system of beliefs or philosophical assumptions that influence the practices of the entire research process (Doyle, Brady, and Byrne 2019: 4). Quantitative research uses statistical evidence, which has the ability to formulate policy decisions that can be generalised, thereby establishing informed strategies (McCusker and Gunaydin 2019: 8). Moreover, quantitative research is judged by replicability and generalisability based on a standard set of structured procedures, whereas qualitative research is specific to the credibility and authenticity of the results (Quinton and Reynolds 2018: 22). The fundamental argument relating to the appropriateness of a paradigm lies within epistemology and ontology centred around truth, causation, and generalisation in that the ontology of positivism is one reality, constructivism as multiple constructed realities, and pragmatism emphasising a single reality alongside individual interpretation of reality (Mertens 2018: 11). Based on the strengths of both traditional paradigms, a combination of both paradigms is ideal for this study to gain in-depth findings from different perspectives, which embrace the mixed methods approach discussed in the next section.

5:4 MIXED METHODS

Although mixed methods were recognised in the late twentieth century, the practice of mixing methods is not new due to the challenge of sharply drawing distinctive divisions between quantitative and qualitative approaches (Bazeley 2018: 3). Integrating quantitative and qualitative methods started in the 1970s, but the actual mixing started way back in time for natural scientists, although it was never addressed as a mixed method (Maxwell 2018: 3). Unlike in the past, where quantitative and qualitative traditions were treated as polar opposites, today the paradigms are treated as a continuum and not a dichotomy, paving the way for a new method that allows data collection and analysis, and drawing conclusions using both quantitative and qualitative approaches in a single study (DeCuir-Gunby and Schutz 2018: 2).

Mertens (2018: 14) recognises Guba and Lincoln as the pioneer proponents of mixed methods in 1989, arguing that quantitative data can support qualitative interpretive evaluation on the basis that qualitative research is also suitable to substantiate causal claims. Nevertheless, both quantitative and qualitative approaches contribute to the study in such a way that causal pathways contribute to regularities assessed through statistical analysis, whereas context mechanisms are described by qualitative pathways with data complementing each other (Bazeley 2018: 10). Pragmatic philosophers argue that quantitative and qualitative methods are distinct but can be commensurate with knowledge production with shared meaning (Doyle, Brady, and Byrne 2019: 4). Depending on the research questions, the qualitative stance can be mixed with the quantitative stance by selecting the suitable research questions that are concomitant with a particular stance. There are several ways in which quantitative and qualitative approaches can be blended, as reflected in the next sub-section.

5:4:1 Mixed method typologies

Normally, the order of mixing is sequential or concurrent, where inferences are integrated, unlike parallel designs, which require separate inferences, while conversion design change data from numbers to words and vice versa, but this study is learning towards a sequential typology (McGregor 2019: 279). Several emerging mixed method design typologies may be confusing to novice and experienced researchers, with explanatory sequential, convergent, and exploratory sequential as the main typologies from which mixed methods researchers normally select based on the research question (Doyle, Brady and Byrne 2019: 5). While parallel designs are done independently, explanatory sequential designs present a temporal ordering where the theory underlying the study is known to allow the quantitative strand to be conducted first (Harbers and Ingram 2020: 1126). Sequential design applies when each approach is considered at different times, unlike concurrent design, which is conducted simultaneously, but both can be explanatory based on theory or exploratory depending on the availability of construct theory (Layder 2019: 51).

DeCuir-Gunby and Schutz (2018: 2) are of the view that mixed methods begin at the stage of theory development in connection with the intended inquiry into worldviews. The exploratory sequential design starts with qualitative strand to build the quantitative study through the development of the measuring tool in the absence of the ideal instrument for the quantitative phase and the indecision on the theory for the unknown variables (Doyle, Brady, and Byrne 2019: 7). The explanatory sequential design was used in this study, where a large quantitative strand dominates the first phase, followed by a small qualitative strand. Mixed methods research considers timing, priority and mixing, where most researchers give priority to quantitative research while others favour qualitative research or equal priority, of which timing is essential based on priority (Creamer 2018: 62). The shortcomings of mixed study are discussed next.

5:4:2 Shortcomings of mixed methods

The disadvantages of the mixed-methods design are that it requires a lot of time, effort, and resources to gain broader skills in research (Molina-Azorin 2019:105). Certainly, mixed methods researchers condemn the rhetorical logic that one strand of data is principally collected to support analysis of the other strand of data, which reduces mixed methods design to mere analytical arguments (McGregor 2019:212). DeCuir-Gunby and Schutz (2018: 5) caution that researchers proposing a mixed study should account for extensive research skills in quantitative and qualitative procedures with confidence because mixed methods are time-consuming, requiring double data collection methods, transcription, coding, statistical analysis and data transformation, which require realistic planning. Therefore, formulating different qualitative and quantitative questions, which are inherently mixed from the onset with one connecting point allowing one phase to fit into the other, is a challenge (Doyle, Brady and Byrne 2019: 11)

Furthermore, combining methods creates tension due to the fact that quantitative methods are linked to positivist philosophy while qualitative methods are associated with interpretivist principles. Bazeley (2018: 12) argues that theoretical backgrounds required by positivists manipulate what is being studied. Also, differences in philosophical assumptions between positivists and constructivists sparked paradigm wars in the 1970s to the 1990s, arguing that the two paradigms cannot be mixed due to their inherent differences in philosophical assumptions of ontology and epistemology (Doyle, Brady and Byrne 2019: 4).

The use of mixed methods is a controversy due to conflicting paradigms and the perception that qualitative methods play an auxiliary role to the superior quantitative research (Brinkmann and Kvale 2018:50). One should not simultaneously assume a single universal absolute reality proven by standard measures and also assume that reality is constructed subjectively with no absolute truth (Bazeley 2018: 13). However, the mixed-methods design can be justified, as reflected in the next sub-section.

5:4:3 Mixed methods rationale

Doyle, Brady and Byrne (2019: 3) propound that the research question is a major determinant of using a mixed method design where qualitative or quantitative is insufficient. Phenomenological research questions are sometimes best answered by integrating quantitative and qualitative approaches because a research question reflects a certain philosophy that dictates the methodology (McGregor 2019: 276). Mixed methods research allows multiple strategies to reconcile approaches with openness and inclusiveness by not reducing social reality to a single dimension reached in the quantitative phase (Layder 2019: 57). However, Creamer (2018: 174) warns that the mixed methods research challenge is about the tendency for researchers to simply collect and analyse multiple data sets without merging the two data sets in a meaningful, integrated way.

Bazeley (2018: 5) treats mixed methods as studies that blend multiple data sources using multiple approaches and integrating analysis, leading to a strong collaborative conclusion of the negotiated account. Mixed methods provide a wider understanding of the problem, where triangulation of methods strengthens the research output with validity (Molina- Azorin 2019: 106). Social science scholars have realised that human behaviour cannot fully be understood using positivism suitable for the natural sciences and that humans have qualitative differences shaped by motives, thinking and reasoned actions (McGregor 2019: 36). Since this study relates to social sciences about e-consumer online interactions, the quantitative stance can be supplemented by the qualitative stance to give a strong collaborative conclusion on a negotiated account.

A mixed methods approach is ideal for dealing with complex questions in a complex real world where there are multiple ways of understanding reality to discover new knowledge (Bazeley 2018: 2). The justification for mixed methods is that inferences are stronger in enhancing confidence due to the multiplicity of evidence from different sources providing a comprehensive illumination of the topic, which may initiate new paradoxical insights (Bazeley 2018: 9). A greater diversity of views can reveal unexplainable findings that can be best investigated using a different approach from the initial one with insufficient explanations (Molina-Azorin 2019:107).

The strengths and limitations of qualitative and quantitative approaches force the decision to combine these two approaches, as quantitative answers what or how much, while qualitative answers the how or why questions (Maxwell 2018: 3). Scholars indicate that complementarity through triangulation enables researchers to mix methods that can produce validated findings (Doyle, Brady and Byrne 2019: 3). Therefore, a mixed methods approach was used in this study. In the next section, the development of hypotheses for the quantitative strand is explained.

5:5 HYPOTHESES DEVELOPMENT

The scientific method of positivist philosophy believes in an objective reality obtained by applying hypothesis tests, which start with a statement of no difference (null hypothesis) that can be maintained or rejected based on the evidence from the sample data (Dawson 2018:3). Due to the possibility of errors, researchers propose that nothing is happening, and that any relationship is due to error until a significant result proves otherwise (Patten and Newhart 2018: 228). The hypotheses are generated propositions that are empirically tested starting with a negative expression that can be nullified in favour of an alternative proposition depending on the level of significance of the observed data (Polonsky and Waller 2021: 225).

The null hypothesis, which is a statement suggesting no difference, is stated in the opposite direction of relationships that may be rejected in favour of the alternative hypothesis using scientific tests of reality measures that are observable (Wagner and Gillespie 2019: 3). A hypothesis refers to the anticipated outcome, usually stated in reverse effect, termed the null hypothesis *(H_o)* upon which the alternative hypothesis *(H_1)* assumes that something real is happening, and the null hypothesis is false (Knapp 2018: 14). The letter p represents the probability value ranging from 0 to 1 used in hypothesis testing, where the results are significant if the pp value is equal to or less than 0.05, which represents the chances of making an error to reject or accept a null hypothesis (McGregor 2018: 336).

Additionally, the proposed theoretical model represents causal mechanisms linked by hypotheses reflecting the real world, which can be valid or invalid after repeated scientific tests (Brauninger and Swalve 2020: 124). A moderator variable is a third variable between the dependent and independent variables that is believed to have a contingency effect on changing the strength of the direction of the relationship (McGregor 2019: 298). Theories are mental models intended to reflect complex reality by explaining predictively what is observed in the universe, which can accumulate knowledge intelligible to add to the scientific community (Gonzalez-Ocantos 2010: 108).

The conceptual framework defines organised concepts with no proposition, while the theoretical framework goes further to state the proposition of relationship, whereas a model is a graphical or symbolic reflection of these frameworks (McGregor 2018: 64) meaning that concepts are descriptive while theories are predictive. Observable variables are assumed to be causing unobserved behaviour, rendering the researcher to develop a conceptual framework based on the theory about the latent variables believed to be influenced by observed indicators associated with the latent variables (Finch 2020: 5), as shown in Figure 5.1 of the proposed model.

Figure 5.1 Proposed model

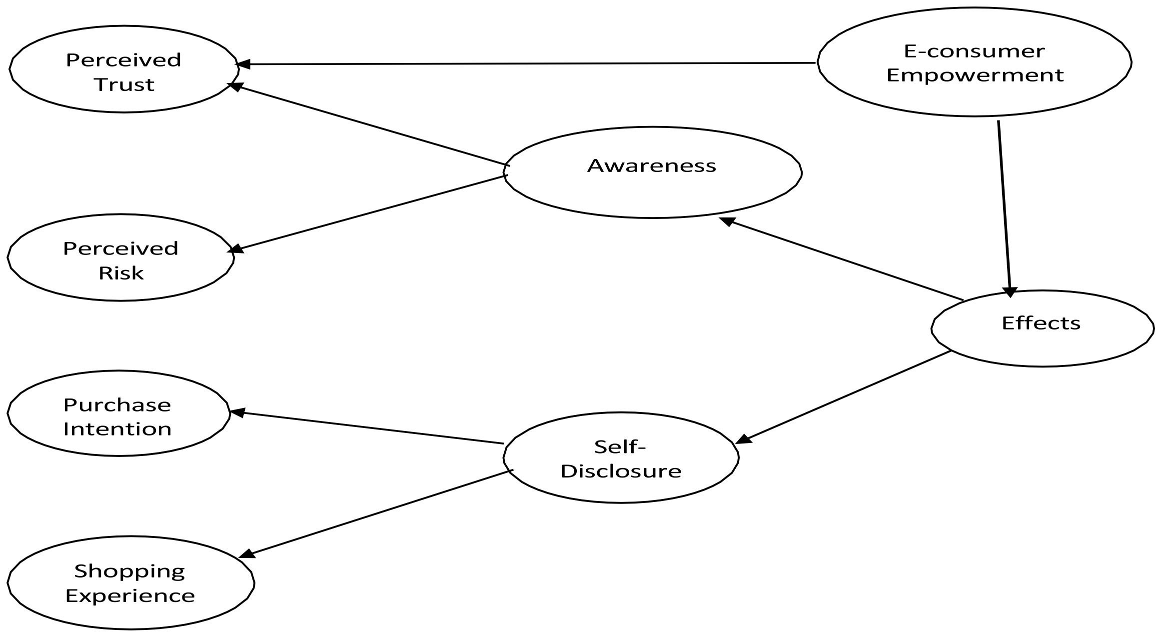


Figure 5. 1 Proposed model developed by the researcher.

Figure 5.1 represents the proposed model to be tested during data analysis. In the next section, the population under study is described.

5:6 POPULATION

Population is the number of units or members from which a sample is drawn (Gray 2018: 147). Population is of interest to researchers to make inferences, as censuses are not practical, which necessitates sampling for the purpose of generalisation provided that all members are listed on the sample frame for random sampling (Patten and Newhart 2018: 89). The population under study was made up of online shoppers from Durban, the Municipality of eThekwini in Kwa-Zulu Natal. In 2001, the Municipality of eThekwini had 3.09 million total population growing at 1.13% per annum, reaching a population of 3.44 million in 2011. Based on the 2011 census, the five-year forecast indicates population projections from 2020 to 2024 are: 2020 (3 947 020), 2021 (4 004 603), 2022 (4 059 719), 2023 (4 112 675), and 2024 (4 164 503), of which 49.8% are males and 50.2% are females (eThekwini municipality draft, IDP 2021: 29).

As for the population of online shoppers in Africa, South Africa is the second largest with 70% of the population, compared with 89% of online shoppers in Nigeria (Rudansky-Kloppers and Strydom 2021: 210). If the research question lends itself to a digital phenomenon, the whole population is indeed originating in a digital environment (Quinton and Reynolds 2018: 122). However, access to a broad population with diverse characteristics can generate a large sample efficiently, which can degrade concerns about representativeness (Hewson, 2017: 67). The sampling procedure for this study is discussed in the next section.

5:7 SAMPLING

A sample is a portion of a large population, which consists of members from whom data is extracted (York 2020: 326). It is practically impossible to contact everyone in a large population study, which necessities selecting a representative sample from, which the survey is conducted to provide valid and reliable data (Polonsky and Waller 2021: 184). When researchers urge representativeness, they do not necessarily intend to mean that the sample is matching the population, but the data outcome from the sample should be consistent with the entire population if a census was conducted (Fricker 2017: 166). Certainly, due to the difference in sampling for qualitative and quantitative approaches, data may not be easily merged in mixed methods studies as any attempt to combine data may affect analytical integrity; however, data collected simultaneously may supplement each other, especially if the study is cross-sectional (Morse, Cheek and Clark 2018:8).

Quantitative sampling involves choosing a portion of the target population using probability methods like random, stratified, cluster, and systemic methods, or non-probability sampling using convenience, snowball, purposive, or quota sampling methods (McGregor 2019:269). Advanced online surveys use an intercept survey embedded in the web pop-up that uses system frequencies to sample every NN^{th} visitor to the website incorporated in the internet protocol addresses (IP) allowing specific sub-sets of visitors and restricting multiple submissions (Fricker 2017: 171). The key wisdom of generalisation can be based on a highly scientific random sampling base or a less scientific logical generalisation where non-random sampling procedures are considered (York 2020: 325). To ensure representativeness, the volunteer sample can be filtered, based on the pre-determined characteristics of the population of interest (Quinton and Reynolds 2018: 13).

Quota sampling, which works like stratified sampling, was used with convenience sampling in this study except that quota sampling is not random probability sampling, but quotas guarantee a sample based on attributes of key categorical variables of the population in order to obtain a representative sample dimension (Wagner and Gillespie 2019: 36). Coleman and Multon (2018: 1357) add that quota sampling is a non-random sampling procedure where a fixed percentage of the population is selected based on population characteristics and the percentage is nonproportional or less restrictive depending on the variety of population data available. Judgement sampling, also used in this study, is the purposeful selection of a sample, which deliberately discriminates members according to the research question, requiring participants to have desired rare characteristics, making probability sampling ineffective (Maul 2018: 914). The rationale for non-probability sampling is explained in the following sub-section.

5:7:1 Rationale for non-probability sampling

Sampling methods can be probability or non-probability, where probability sampling selects respondents randomly in that every member has a chance to be selected even if the chances vary, while non-probability sampling is considered when probability cannot be determined, giving every individual of the target population the freedom of choice to participate (Fricker 2017: 167). Running a non-probability sampling technique is acceptable provided that its justification and limitations are acknowledged (Gray 2018: 61). Sampling errors where the sample selected is not representative of the population arise in both probability and non-probability sampling (Polonsky and Waller 2021: 187). Hewson, Vogel and Laurent (2018: 74) agree that since no central register for online shoppers exists, it is very difficult to select participants using random sampling. But if the population is homogenous, there is a possibility that the incidence of sampling errors is reduced to a certain extent (Patten and Newhart 2018: 237).

Probability sampling is possible only if the probability of each member of the study population is known, even if the probabilities for all members of the population targeted are not the same but calculable using a sample frame (Wagner and Gillespie 2019: 28). A sampling frame is a list of all the units or members of the population under study from which a sample is selected, where every member has a chance of being selected (Gray 2018: 148). Nevertheless, if the probability of selecting a member from the population is unknown, the best alternative is to choose nonprobability sampling, regardless of whether the study is probability or nonprobability (Hewson, Vogel and Laurent 2018:89). Online surveys are normally based on invitations posted on websites using quota stratification and judgement sampling matching the inference population (Vehovar and Manfreda 2017: 150).

Nonprobability sampling works well if the key characteristics of the population are identical in relation to the phenomenon, which fits with the current study of online shoppers who may display similar online behaviour (York 2020: 330). Non-probability sampling does not use chance procedures to select respondents but relies on judgement expertise based on characteristics that fit the target population (Polonsky and Waller 2021: 185). In the instances where probability sampling is not feasible, such as with hard-to-reach or identified populations, nonprobability option can be exercised properly towards providing a representative sample (Wagner and Gillespie 2019: 33). In the next sub-section, convenience sampling rationale is discussed.

5:7:2 Rationale for convenience sampling

Convenience sampling used in this study allows the researcher to select a sample from hard-to-reach populations based on the availability of members (Wagner and Gillespie 2019: 34). The convenience of the demographic characteristics to compare with the representative population and participants must be theoretically relevant to the research, not simply convenience (Waterfield 2018: 403). Convenience sampling is conducted with the logic that a hard-to-reach population can conveniently volunteer to be selected, whereas purposive sampling is selected on the basis of certain characteristics of the target population meeting the criteria in relation to the phenomenon (York 2020: 334). Convenience sampling involves selecting participants due to their availability and does not require a sample frame because the entire target population cannot be accessed (Waterfield 2018: 403). The sample size is selected in the next sub-section.

5:7:3 Sample size

The sample size is determined by the expected range of the population parameter, or confidence interval, and a 95% confidence level (Gray 2018: 149). The sample mean is not necessarily a reflection of the population mean because of the variations in the population composition, which can be formalised as sampling error, but the mean sample distribution tends to concentrate around the population mean as the sample increases in size, thereby reducing the sampling error as larger samples are taken (Blair and Blair 2021: 5). Quantitative research is concerned with analysing a large sample where data generated from the respondents can be attributed to the population of the study using statistical tools that are descriptive or inferential (Polonsky and Waller 2021: 178). Therefore, Sample size selection can be determined by the purpose of the study and population variability (Patten and Newhart 2018: 111).

Probability and non-probability sampling are all exposed to bias where the sample may not be representative of the population of inference, which can be minimised by improving the sample size at least if random sampling is not possible (Fricker 2017: 168). The logic of selecting any unbiased sample size considers that sample means are normally distributed across repeated samples, or 95% of values fall within ± 1.96 standard deviation from the mean (Blair and Blair 2021: 6). The sample size formula is nn = Z^{2} x SD^{2} /*e* where nn is the minimum sample size, Z is degree of confidence required, which is 1.96 at 95% level of confidence, SD is the standard deviation usually that of a pilot study or previous studies, and *e* is the acceptable sampling error (Gray 2018: 227). But as the sample size increases, the sampling error decreases until the error is completely cleared or negligible. Suppose the sample size is denoted as nn and the population is denoted as N, then the finite population correlation $(ffppff)$ is equal, which adjusts with sample size in that if a large or entire population is taken for the study, $(ffppff)$ and the sampling error tends to drop to zero gradually (Blair and Blair 2021: 6).

Sample size is vital in determining the sampling error. Even if the sampling is random, the sample size may weaken the generalisation (York 2020: 329). Statistical power is practical when taking a larger sample, which normally produces statistically significant results compared with a small sample (McGregor 2018: 340). For example, if a sample of 50 members and another sample of 3000 members required an additional sample of 50 each, the smaller sample of 50 would have added 50%, while the bigger sample of 3 000 would have added 1.6% to the sample (Patten and Newhart 2018: 111). Therefore, larger samples facilitate robust statistical results, which can be generalised (Knapp 2018: 22). Figure 5:2 provides an alternative method of selecting the right sample size depending on the acceptable sampling error.

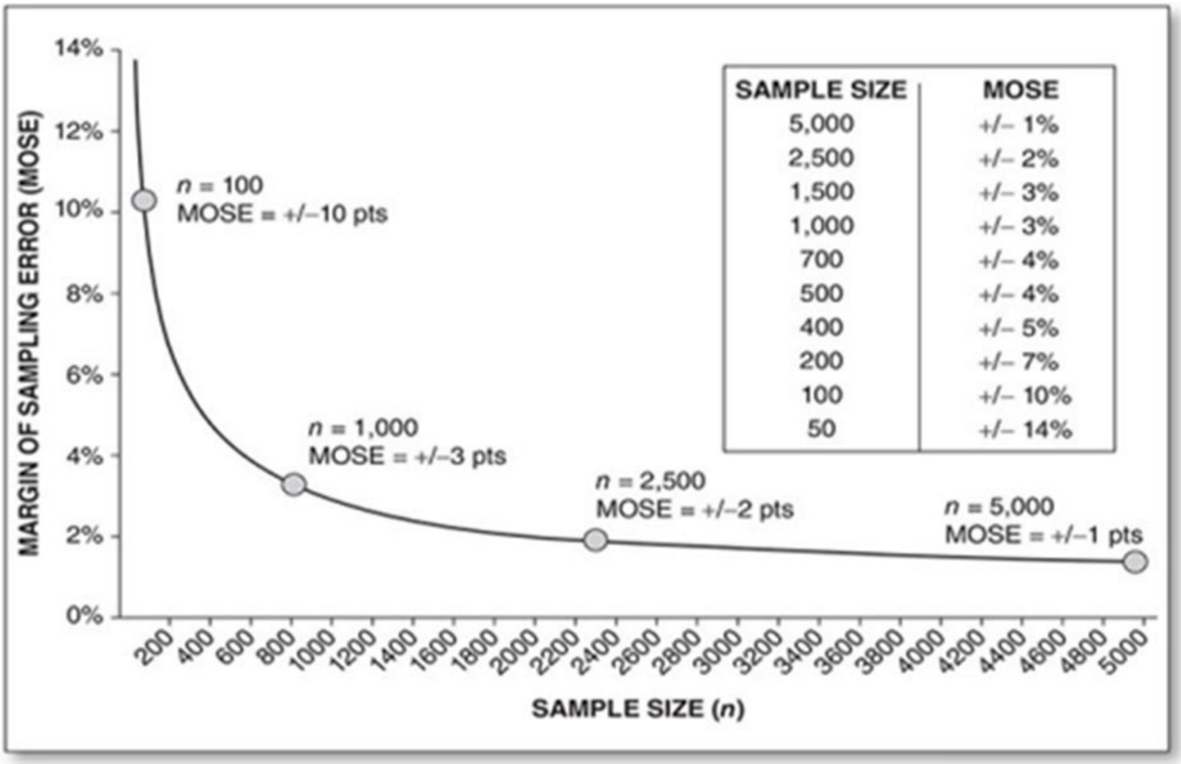


Figure 5. 2 Sampling error versus sample size

Extract from Blair and Blair (2021: 106).

As reflected in Figure 5:2, the margin of sampling error proportionately decline as the sample size increases until there is a steep decline at the sample size of 200 with a less dramatic decline up to the sample size of 1 000, from which the curve flattens, making any sample from 200 to 1 000 ideal for any research and 1 000 to 1 500 for national polls (Blair and Blair 2021: 15). Irrespective of the population size, national survey polls use a sample size of 1 500 participants due to the diminishing returns from adding an extra participant after 1 500 respondents (Patten and Newhart 2018:

111). The sample size for the quantitative strand of this study is 400 participants and the sampling error is 5%, as reflected in Figure 5:2 of sample size against sampling error. Qualitative sampling follows in the next subsection.

5:7:4 Qualitative sampling

Obtaining a sample size in qualitative research is problematic because, in most instances, more and more participants are selected until the data collected becomes redundantly saturated depending on the ontological and epistemological proposition of the study (Saunders and Townsend 2019: 489). Saturation can be noticed when the marginal interview replicates data where certainty is used, as long as the researcher has defensible logic that the data is sufficient to answer the question provided that the qualitative component is visible (Morse, Cheek, Clark 2018:6). Saturation means that there is no more data worth reviewing based on the available data that has already been generated, and no new ideas are yielded from the continuation of additional responses from participants (York 2020: 461). Qualitative researchers usually consider 15 ± 10 interview participants depending on diminishing returns, where data obtained from an additional participant may add no value (Brinkmann and Kvale 2018:48). The next stage of this research design is data collection methods starting with an online survey.

5:8 ONLINE SURVEY

A survey is non-experimental research that uses an instrument to obtain data relating to polls, views and opinions of participants (McGregor 2019: 308) but cannot be manipulated like in experimental research. Ruel (2019: 3) defines a survey as a method of collecting large volumes of data from a large group where the survey instrument is a questionnaire, which is carefully designed and administered in a way that will provide answers to the research questions using empirical evidence. A survey uses a well-structured questionnaire designed to elicit data from the sample's motivations, intentions, awareness and overall behaviour with reference to a particular situation (Polonsky and Waller 2021: 179). Technological advancement has led to the evolution of internet surveys with a speedy standardised web browser scraping email surveys for a more advanced transmission procedure where respondents can access the questionnaire on a smart device, allowing real-time responses (Vehovar and

Manfreda 2017: 145).

Although email-based surveys have gained traction, web-based surveys are dominating internet-mediated research due to the ease of publishing the survey on websites resulting in pop-up survey feedback, which is cheaper and attracts large volumes of responses (Hewson, Vogel and Laurent 2018: 7). Online surveys access the sample electronically, allowing the mailing or website embedding of the questionnaire using www.surveygizmo.com, www.mturk.com www.qualtrics.com or www.surveymonkey.com (Polonsky and Waller 2021: 180). Web-based surveys check for response completeness, generate high-quality data due to anonymity, and prompt the formatting of responses (Hewson, Vogel and Laurent 2018: 8). Online questionnaire design is explained in the next section.

5:8:1 Online questionnaire

Attitude scaling can be defined as the evaluation of individual opinions based on cognitive or affective influences, which can be favourable or unfavourable (Rosenberg and Silva 2018: 14). Surprisingly, social science positivists use a questionnaire, which attempts to measure a construct of perception and not reality, where individual responses depend on the subjective interpretation of the question, which is popular in qualitative inquiry (Dawson 2018: 12). The questionnaire used in the survey is clear, does not involve sensitive questions, avoids social desirability responses, and is relevant, simple, not double-barrelled, not negative, short, mutually exclusive and exhaustive (York 2020: 330).

A continuous variable has infinite possible values, usually measured by a Likert-type scale where the participant chooses from the range of strongly disagree to strongly agree (Wagner and Gillespie 2019: 17). The Likert scale, named after the American psychologist Rensis Likert, measures constructs that cannot be easily measured directly and therefore require respondents to give their opinions to ascertain the extent of disagreement or agreement with the proposed statement (Dawson 2018: 5). Rensis Likert developed the attitude scaling in 1932, which improved Guttmann’s agree or disagree options by simply adding a neutral option in the middle and a strongly disagree and strongly agree at the beginning and end of a five-point attitude scale, respectively (Rosenberg and Silva 2018: 144). The questionnaire was developed by the researcher. It is essential to conduct pretesting after designing the questionnaire, as described in the next subsection.

5:8:2 Pretesting

Pretesting is necessary to test the measuring instrument's reliability, length and structure, and eliminate errors and delete unnecessary items (Gray 2018: 241). Surely, pretesting is very important in cleaning up the questionnaire for the final full-scale survey (Patten and Newhart 2018: 110). Pretesting with 42 online shoppers in Durban was conducted to ensure the reliability of the measuring tool before conducting the full-scale survey. The assessment of a measurement model was conducted by testing reliability and validity with Cronbach's alpha and composite reliability (CR) confirming reliability (Salloum, Al-Ahbabi, Habes, Aburayya and Akour, 2021: 328). There were some modifications in the questionnaire after the pretesting results. Please Annexture 2 at the back of this thesis.

5:8:3 Validity and reliability

Validity is measuring what is intended to be measured where: face validity is ensured by experts; internal validity is ensured by proving causal claims; external validity is ensured by generalisability; statistical validity is ensured by appropriate design; construct validity is ensured by indicator relationships; and criterion validity is ensured by tool similarity with old tools (Gray 2018: 153). Empirical studies must ensure that the study is valid and reliable to instil trust in the readers that the research measured what it was intended to measure with enough information to replicate the study based on competent standards of quantitative research (McGregor 2019: 274). Surely, both validity and reliability are complementary in ensuring the usefulness of the measuring instrument to establish whether it is free from errors, where reliability ensures the consistency of repeated tests and validity ensures that the tool measures what it was intended measures (Dawson 2018: 3).

Reliability, which is a complement of validity, ensures that the tool is free from errors and is consistent if repeated measurements are taken, while validity ensures proper use of the tool for what it is intended (Dawson 2018: 13). Reliability refers to whether the research design with a similar sample can produce similar results, indicating a constant pattern of repeated studies, while transferability relates to whether the finding can be applied or used in other instances (McGregor 2019: 222). Reliability emphasises that the method selected produces data with consistent results if it is repeated, indicating that the measurement is free from random errors, which is ensured by an internal consistency test referred to as the Cronbach's alpha (Polonsky and Waller 2021: 168). Validity was ensured by factor analysis while reliability was ensured by the Cronbach's reliability test. The drawbacks of online surveys are discussed in the next section.

5:8:4 Online survey shortcomings

Digital research requires participants to be connected to the internet with a substantial level of access to bandwidth, allowing respondents to participate without connectivity interruptions (Quinton and Reynolds 2018: 205). The disadvantage is that surveys are uniform with no flexibility compared to open-ended interviews (York 2020: 121). Additionally, IMR requires technical expertise and proper use of online survey software packages (Hewson 2017: 61), which include Survey Monkey, Qualtrics and Lime Survey, among other types.

Earlier web surveys encountered uneven internet access, technical abilities of responses, and computing power of researchers, but wider internet access with technical skills has eased the barriers for online surveys, where the online questionnaire software support has allowed user-friendly answering structures (Rasmussen 2017:45). Although the digital environment supports anonymity, where even the researcher may not know the participants personal details, psychological harm is not an issue due to the absence of face-to-face participation (Quinton and Reynolds 2018: 140). But the benefits of an online survey outweigh the shortcomings, as reflected in the next sub-section.

5:8:5 Online survey rationale

Vehovar and Marifreda (2017: 144) state that computer-assisted survey information collection (CASIC) has outpaced the traditional paper-and-pencil offline survey due to the instant data processing which limits various errors associated with paper questionnaires with the skip and filter options. The survey has credibility due to its standardised manner because participants respond to exactly the same seminal questions, thereby reducing the guesswork about what the respondents want to say (York 2020: 121). Online participation is easy to access and tends to be homogenous in terms of population interests, with characteristics favourable to the digital environment (Quinton and Reynolds 2018: 117).

Emails are not secure, have low response rate and reside on numerous servers, unlike web-based surveys, which are ideal (Hewson, Vogel and Laurent 2018: 108). The advantages of IMR are cost saving, time efficiency, vast geographical diversity, ease of access, and high anonymity levels of IMR reduce social desirability effects (Hewson, 2017: 60). Therefore, online surveys have minimal issues of social desirability provided the questions are matching with the constructs.

The internet reaches a very large, varied sample that is hard to reach by other methods, is cost-efficient, is perceived as automated and convenient, and reaches segments. It has a high level of disclosure and convenience but lacks control over obtaining probability samples, and technology hinders the process (Hewson, Vogel Laurent 2018: 6). Even with 24/7 access to digital environment, it does not necessarily imply easy access, but there is an opportunity for participants to feel safer responding online in their free time (Quinton and Reynolds 2018: 121).

Additionally, online survey methods offer a high level of anonymity while enabling a high level of interactivity, functionality and flexibility, thereby reducing bias resulting in a high degree of condor pertaining of data (Hewson, Vogel and Laurent 2018: 13) and self-disclosures that are honest. Surveys have self-reporting capabilities enhanced by a predetermined, structured questionnaire (Tan and Siegel 2018: 644). The face-to-face survey is vulnerable to incompleteness and usually takes advantage of a captive audience such as clients or students; the mail survey has a very low response rate, and the online survey is the most efficient (York 2010: 115). The online survey participants have similar issues about trust and risks related studies. Most of the responses about perception regarding online shopping tend to yield similar results. The interview process is explained in the next section.

5:9 INTERVIEWS

Phenomenological interviews in this study focus on dialogue reflections where the researcher takes a neutral, non-directive position, allowing the study to seek justifications through a shared dialogue of in-depth thoughts (Roulston and Choi 2018: 236). Brinkmann and Kvale (2018: 62) warn that the interviewer must make sure that the interviewee grasps the study while ensuring respect for the interviewee with a brief introduction informing the interviewee about sound recording and debriefing with feedback. The interviews in this study were conducted with online retailers who have a dual role of buyer and seller on the online shopping platforms. In-depth interviews are lengthy one-to-one interfaces that illuminate prejudices, allowing more probing in a structured or unstructured style for the researcher to interpret strong attitudes using recorders and transcripts (Polonsky and Waller 2021: 177). This study uses semi-structured interviews. Polonsky and Waller (2021: 203) state that semi-structured interviews are common in qualitative research because they cover a wide range of open-ended questions, guided by the theoretical framework, giving in-depth responses and generating unexpected revelations.

5:9:1 Interview process

Virtually, there are no standard procedures for conducting a qualitative interview, but there are a few standard methods that allow the interviewer to stick to an interview guide (Brinkmann and Kvale 2018: 40). The golden rule is to write early and often because it becomes a habit, especially when using a research diary at all stages of fieldwork and data analysis (Gibbs 2018: 39). The preparation of audio recordings or smartphone recordings, notebooks, recruiting participants by email and arranging meeting are done prior to the commencement of the first field interviews (Roulston and Choi 2018: 240). Interview protocols are used to plan the direction, scripts, question prompts and notes, and the initial interviews build a rapport with the participants (Patten and Newhart 2018: 161). Field notes are mental notes to remember the where, what, who, when and why records or phrases during the investigation (Gibbs 2018: 40) involving what is relevant to the research and self-interpretation of what is happening.

The recording of interviews by notetaking, audio recording, and remembering is the main function of field work, which supports analysis after transferring the recording and summarised transcripts to the computer (Brinkmann and Kvale 2018: 107). Also, diaries record thoughts, actions, conversations, events, opinions, views, and issues, which must be noted immediately (Thomas 2017: 208). Memorandums theorise comments that guide thematic coding and grouping ideas to find relationships with little conceptual elaboration based on points of view that can be recalled during the final analysis (Gibbs 2018:43), which help to organise the report in an orderly manner. Transcripts as a representation of original reality are interpretive constructions of decontextualised interviews, which must reflect a valid transcription in relation to the research question (Brinkmann and Kvale 2018: 112).

5:9:2 Credibility and trustworthiness

Credibility from the perspective of Lincoln and Guba refers to the believability regarding the research design and approaches employed to analyse data supporting the findings; in other words, the confidence that the design is comprehensively described in relation to the research question (Sultan 2019: 181). In fact, credibility is about accuracy; transferability is about providing enough detail to allow the applicability of the findings in other situations; confirmability is about providing evidence of a link between data and findings; and authenticity provides a balanced view from different perspectives (Mertens 2018: 36). Credibility means making sure that the truthfulness of the study is based on time spent in interviews, including negative findings, participants, acceptance of observations, and the inclusion of contradicting findings (York 2020: 325).

5:9:3 Interview shortcomings

Premature judgement, where the researcher hurriedly makes conclusions based on preconceived thinking rather than what is actually in the field, can lead to a dead end (Sternberg 2020:224). It is the responsibility of the interviewer to introduce a topic, pose questions, and terminate the interview, but interviewer dominance of the interview may result in withholding information or just talking around the topic in preparation to withdraw (Brinkmann and Kvale 2018: 18). Saunders and Townsend (2019: 481) assert that qualitative research relies on gaining access to participants who receive relatively little in return, weighted against the value of research sensitivity, time required and researcher credibility. Also, respondents may respond in a socially desirable mode to please the researcher rather than reflecting on reality, or they might be hesitant to respond honestly (Tan and Siegel 2018: 1646). The purpose of the research was clearly explained to the participants and simple questions were asked to avoid social desirability issues.

5:9:3 Rationale for interviews

The advantage of interviews is that bodily presence guarantees an honest response, and a further discussion generates a genuine opinion with useful gestures like hesitation or a glance (Thomas 2017: 202). The rationale for interviews is that they generate detailed responses about human interactions concerning lived experiences, attitudes, behaviour and values (Gray 2018: 378). Interviewing is an epistemological concept of knowledge constructed through data mining as the interviewer confronts the landscape of people in unknown territory and asks inhabitants questions to unveil their world view of the situation at hand (Brinkmann and Kvale 2018: 19).

Open-ended interviews allow full self-disclosure without limit, but unstructured data limits uniformity, although it allows the interviewee to intervene, and sometimes prevents the interviewee from going off topic (Thomas 2017: 204). Nuanced behaviour added to in-depth consideration of hums, nods, nose blowing, blinks and winks along, with the spoken words and provide rich data (Thomas 2017: 111). Data relating to physical expression was incorporated in transcription. The interviews were administered to online traders to collaborate the findings with online shoppers. Requests were sent to selected online shoppers using convenience sampling. The unstructured data was managed by note taking during the process of interviews.

5:10 DATA ANALYSIS

Categorical variables are discrete groups that are assigned meaningless numbers for the purpose of identification, for example, nominal variables with no rank, dichotomous variables with two responses, and ordinal variables placed in relative rank order (Wagner and Gillespie 2019: 12). Categorical variables can be nominal like occupation, binary like sex, or ordinal from lower to upper like education level, while numerical variables include continuous intervals, like the Likert scale, continuous ratios like height, and discrete ones like the number of elements (Dawson 2018: 4). Nominal is about names, ordinal is about ranking, and both are categorical, but on the other hand, continuous variables include intervals on the scale continuum with a meaningful zero and ratios as scales where zero is meaningless (Patten and Newhart 2018: 74).

5:10:1 Descriptive statistics using SPSS

Statistical Package for Social Sciences (SPSS) has easy data manipulation procedures and a simple command language to transform, analyse and build graphs, with extra features to identify duplicates, compute anonymised data, and recode data (Courtney 2018: 1579). SPSS, launched in 1968, is the most widely used software for descriptive, bivariate, ANOVA, correlation, predictive linear regression, and factor analysis (Gray 2018: 594). Courtney (2018: 1578) asserts that SPSS eliminates tedious tasks of data preparation using a syntax-driven, time-saving interface that is user-friendly and ubiquitous.

While cross-tabulation deals with the description of the relationship between two categorical variables, chi-square deals with significance of two categorical variables, ANOVA lists differences in three or more groups, and multiple regression deals with one dependent predicted by multiple independent variables (Polonsky and Waller 2021: 229). Chi-square denoted by (xx^2) measures the difference between frequencies, while ANOVA measures the difference between means, and multiple regression measures one dependent against several or one independent variables (Patten and Newhart 2018: 245).

Descriptive statistics simply describe what exists to determine the frequency, thus nothing can be known about the phenomenon because variables are not manipulated to determine casual effect (McGregor 2019: 259). Descriptive statistics comprehend the distribution, frequency, percentages and averages of univariate variables (Patten and Newhart 2018: 203). Descriptive statistics compare standards about what is happening without explaining why it is happening (Gray 2018: 37). Correlation seeks to measure the association between variables, but simply because one variable varies with another does not mean one causes the other, and it takes more effort to determine whether a change in one variable change another by creating a hypothetical statement (McGregor 2019: 260).

5:10:2 Inferential statistics using SPSS

Inferential statistics is used to generalise whether descriptions of the sample data have significant relationships that can be applied to the whole population (Patten and Newhart 2018: 204). Correlation simply shows that two variables are moving in a certain direction but does not indicate that the change in one variable is caused by another (Knapp 2018: 307). Focusing on the association of variables can result in misleading research but measuring the causation of association further assists in policy and program effectiveness; hence, inferences or causation is a valuable tool of analysis (McGregor 2018: 327). Inferential analysis measures the degree of representativeness of the sample data relevant to the population (Dawson 2018: 9). A false positive, or Type I error, is represented by *alpha* and a Type II error where the researcher fails to reject a null hypothesis is represented by *beta* (Wagner and Gillespie 2019: 158).

5:10:3 Structural Equation Modelling (SEM)

Sandoval and Ramos-Diaz (2018: 1) define structural equation modelling (SEM) as a multivariate analysis that combines factor analyses with multiple regressions, allowing simultaneous calculations of several inter-connected variables and latent constructs. Tan-lei and Lin (2018: 79) propound that IBM SPSS Amos is computer software that performs covariance structures with structural equation modelling (SEM) where Amos stands for analysis of moment structures. Finch (2020:2) argues that latent variables are variables that cannot be directly measured, for example, personality, mood, and intelligence, but can be inferred with respect to observable variables that have a causal impact on the latent variable.

In SEM, exploratory factor analysis (EFA) is used when there is little information about the expected latent structure for observed indicators, whereas confirmatory factor analysis (CFA) works well when there is a strong theoretical expectation of the structure before empirical evidence is available to establish whether the hypothesised latent variables fit the model based on the data (Finch 2020: 6). CFA is a more advanced technique established where the assigned items are in correlation by comparing the actual relationship with the hypothesised structure and establishing how well the data fits the model (Dawson 2018: 32). Confirmatory factor analysis (CFA) measures the relationship between observed variables and latent variables depending on the hypothesised structure (Ma and Shek 2018: 1629).

Factor loading is the measure of the relationship between each latent variable and the observed indicator, where the unique variances are parts of the indicator that are not concomitant to the observed variable (Finch 2020: 26). Confirmatory factor analysis ensures that items from the questionnaire fit within the construct based on the data; in other words, there must be a correlation between the latent variable and the observed items of the questionnaire assigned to the latent variable (Dawson 2018: 59). Amos is also capable of executing confirmatory factor analysis (CFA) multi-group analysis, path analysis and multi-level analysis to test the theoretical model (Tan-lei and Lin 2018: 79).

It is worth noting that in SEM, a pp value linked to the chi-square with a satisfactory model that fits the data has to be nonsignificant, making a significant chi-square represent a poor model fit with the data (Wesolowski 2018: 1081). However, estimating the model to ensure that data fits the model where a nonsignificant chi-square reflects a good fit is often influenced by the large sample size inflating the chi-square (Ma and Shek 2018: 1628). Using Amos, the CMIN/DF, which is the minimum chi-square value discrepancy per degree of freedom in the model of fit indices, should not be significant for the model to be acceptable where a CMIN/DF>2.00 is a poor fit (Tan-lei and Lin 2018: 82). However, the chi-square is silent on sample size as well as correlations, which can result in committing Type I errors in cases where a more robust transformed asymptotic Chi-square is used (Wesolowski 2018: 1081).

Still in Amos, while the absolute fit index (AFI) and the goodness of fit index (GFI) evaluate how well the data fits the hypothesised model, the residual fit index (RFI) establishes the difference between the hypothesised model and the data (Ma and Shek 2018: 1628). The comparative fit index (CFI) compares the chi-square fit value of the hypothesised model with the chi-square fit value of the null model (Wesolowski 2018: 1082). The CFI and the Tucker-Lewis index (TLI), which compare the fit of baseline model against the hypothesised model, with values > 0.90 indicating acceptable fit and > 0.95 being a good fit, while the RMSEA, which is the root mean square error of approximation > 0.08 is acceptable fit and RMSEA < 0.05 a good fit (Tan-lei and Lin 2018: 83). So, the CFI ≥ 0.95, TLI ≥ 0,95, NFI ≥ 0.95, adjusted GFI ≥ 0.95, RMSEA ≤ 0.06, and SRMSR (standardised root means square residual) ≤ 0.08 indicate that the data fits the model (Ma and Shek 2018: 1629). All these indicators are found in the Amos model test results.

On the other hand, SmartPLS is a complete SEM tool that measures hypotheses, preferred composite reliability, and Cronbach's alpha, where the reliability coefficient of Cronbach's ranges between 0 and 1, with greater or equal to 0.80 as a good scale, 0.70 as an acceptable scale, and 0.60 as a new scale (Rouf and Akhtaruddin, 2018: 1503). SmartPLS eradicates a great deal of explanation, which academic research normally emphasises, by rather focusing on prediction for meaningful implications (Sarstedt, Ringle, Cheah, Ting, Moisescu and Radomir. 2019: 532). Partial least squares path modelling (PLSPM) is widely used as the SEM composite approach that uses an estimator to simultaneously measure models with latent variables (Cheah, Thurasamy, Memon, Chuah and Ting 2020: 2). Partial least squares modelling is gaining greater traction among academic researchers from various disciplines in comparison to Amos' covariant-based SEM because it incorporates numerous techniques that are prediction-oriented (Sandoval and Ramos-Diaz 2018: 1).

PLS-SEM is now a standard tool ideal for analysing the complex relationships even with little data where model path estimations are assumed to have linear relationships, but nonlinearities are also addressed in SmartPLS to map relationships between variables (Sarstedt *et al.* 2019: 531). SmartPLS calculates PLSPM results for various types of variables, facilitating the inclusion of formative measurement model's concomitant with the direction of causality from the construct (Sandoval and Ramos-Diaz 2018: 1). SmartPLS, which maximises the variance explained in the endogenous constructs to facilitate the explanation of the model's relationships, is an alternative method to the covariance approach of structural equation modelling, which is dominated by Amos (Cheah et al. 2020: 2). However, model relationships are sometimes influenced by the mediators and moderators. Also, in SEM, a moderating effect comes up if other factors influence the dependent variable, while mediation comes between the independent and dependent variables (Gray 2018: 138).

The disadvantage of PLS-SEM is that unobserved heterogeneity may occur if subgroups of data exist, and estimating the model using the entire data set may lead to misleading structural modelling where positive and negative effects reconcile with each other (Sarstedt *et al.* 2019: 538). However, the easy-to-access standard SmartPLS software is helpful, especially if the path coefficient with the minimum absolute magnitude is unknown (Cheah et al. 2020: 3). Moreover, Confirmatory Factor Analysis (CFA) in SmartPLS involves testing convergent and discriminant validity, where convergent validity is measured by factor loadings and Average Variance Extracted (AVE) with acceptable factor loading values ≥ 0.70, and an AVE of ≥ 0.50 being acceptable (Salloum *et al*. 2021: 328).

Average Variance Extracted (AVE) measures both convergent and divergent validity, where AVE above 0.5 means that factors represent at least half the variance of their indicators (Rouf and Akhtaruddin, 2018: 1503). The Fornell-Lacker criterion indicates reflective and formative constructs generating reliability measures through Composite Reliability (CR), Cronbach's Alpha, and convergent validity reflected by the AVE with cross-loading (Sandoval and Ramos-Diaz 2018: 1). The AVE value should be above 0.50, the values of composite reliability should be ≥ 0.70, and the discriminant validity based on the Fornell-Larcker criterion should have lower values of correlations between the constructs compared to the square roots of the AVE values in the main diagonal of the SEM output (Polas and Raju 2021: 101).

Composite reliability is better than Cronbach's alpha in testing convergent validity because Cronbach's alpha can overestimate or underestimate reliability (Rouf and Akhtaruddin, 2018: 1503). SmartPLS uses a bootstrapping calculation to indicate that the model path coefficients are significant (Sarstedt *et al.* 2019: 540). Bootstrapping in SmartPLS calculates the level of statistical significance in relation to the path coefficient, the t-values, and the square root of AVE, which must be higher than the correlations of the constructs for acceptable discriminant validity (Rouf and Akhtaruddin, 2018: 1503). Upon completion of the quantitative data analysis, transcribing and facilitating the qualitative data analysis is discussed in the next subsection.

5:10:4 Transcribing

Qualitative data involves any form of human communication that is commonly transcribed into text (Gibbs 2018:3). The interactive analytical process during the fieldwork entails seeking explanations by interpreting descriptions by filtering sensible data (Durdella 2020: 265). Recorders and notes were used to easily capture the views and opinions of the interviewees for transcription. One hour of interviews took seven to ten hours to transcribe (Gray 2018: 392). Transcripts are data from the interpretations, which are awaiting coding and thematising to facilitate data analysis (Patten and Newhart 2018: 162). Transcripts originate from recording playbacks, which are interpreted into text awaiting further analysis (Thomas 2017: 203).

5:10:4 Pattern matching

Non-Numerical Unstructured Data Indexing, Searching, and Theorising (NUDIST) is the mother version of the now updated NVivo 12, with full range support of complex queries and artificial intelligence incorporating automatic coding (Davidson 2018: 1169). Interpreting qualitative data allows the researcher to create a broader meaning of thematised patterns by frequently drawing conclusions about contrasts, irregularities, and paradoxes based on a theoretical perspective (Durdella 2020: 274). NVivo software allows user-friendly coding, identifying nodes and subthemes, and linking nodes with subthemes like a branchlike structure, while other software requires the researcher to define the overarching nodes (Polorisky and Waller 2021: 214). Thematically grouped data eases complementary analysis of different sources, offering a confirmatory account of the situation by matching cases to reveal comparisons relevant to the topic (Bazeley 2018: 129) and clarifying contradiction.

5:10:5 Coding using NVivo

Coding involves identifying, defining and recording data parts that exemplify similar ideas linked in such a way that the code categories are ordered to build a framework of ideas in a thematic manner (Gibbs 2018:154). Coding is done through constant comparisons by seeking words of interest to represent themes summarised in the contents of the data (Thomas 2017: 248). NVivo software assists in auto-coding, case classification, and word count, which facilitate the easy analysis of qualitative data (Gray 2018: 655). Codes can be concept-driven in relation to the literature, which assists in providing thematic ideas, but they are amended with new ideas during the final analysis (Gibbs 2018: 60). Cases are organisations, individuals, places, events, objects, or any unit linked to the source of data for analysis (Bazeley 2018: 129).

5:11 RESEARCH ETHICS

The Institution Review Board must approve any research involving human beings (Thomas 2017: 40); thus, this research was approved by the Institution Research Ethics Committee (IREC) of Durban University of Technology. In conceptualising the study, Mertens (2018: 36) states four inter-related assumptions, which are ontology as the nature of reality, epistemology as the nature of knowledge, methodology as the nature of systematic inquiry to obtain new knowledge, and axiology as values relating to ethics. Ethics for the assumption of axiology is about moral principles requiring the researcher to produce happiness, keep promises, justify means, and avoid overlapping (Gray 2018: 71). Common rules of ethics are derived from biomedical research into social sciences with less restrictive procedures (Adams 201: 63). Research ethics, as defined by Whiting and Pritchard (2019: 563), refer to the moral principles guiding the research from the beginning of the project to the publication ofthe findings mainly focusing on mitigating harm while maximising the benefits of the study.

The Belmont Report is based on three principal guidelines that include beneficence, justice and respect, with six research norms that hold that a valid research design requiring the researcher's competence to identify research consequences and select a valid sample while taking into consideration informed consent (Mertens 2018: 40). Also, we Researchers must remain compliant with Nuremberg Code insisting on voluntary participation and the Belmont Code, stressing beneficence against non-maleficence advocating for equal justice and consent (Patten and Newhart 2018: 34). Therefore, this research ensures securing informed consent, monitoring risks and benefits based on reactions from participants, maintaining anonymity, respecting participants, and ensuring the validity and reliability of the study for scientific and social values (Hewson, Vogel and Laurent 2018: 113).

5:11:1 Informed consent

Informed consent requires a clear procedure that alerts the subjects about potential risks and the standard procedure to inform voluntary participation (Adams 2021: 63). Certainly, informed consent provides information about the research, risks involved, time to be spent, and benefits (Gray 2018: 70). Before data collection, participants are provided with a simple information sheet sufficient for them to consent or refrain from participation (Polonsky and Waller 2021: 94). Informed consent prior to the commencement of the interview is important for participants to make informed decisions, which may involve asking follow-up questions for more clarity to support willingness (Roulston and Choi 2018: 240). Informed consent letter was attached to the survey and distributed to interviewees.

5:11:2 Voluntary participation

Based on the famous Nuremberg Code of 1947 after the Second World War, voluntary participation ensured by consent is key to any research involving human beings (Gray 2018: 71). Adams (2021: 62) cautions that the Belmont Report consolidating ethical guidelines for human subjects give the right of informed consent, leading to voluntary participation with the right to withdraw. Ensuring voluntary decisions is accomplished by providing information about the research's negative and positive consequences in terms of research methods administered to participants, considering anonymity, voluntary participation, harm and confidentiality (Polonsky and Waller 2021: 91).

5:11:3 Anonymity

It is always important to keep the confidentiality of participants by anonymising names, places of stay, and any other information that can identify the participant (Gibbs 2018: 20). The principles concerning autonomy enables a participant to choose to join or drop out if an understanding of the research is not initially clear (Adams 2021: 63). Privacy involves democratic principles to protect personal information that can be traced back to the participant (Gray 2018: 79). Using an online survey in this study, the issue of traceability was mitigated by making sure that participants remain anonymous (Hewson, Vogel and Laurent 2018: 102). Identifiable information about the participants was kept away from public view through confidentiality and privacy protection (Brinkmann and Kvale 2019: 32).

5:11:4 Beneficence and non-maleficence

Balancing possible risks with benefits allows the researcher to assess the trade-off between risks and benefits where risks can be minimised by anonymity, which reduces the risk of information disclosure while also ensuring confidentiality (Adams 2021: 66). Justice, or distributive justice, is about fair participant selection, including the fair distribution of benefits as well as risks, so that people involved in the research should be the ones to benefit from the research (Mertens 2018: 41). There are several ways in which participants can be harmed, which include bodily harm, emotional harm, and psychological harm, usually due to embarrassment (Adams 2021: 74). Harm can be physical, ridicule, anxiety, belittling, embarrassment, stress, or emotional harm (Gray 2018: 75). Polonsky and Waller (2021: 86) caution that researchers must ensure that psychological harm by offending the human soul, financial harm like participants getting fired or losing competitive advantage, social harm like sexual orientation data requests must be avoided.

5:11:5 Integrity and dignity

Deontological ethical standards are met if the researcher demonstrates moral behaviour, which is universally accepted where people are treated with value and arenot exploited while ensuring social justices of liberty relating to equal rights (Mertens 2018: 35) to do with dignity without harm and supporting social transformation. Deception intentionally happens when researchers modify their appearance to associate themselves favourably with the socio-cultural context under study (Bengry 2018: 106). The conflict of interest where both the researcher and participant have different interests can be ethically inappropriate due to biased responses (Adams 2021: 75).

5:11:6 Scientific value

The Helsinki Declaration stresses the balance of interest and scientific value (Gray 2018: 71). The legitimacy of the research design emphasises scientific research, where the researcher must demonstrate that a causal relationship exists (internal validity) and that the findings of the study are capable of universal application (Wagner and Gillespie 2019: 21). Unethical behaviour in the form of methodology grooming, where the researcher creates an impression that may conceal or misrepresent the actual aims, which might have problematic aspects by exaggerating the positive or minimising the negative, raises ethical dilemmas of deception (Bengry 2018: 105).

5:11:7 Online ethics

Digital ethics refers to behavioural ethics that concern researchers using web-based intermediaries to conduct the study (Whiting and Pritchard 2019: 563). Like offline research, participants must be explicitly informed of the right to withdraw at any time without proffering a reason for withdrawal (Quinton and Reynolds 2018: 197) including post-submission withdrawal rights. It is ideal to provide a withdraw button that is more visible than the submit button to enhance voluntary participation online (Hewson, Vogel and Laurent 2018: 106). The official ethical guideline for internet-mediated research has been particularly slow to implement ethics; however, the British Sociological Association (BSA) vaguely advises online researchers to acknowledge ethical standards with special care due to the constant update of computer-mediated techniques and ethical issues (Bengry 2018: 104). Hewson, Vogel and Laurent (2018: 100) argue that internet-mediated research (IMR) ethics principles are similar, but the public and private issues in the online space are still problematic ethical dilemmas. The ethics clearance certificate for this study is attached in Annexure 1 at the end of the thesis.

5:12 CONCLUSION

In general, a cross-sectional mixed methods approach is ideal for this study based on the discussion in this research methodology chapter. Certainly, mixed methods prove to be ideal for offsetting the weaknesses of quantitative and qualitative approaches. The study is sequentially dominated by the quantitative strand followed by an abductive qualitative strand explaining and widening the depth of the research. The quantitative strand uses deductive logic, while the qualitative research uses abduction, which is a combination of deductive and inductive logic. However, qualitative interviews are conducted face-to-face because small samples are required as long as they can provide rich information. Finally, quantitative data is analysed by SPSS and Amos for SEM, while qualitative data is analysed using NVivo software in the next chapter.

CHAPTER: 6 FINDINGS, ANALYSIS, AND INTERPRETATION

6:1 INTRODUCTION

Chapter 5 covered the research methodology espoused by this study. This chapter discusses the empirical study, focusing on the analysis and interpretation of the findings. The chapter is organised into nine sections, which include: 6.1 introduction, 6.2 demographic results, 6.3 demographics p-values, 6.4 Likert scale and Cronbach's alpha, 6.5 exploratory factor analysis, 6.6 structural equation modelling, 6.7 hypotheses, 6.8 field interviews, and 6.9 the conclusion. A positivist and interpretivist pragmatic approach was adopted with the quantitative survey, consisting of a sample of *n*= 400 respondents, and the qualitative interview, consisting of a sample of *n*= 20 respondents. Since the study relates to a digital phenomenon, the quantitative data was collected using an online five-point Likert-type questionnaire supported by QuestionPro software linked to the Cint data base website. The focus was centred on the population of online shoppers residing in Durban, South Africa. However, since online traders play a buyer-seller role in e-commerce, it was necessary to amalgamate their opinions with online shoppers. Therefore, twenty online traders were selected to participate in the unstructured qualitative interviews. The interviews were analysed using NVivo, the quantitative data was analysed using SPSS Amos along with R software. Therefore, this chapter focuses on providing a broad understanding of the findings with a focus on analysis and interpretation.

6:2 DEMOGRAPHIC RESULTS

6:2:1 Response rate

The response rate of the quantitative and qualitative stances was 100%, and there was no missing data from all the items of the measuring instrument. A copy of the tool is attached in Annexure 2 at the end of this thesis.

6:2:2 Demographics

Nine demographic variables were considered for the survey. Table 6.1 indicates a summary of the demographic data of the survey.

Table 1 Overall demographic scores

Demographic variables	Overall score n=400
Shopping frequency	
Daily	16 (4.0%)
Weekly	123 (30.8%)
Monthly	176 (44.0%)
Yearly	14 (3.5%)
Any time	71 (17.8%)
Daily	16 (4.0%)
Weekly	123 (30.8%)
Gender	
Male	261 (65.2%)
Female	139 (34.8%)
Employment	
Full-time	208 (52%)
Part-time	46 (11.5%)
Unemployed	22 (5.5%)
Self-employed	53 (13.2%)
Homemaker	62 (15.5%)
Student	9 (2.2%)
Age	
18-24yrs	110 (27.5%)
25-34yrs	170 (42.5%)
35-44yrs	77 (19.2%)
45-54yrs	32 (8.0%)
55-64yrs	11 (2.8%)
Race	
Black	251 (62.8%)
Coloured	15 (3.8%)
Indian	107 (26.8%)
White	27 (6.8%)
Marital status	
Married	119 (29.8%)
Single	273 (68.2%)
Divorced	5 (1.2%)
Widowed	3 (0.8%)
Dwelling	
City Centre	125 (31.2%)
Location	47 (11.8%)
Suburb	223 (55.8%)
Farmland	5 (1.2%)
Education	
Below Matric	10 (2.5%)
Matric	117 (29.2%)
Tertiary	273 (68.2%)
Income	
R00 000-10 000	173 (43.2%)
R10 001-20 000	120 (30.0%)

R20 001-30 000	57 (14.2%)
R30 001-40 000	34 (8.5%)
R40 000+	16 (4.0%)

Source: compilation from the researchers' statistical output

As reflected in Table 6.1, 44% of respondents shop online monthly, which indicates that they are full-time employees who earn a monthly salary. The gender shows a score of 65.2% for male online shoppers. However, existing literature proves that females do more online shopping than males (Lipschultz 2020: 278). Contrary, to popular belief, the current study shows that males are more likely to be vulnerable to free data exploitation due to their high level of online engagement, which leads to online data self-disclosures that are exploited by retailers.

By the same token, 52% of the respondents are full-time employees who seem to have access to the internet compared 2.2% the respondents who are students. Therefore, online shoppers who unwittingly fall prey to free e-consumer data exploitation are mostly people who have full employment status due to their frequency online. The age bracket engaging online is 25–34 years old with a score of 42.5%, which shows that the youth are vulnerable to free data resource exploitation compared to other age groups because of their frequent exposure to the online platforms that enable free data exploitation.

Also, the single respondents score of 68.2%, as reflected in Table 6.1, indicates that single people engage more online, thereby becoming the most exposed to free e-consumer data resource exploitation. Respondents living in the suburbs have a score of 55.8%, probably due to easy access to the internet, which facilitates online engagements, ultimately prompting online self-disclosure of valuable browsing data that is exploited by online traders without the awareness of the online shoppers. In terms of education, those in the tertiary group have self-efficacy in the digital environment, enabling them to engage online, ultimately leading to self-disclosures linked to free e-consumer data exploitation. Finally, the lower income group earning between R0 and R10 000, with a score of 43.2% usually shops online, thereby exposing themselves to free data resource exploitation due to their tendency to shop online. In the next section, the *p*-values of the demographics are presented.

6:3 DEMOGRAPHICS *P*-VALUES

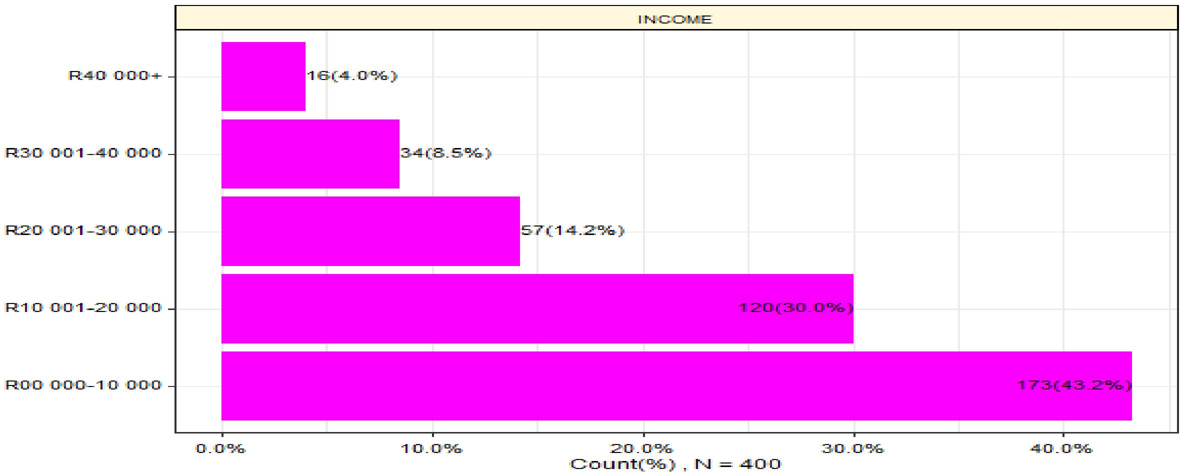
The p-values of each demographic variable are indicated in the subsequent sub-sections. Table 6.2 reflects the *p*-values of the income groups, and Figure 6.1 represents the bar chart scores of each income group.

Table 6. 2 Income group p-values

Income: frequencies diff p-values	16	34	57	120
34	0.012	-	-	-
57	<0.001	0.016	-	-
120	<0.001	<0.001	<0.001	-
173	<0.001	<0.001	<0.001	0.002

Source: compilation from the researchers' statistical output.

Figure 6. 1 Income groups



Source: compilation from the researchers' statistical output.

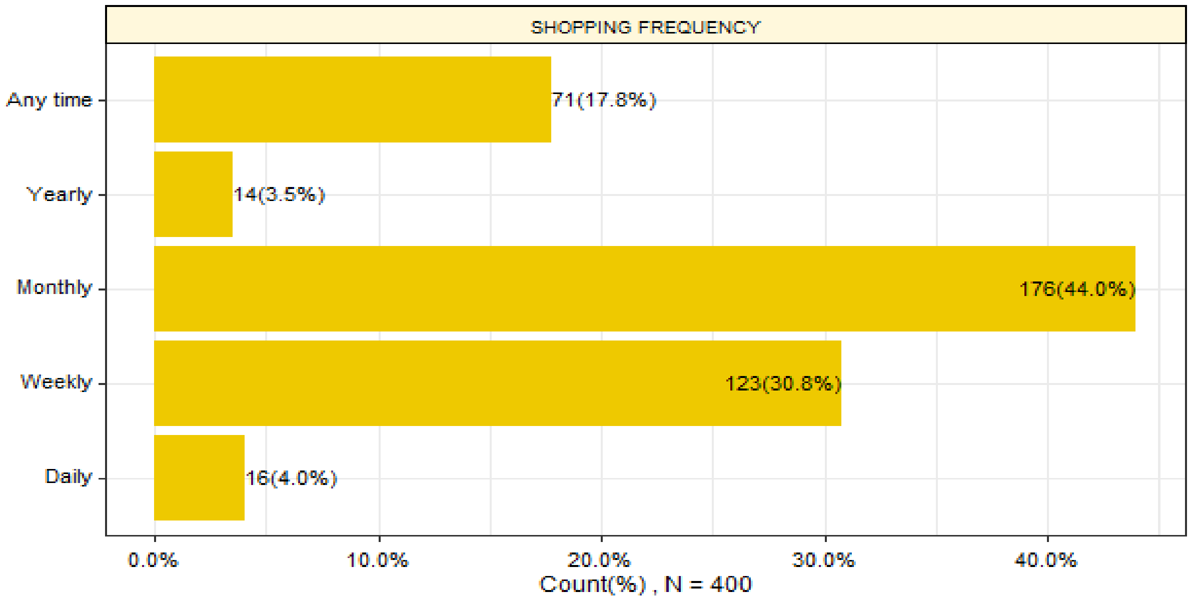
As reflected in Table 6.2, the *p*-value for the income group of over R40 000 with a score of 16 in comparison with the income group between R30 001 and R40 000 with a score of 34 is not significant at *p*= 0.012 as the recommended level of $p \leq 0.001$ is exceeded. These groups are not significantly different, and those with a $p \leq 0.001$ are significantly different. Recent literature reveals that e-consumers with a higher income engage more online and are therefore more vulnerable to becoming prey to free data exploitation (Chipp, Ismail, Meiring 2017:117). However, the empirical data contradicts existing literature in that the higher the income level, the less likely respondents are to transact online, thereby avoiding exposure to e-consumer free data resource exploitation. As income increases online engagement decreases, with only 4% of the respondents engaging online in the highest income group (R40 000 and above). In the next section, Table 6.3 reflects the *p*-values of shopping frequency and Figure 6.2 represents the bar chart scores of each shopping frequency.

Table 6. 3 Shopping frequency p-values

Shopping frequency: diff p-values	14	16	71	123
16	0.715	-	-	-
71	<0.001	<0.001	-	-
123	<0.001	<0.001	<0.001	-
176	<0.001	<0.001	<0.001	0.002

Source: compilation from the researchers' statistical output.

Figure 6. 2 Shopping frequency



Source: compilation from the researchers' statistical output.

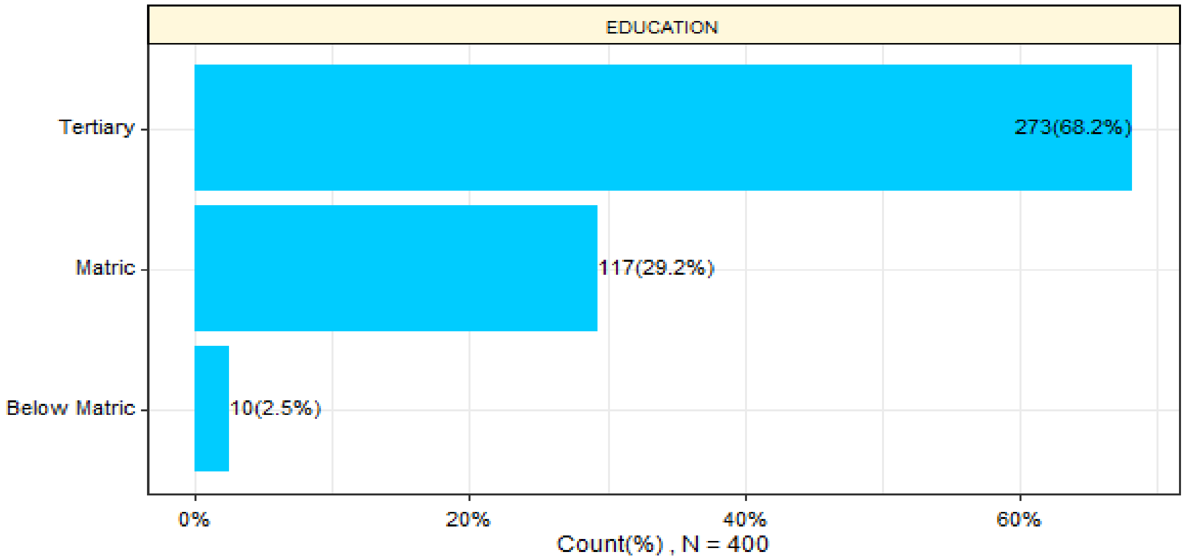
The scores reflected in Table 6.3 for respondents shopping online yearly is 3.5% and for those shopping daily is 4.0%, which is not significantly different at *p*=0.715 higher than the recommended level of $p \leq 0.001$ for categorical variables. Therefore, those who shop online less often are less likely to unwittingly fall prey to free data resource exploitation (Ghosal et al. 2020: 1402). In the next section, Table 6.4 covers the *p*-values for education levels and Figure 6.3 represents the bar chart scores.

Table 6. 4 Education level p-values

Education: frequency diff p-values	10	117
117	<0.001	-
273	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 3 Education level



Source: compilation from the researchers' statistical output.

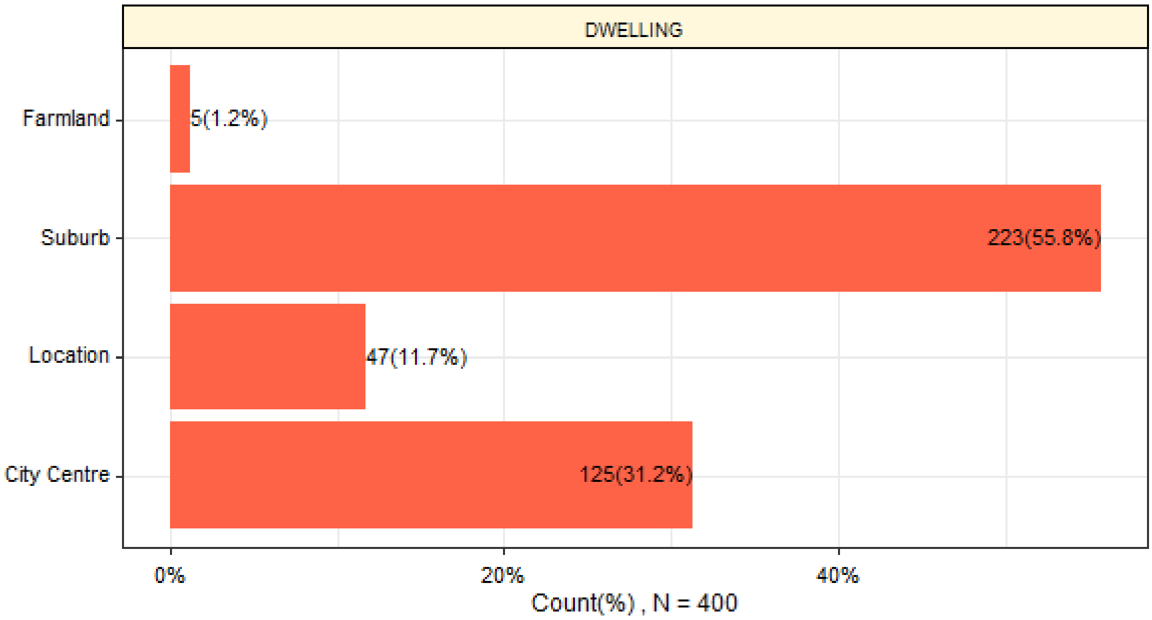
As reflected in Table 6.4, respondents with higher education versus those with lower education are significantly different at $p<0.001$, with the less educated being less likely to shop online and less likely to be exposed to free e-consumer data exploitation. This is in conformity with existing literature alluding that e-consumers with good education are computer literate, allowing them to engage on the internet with ease, which renders them able to disclose online data without noticing (Chipp, Ismail, Meiring 2017:117). In the next section, Table 6.5 covers the *p*-values of dwelling and Figure 6.4 represents the bar chart scores of each dwelling category.

Table 6. 5 Dwelling p-values

Dwelling: frequency diff p-values	5	47	125
47	<0.001	-	-
125	<0.001	<0.001	-
223	<0.001	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 4 Figure 6:4 Dwelling



Source: compilation from the researchers' statistical output.

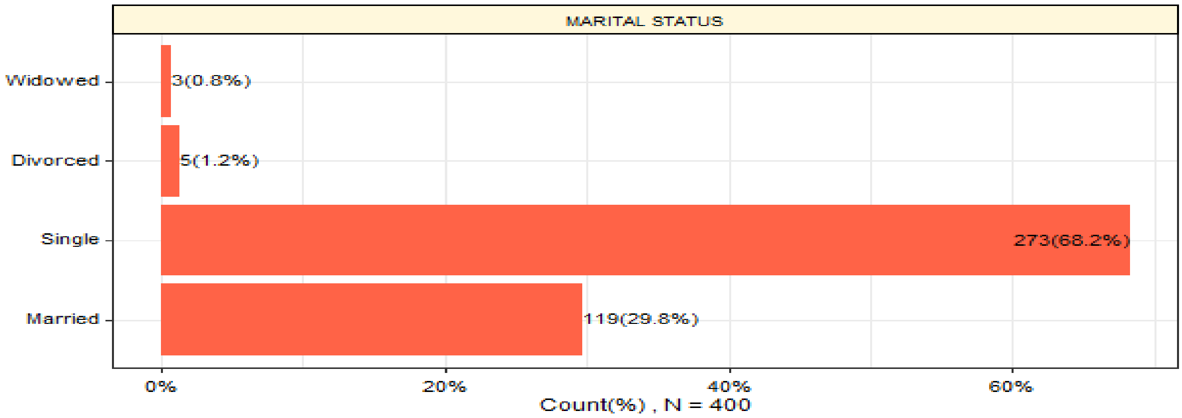
All the categories in Table 6.5 are significantly different at *p*<0.001, with respondents living in the city and suburbs being more vulnerable to inadvertent online self-disclosures, leading to free e-consumer data exploitation. Hirt, Kuhl, and Satzger (2019; 95) concur with the empirical evidence that urban areas engage more online, which traps them into online self-disclosures, leading to free data exploitation. In the next section, Table 6.6 covers the *p*-values of marital status and Figure 6.5 represents the bar chart scores of marital status categories.

Table 6. 6 Marital status p-values

Marital status: frequency diff p-values	**3**	**5**	**119**
5	0.480	-	-
119	<0.001	<0.001	-
273	<0.001	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 5 Marital statuses



Source: compilation from the researchers' statistical output.

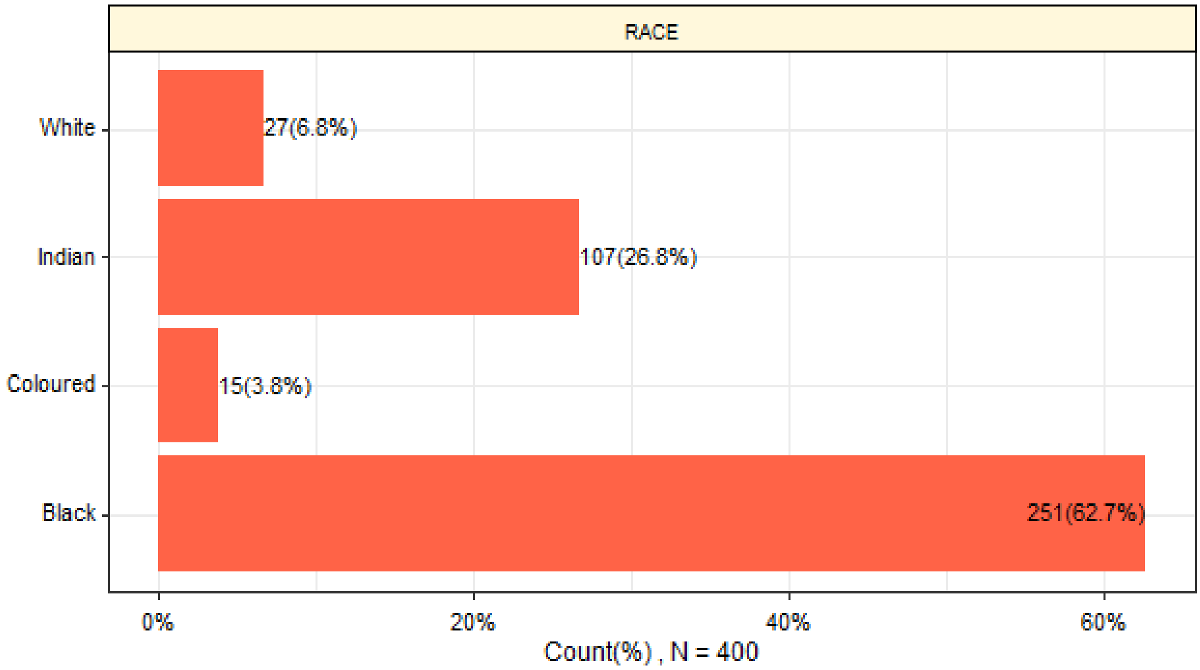
Table 6.6 reflects a *p*-value of 0.480 between the widowed and the divorced, which is higher than the recommended value of $p \leq 0.001$, and therefore the divorced and the widowed are not different. Demographic variables such as marital status have an influence on online shopping (Plangger and Montecchi 2020: 32). The singles with a 68.2% score are the majority of the respondents shopping online, which exposes them to online self-disclosure and free data resource exploitation. In the next section, Table 6.7 covers the *p*-values of the race groups, and Figure 6.6 represents the bar chart scores of each race.

Table 6. 7 Race p-values

Race: frequency diff p-values	**15**	**27**	**107**
27	0.064	-	-
107	<0.001	<0.001	-
251	<0.001	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 6 Race



Source: compilation from the researchers' statistical output.

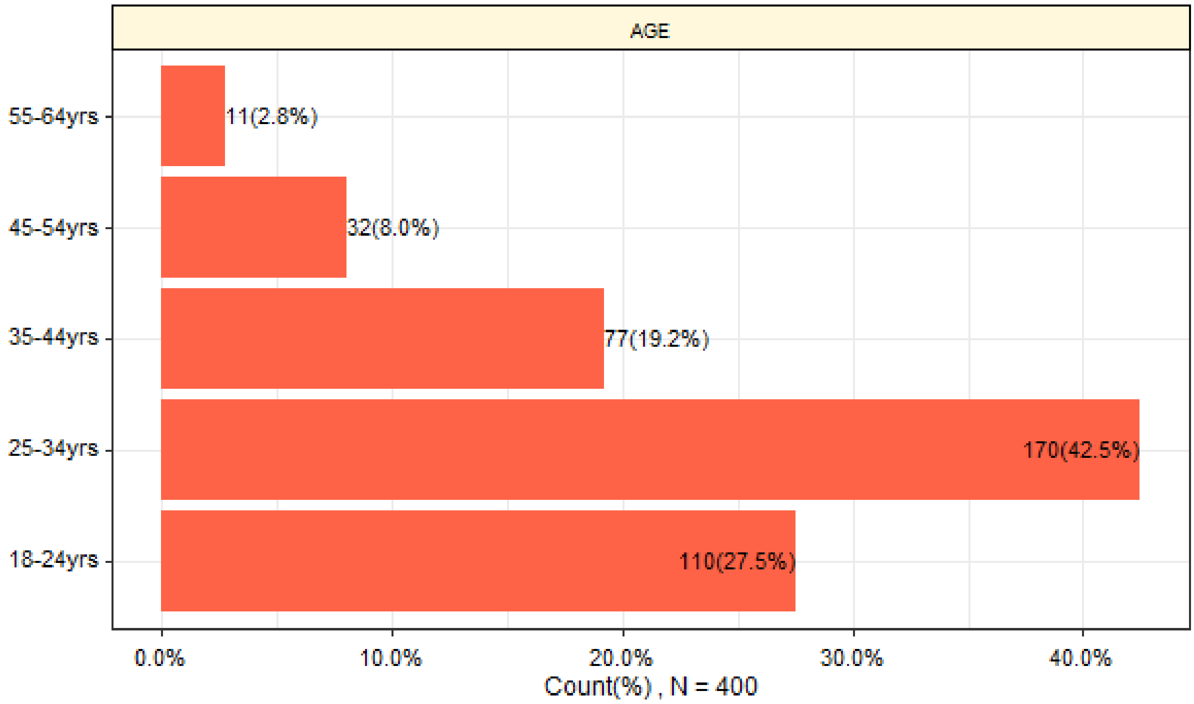
In Table 6.7, with a *p*-value of 0.064, which is higher than the acceptable $p \leq 0.001$ value, there is no significant difference between the whites and the coloureds probably due to the low population of the whites and coloureds compared to the blacks and Indians residing in Durban. Therefore, due to their low level of online engagement, the whites and the coloureds are less likely to engage online, thereby limiting exposure to free data resource exploitation compared to the blacks and Indians, with a $p<0.001$ value. Sponder and Khan (2018: 44) agree that demographic factors like race have an influence on the level of online shopping. In the next section, Table 6.8 covers the *p*-values of the age groups, and Figure 6.7 represents the bar chart scores of each age group.

Table 6. 8 Age groups p-values

Age: frequency diff p-values	11	32	77	110
32	0.002	-	-	-
77	<0.001	<0.001	-	-
110	<0.001	<0.001	0.016	-
170	<0.001	<0.001	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 7 Age groups



Source: compilation from the researchers' statistical output.

Table 6.8 reflects a *p*-value of 0.002 between the age groups of 55–64 and 45–54 and a p-value of 0.016 for the age groups between 35–44 and 18–24, which indicates that there is no significant difference between these groups. Pentz, Du Preez and Swiegers (2020: 235) argue that the young generation is impulsive and prefers toshop online, which renders them prey to online self-disclosure and free data resource exploitation. But all other groups at *p*<0.001 are significantly different, with the adult youth being more engaged in online shopping, leading to free e-consumer data exploitation. In the next section, Table 6.9 covers the *p*-values of the employment categories, and Figure 6.8 represents the bar chart scores of each employment status.

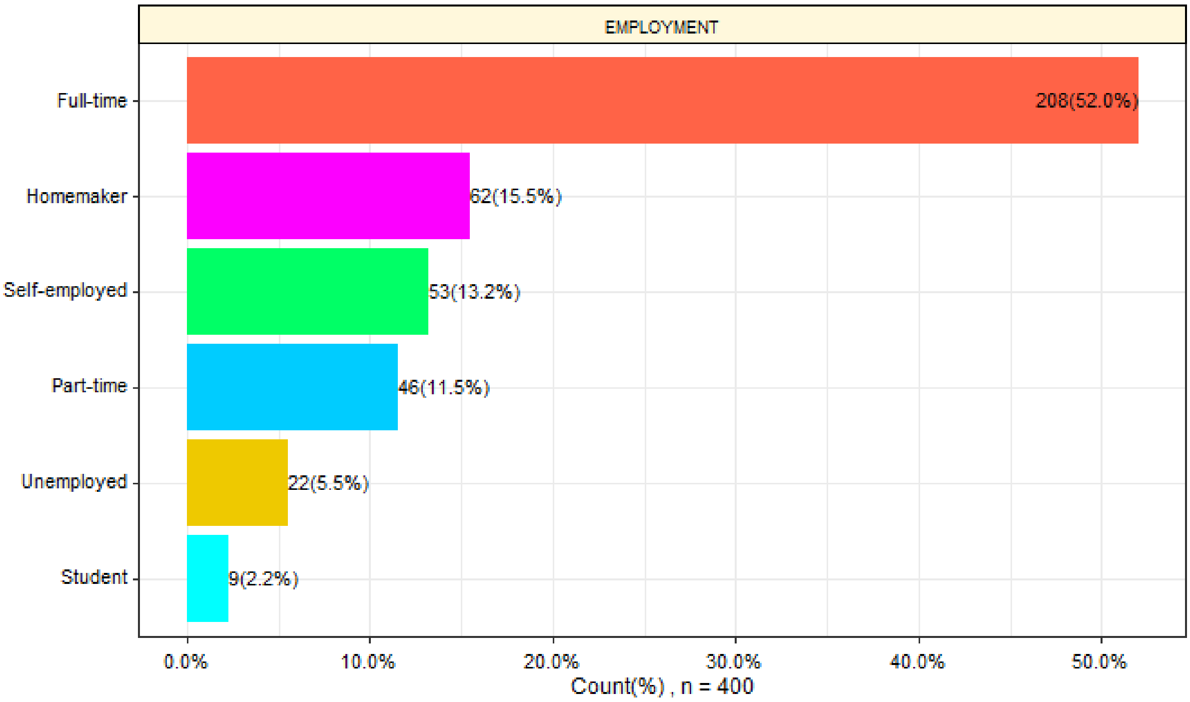
Table 6. 9 Employment p-values

Employment: frequency diff p-values	**9**	**22**	**46**	**53**	**62**
22	0.024	-	-	-	-
46	<0.001	0.005	-	-	-
53	<0.001	<0.001	0.482	-	-
62	<0.001	<0.001	0.143	0.430	-
208	<0.001	<0.001	<0.001	<0.001	<0.001

Source: compilation from the researchers' statistical output.

Figure 6. 8 Employment

Source: compilation from the researchers' statistical output.



As reflected in Table 6.9, students have a score of 9 against the unemployed, with a score of 22, making the *p*-value=0.024, indicating that there is no difference between these groups. Socio-demographic factors have an influence on e-consumers' online shopping decisions (Bilder *et al.* 2020: 507). The same applies to all the combinations with a *p*-value greater than 0.001 in Table 6.9 about employment status. However, the category of the full-time employed respondents against all other groups has a *p*-value <0.001, indicating that the full-time category is different from all other groups with the maximum likelihood of engaging in online shopping, leading to online self-disclosure and free data resource exploitation. In the next section, scores from the Likert scale are analysed.

6:4 LIKERT SCALE AND CRONBACH'S ALPHA

After analysing the demographic variables, scores on the Likert scale were analysed and the reliability test was conducted using Cronbach's alpha. Although the pilot study provided a clue on item grouping after the exploratory factor analysis, items have been grouped arbitrarily based on face validity due to the dynamics of the digital phenomenon pertaining to the current study. The reliability coefficient of Cronbach's alpha ranges between 0 and 1, with greater or equal to 0.80 as good scale, 0.70 as an acceptable scale, and 0.60 as a new scale (Rouf and Akhtaruddin, 2018: 1503). The items in the measuring tool have been preliminarily grouped as effects (EF), perceived risk (PR), perceived trust (PT), purchase intention (PI), shopping experience (SE), and e-consumer empowerment (EE). The groupings are analysed in the next sub-section.

6:4:1 Effects (EF)

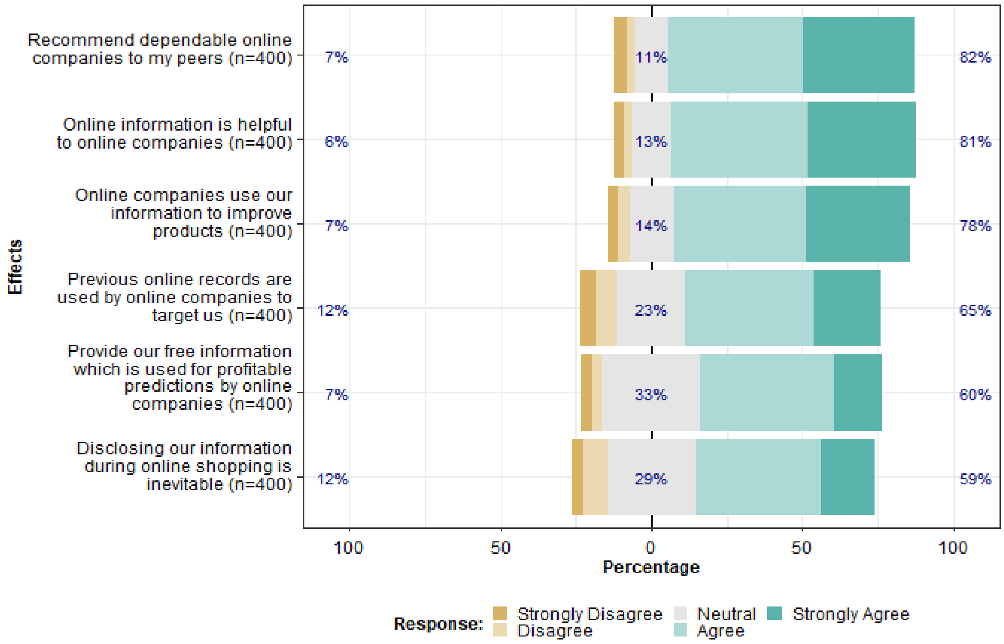
The effects of digital consumerism concerning free data resource exploitation contain six items that were answered using a five-point Likert scale. The effects are positive and negative, where the positive effects improve the e-consumer shopping experience, while the negative effects are a deterrent to the e-consumer shopping experience. The following scores as shown in Figure 6.9 were obtained followed by the effects mean score summary covered in Table 6.10.

Table 6. 10 Effects mean scores summary

Item	Mean (SD)	Low	Neutral	High
Recommend dependable online companies to my peers (n=400)	4.08(0.99)	7.00	11.00	82.00
Online information is helpful to online companies (n=400)	4.08(0.94)	5.75	13.00	81.25
Online companies use our information to improve products (n=400)	4.02(0.97)	7.25	14.25	78.50
Previous online records are used by online companies to target us (n=400)	3.69(1.07)	12.50	22.75	64.75
Provide our free information, which is used for profitable predictions by online companies (n=400)	3.66(0.91)	7.00	32.75	60.25
Disclosing our information during online shopping is inevitable (n=400)	3.62(0.98)	11.75	29.00	59.25
Overall	**3.86(0.98)**	**8.54**	**20.46**	**71.00**

Source: compilation from the researchers' statistical output.

Figure 6. 9 Effects



Source: compilation from the researchers' statistical output.

Table 6.10 presents an overall score of 71% of the 400 respondents who strongly agree and agree to all the items in the effects construct. Figure 6.9 reflects the scores summarised in three groups where the percentages in the left column represent a combination of strongly disagree and disagree, the percentages in the middle column represent neutral, and the percentages in the right column represent strongly agree with agree. For example, 82% of the respondents strongly agree and agree, while 11% are neutral, and 7% strongly disagree and disagree that they recommend dependable online companies to their peers.

Furthermore, 81% strongly agree and agree that their information is helpful to online companies, which suggests that online companies use e-consumer data for economic benefits without rewarding the owners of the data input. Rust (2020: 19) shares the sentiment that e-consumer data is useful for informed decision-making. Virtually all the online retailers interviewed in the current study accept that e-consumer data is helpful for the smooth running of their online businesses. When respondents were asked whether their data is used to target them, 65% strongly agreed, while 60% strongly agreed and agreed that their data is profitable for company predictions. However, 59% strongly agreed and agreed that disclosing their information online is inevitable, and therefore they are not aware that their data is being exploited for free. Table 6.11 presents the reliability tests of the effects.

Table 6. 11 Effects reliability test

Items	Mean	Item-rest correlation		Alpha-if-deleted
Recommend dependable online companies to my peers	4.077	0.498		0.696
Provide our free information, which is used for profitable predictions by online companies.	3.658	0.510		0.694
Previous online records are used by online companies to target us	3.692	0.463		0.708
Online information is helpful to online companies	4.080	0.550		0.683
Disclosing our information during online shopping is inevitable	3.618	0.367		0.733
Online companies use our information to improve products	4.022	0.479		0.702
Overall	**3.858**	**-**		**0.740**
ITEMS DROPPED	Improvement	Items Alpha	Max	Overall , Alpha
#N/A	#N/A	#N/A		#N/A
ITEMS SCALE REVERSED	-	-		-
#N/A	#N/A	#N/A		#N/A

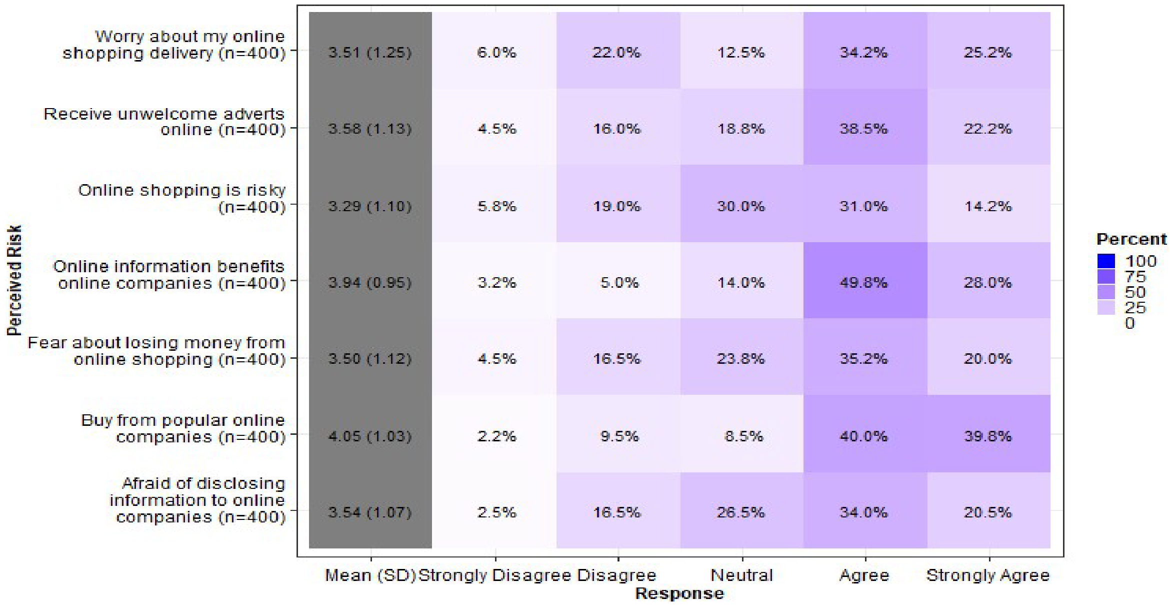
Source: compilation from the researchers' statistical output.

As observed in Table 6.11, the overall Cronbach's alpha is 0.740, which is higher than the acceptable Alpha of 0.7. Therefore, all the items in the effects construct are consistent with each other. Perceived risk is analysed in the next sub-section.

6:4:2 Perceived risk (PR)

Online shoppers believe that transacting online is risky based on the scores in Figure 6. 10 which represents the scores of perceived risks in percentage format.

Figure 6. 10 Perceived risks



Source: compilation from the researchers' statistical output.

Table 6.12 reflects the mean scores and the level of responses.

Table 6. 12 Perceived risk mean scores summary

Item	Mean (SD)	Low	Neutral	High
Buy from popular online companies (n=400)	4.05 (1.03)	11.75	8.50	79.75
Receive unwelcome adverts online (n=400)	3.58 (1.13)	20.50	18.75	60.75
Worry about my online shopping delivery (n=400)	3.51 (1.25)	28.00	12.50	59.50
Fear about losing money from online shopping (n=400)	3.50 (1.12)	21.00	23.75	55.25
Afraid of disclosing information to online companies (n=400)	3.54 (1.07)	19.00	26.50	54.50
Online shopping is risky (n=400)	3.29 (1.10)	24.75	30.00	45.25
Overall	**3.58 (1.12)**	**20.83**	**20.00**	**59.17**

Source: compilation from the researchers' statistical output.

The overall percentage score is high at 59.17 for respondents who strongly agree and agree to all the items in Table 6.12 pertaining to perceived risk. The thicker the colour texture in Figure 6.3, the higher the percentage scored. For example, a score of 49.8%, which is the darkest, reflects respondents who agree that e-consumer online information benefits online companies, while a score of 2.2%, which is the lightest colour, reflects the percentage score of respondents who strongly disagree that they buy from popular online companies while, 40% agree that they buy from popular online companies. Arya, Sethi and Paul (2019: 144) argue that popular online brands influence e-consumers to shop online. The higher percentage score of buying from popular online companies exposes respondents to online self-disclosures that are exploited by the popular online companies to make economic predictions without the awareness of the online shopper, who is the producer of the information used as a valuable input for economic predictions. Table 6.13 covers the perceived risk reliability tests.

Table 6. 13 Perceived risk reliability tests

Items	Mean	Item-rest correlation	Alpha-if-deleted
Worry about my online shopping delivery	3.507	0.479	0.660
Buy from popular online companies	4.055	0.243	0.726
Afraid of disclosing information to online companies	3.535	0.530	0.646
Online shopping is risky	3.290	0.575	0.630
Receive unwelcome adverts online	3.580	0.324	0.708
Fear about losing money from online shopping	3.498	0.522	0.647
Overall	3.578	-	0.711
ITEMS DROPPED	Improvement	Items Max Alpha	Overall, Alpha
Online information benefits online companies	1	0.7108	0.6890
ITEMS SCALE REVERSED	-	-	-
#N/A	#N/A	#N/A	#N/A

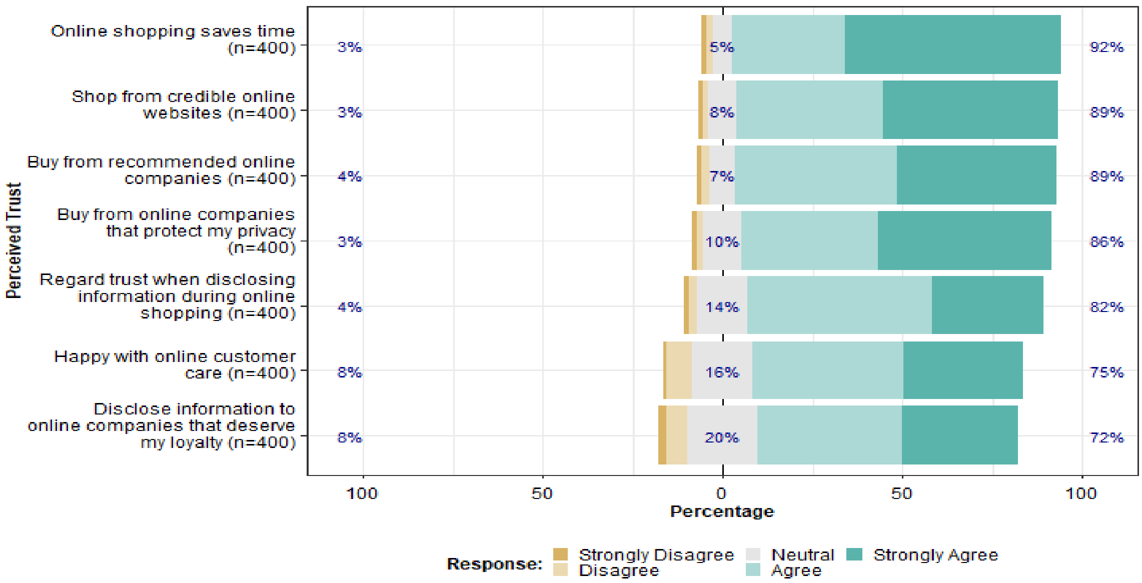
***Source: compilation from the researchers' statistical output*.**

The overall Cronbach's alpha for the items constituting perceived risk is 0.711, which is 0.70 and above acceptable.

6:4:3 Perceived trust (PT)

Perceived trust of online shopping exposes innocent e-consumers to free e-consumer data exploitation as they gain confidence in the online platforms, thereby downplaying the risks of transacting online. Seven items were tested, and the results obtained are presented in Figure 6.11 concerned with perceived trust.

Figure 6. 11 Perceived trusts



***Source: compilation from the researchers' statistical output*.**

Table 6.14 reflects the mean scores and the level of responses.

Table 6. 14 Perceived trust mean scores summary

Item	Mean (SD)	Low	Neutral	High
Online shopping saves time (n=400)	4.47(0.79)	3.25	5.25	91.50
Buy from recommended online companies (n=400)	4.28(0.80)	3.75	7.00	89.25
Shop from credible online websites (n=400)	4.34(0.80)	2.75	8.00	89.25
Buy from online companies that protect my privacy (n=400)	4.29(0.84)	3.25	10.50	86.25
Regard trust when disclosing information during online shopping (n=400)	4.08(0.82)	3.75	14.25	82.00
Happy with online customer care (n=400)	4.00(0.93)	8.25	16.50	75.25
Disclose information to online companies that deserve my loyalty (n=400)	3.94(0.98)	8.00	19.75	72.25
Overall	**4.20(0.85)**	**4.71**	**11.61**	**83.68**

***Source: compilation from the researchers' statistical output*.**

As reflected in Table 6.14, the overall percentage score of respondents who strongly agree and agree to all the items pertaining to perceived risk is 83.68%, compared to those who strongly disagree and disagree at 4.71% and those who were neutral at 11.61% out of the 400 respondents. In Figure 6.11, 92% of the respondents strongly agree and agree that online shopping saves time. Gauri *et al.* (2021: 44) report that online shoppers continue to engage in online activities because it saves time, but are unaware that while they are transacting online, they leave a lot of browsing behavioural data, which is exploited by online traders without compensating the producers of the data input. Bornschein, Schmidt and Maier (2020: 139) affirm that e- consumers shop from credible websites. Similarly, when respondents were asked whether they buy from credible websites and recommended online companies, 89% strongly agree and agree to both questions, resulting in e-consumers inadvertently disclosing free data as they are transacting online, thereby attracting online firms to exploit free e-consumer data for profitable predictions. Table 6.15 covers the reliability test for perceived trust.

Table 6. 15 Perceived trust reliability tests

Items	Mean	Item-rest correlation	Alpha-if-deleted
Buy from recommended online companies	4.282	0.537	0.802
Buy from online companies that protect my privacy	4.295	0.675	0.779
Shop from credible online websites	4.338	0.638	0.786
Online shopping saves time	4.470	0.616	0.790
Disclose information to online companies that deserve my loyalty	3.938	0.521	0.807
Happy with online customer care	3.995	0.451	0.818
Regard trust when disclosing information during online shopping	4.077	0.541	0.801
Overall	**4.199**	**-**	**0.821**

ITEMS DROPPED	Improvement	Items Max Alpha	Overall, Alpha
#N/A	#N/A	#N/A	#N/A
ITEMS SCALE REVERSED	-	-	-
#N/A	#N/A	#N/A	#N/A

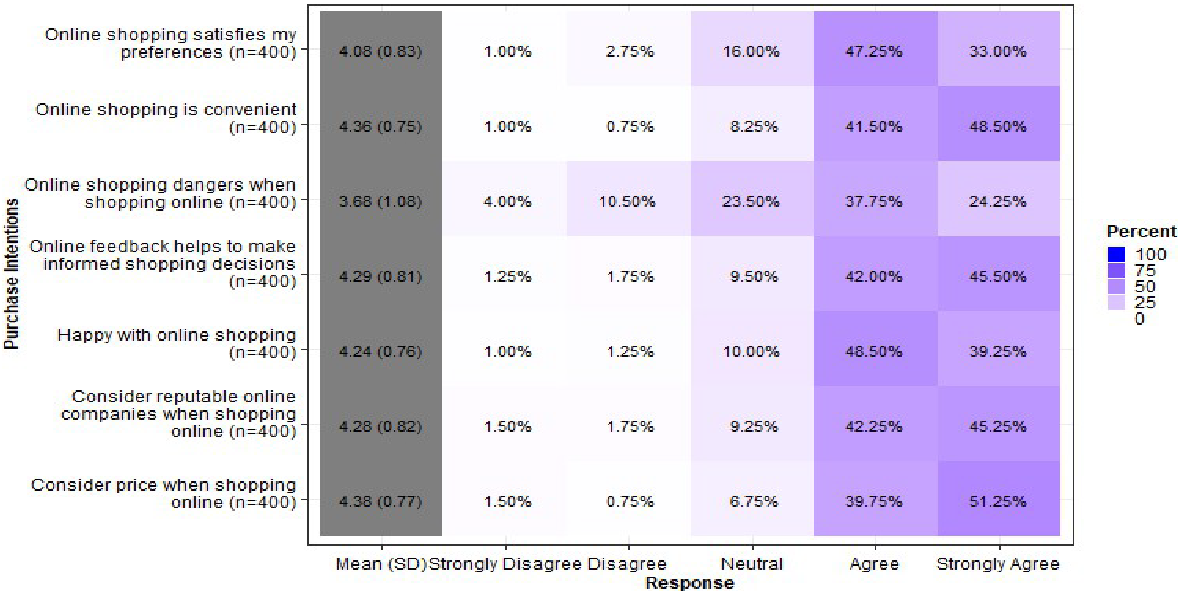
Source: compilation from the researchers' statistical output.

As shown in Table 6.15, the overall reliability test using Cronbach's alpha is 0.821, which is very good compared to the minimum acceptable alpha of 0.70, which means that all the items are measuring perceived trust with each item contributing above a 0.07 Alpha value. In the next section, the results of purchase intention are described, followed by the reliability tests pertaining to purchase intention.

6:4:4 Purchase intention (PI)

Seven items were selected to test how purchase intention influence online consumers and the following results were recorded as indicated in Figure 6.12 below.

Figure 6. 12 Purchase intention



Source: compilation from the researchers' statistical output.

Table 6.16 reflects the mean scores and the level of responses.

Table 6. 16 Purchase intention mean scores summary

Item	Mean (SD)	Low	Neutral	High
Consider price when shopping online (n=400)	4.38(0.77)	2.25	6.75	91.00
Online shopping is convenient (n=400)	4.36(0.75)	1.75	8.25	90.00
Happy with online shopping (n=400)	4.24(0.76)	2.25	10.00	87.75
Online feedback helps to make informed shopping decisions (n=400)	4.29(0.81)	3.00	9.50	87.50
Consider reputable online companies when shopping online (n=400)	4.28(0.82)	3.25	9.25	87.50
Online shopping satisfies my preferences (n=400)	4.08(0.83)	3.75	16.00	80.25
Online shopping dangers when shopping online (n=400)	3.68(1.08)	14.50	23.50	62.00
Overall	**4.19(0.83)**	**4.39**	**11.89**	**83.71**

***Source: compilation from the researchers' statistical output*.**

As reflected in Table 6.16, 91% of respondents strongly agree and agree that they consider price when shopping online, and the overall score for strongly agree and agree is 83.71%, as reflected graphically and in tabular form. Moran (2020: 894) confirms that prices are considered when shopping online. Once the price is in their favour, they unwittingly disclose their valuable data online as they transact, thereby providing free data resources for the online firm to make profitable predictions without considering the producer of the data.

Also, online shoppers consider convenience with a score of 90%, and are happy with online shopping, not realising that behind the scenes, online companies are tracking their valuable data for the economic benefit of online companies who exploit e-consumer data at virtually no cost. The factor, online shopping satisfies my preferences, scored of 80.25% and once their preferences were met, they downplayed free data resource exploitation, which benefits online companies more than e-consumer satisfaction which comes at a cost. Reliability tests for purchase intention are shown in Table 6.17, and then explained.

Table 6. 17 Purchase intention reliability tests

Items	Mean	Item-rest correlation	Alpha-if-deleted
Happy with online shopping	4.237	0.560	0.731
Consider price when shopping online	4.385	0.550	0.733
Online feedback helps to make informed shopping decisions	4.287	0.567	0.728
Consider reputable online companies when shopping online	4.280	0.619	0.717
Online shopping satisfies my preferences	4.085	0.586	0.724
Online shopping is convenient	4.357	0.589	0.726
Online shopping dangers when shopping online	3.678	0.147	0.832
Overall	**4.187**	**-**	**0.772**
ITEMS DROPPED	Improvement	Items Max Alpha	Overall , Alpha
#N/A	#N/A	#N/A	#N/A
ITEMS SCALE REVERSED	-	-	-
#N/A	#N/A	#N/A	#N/A

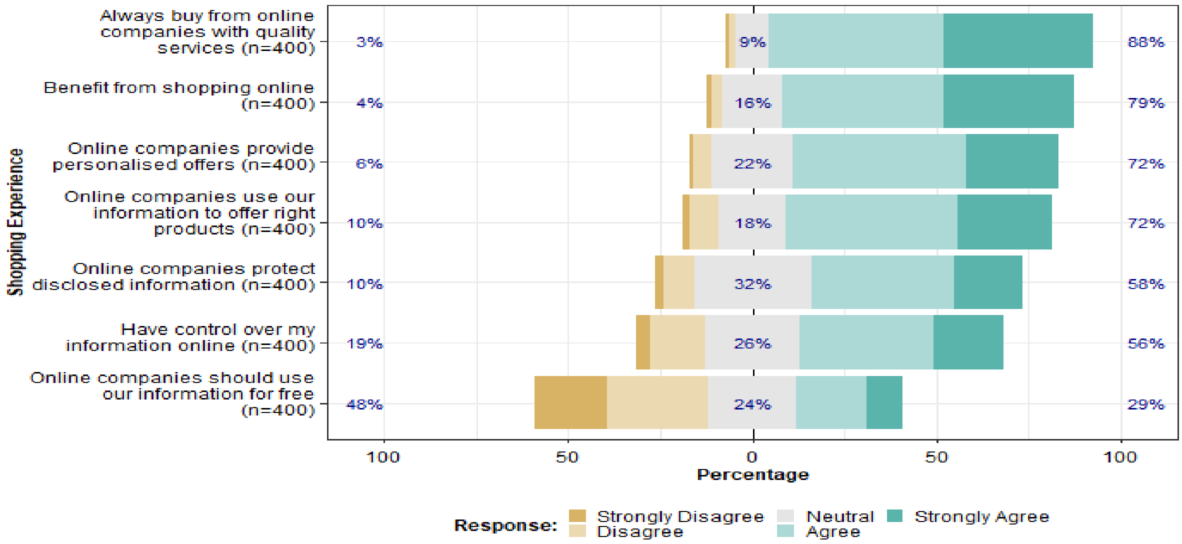
Source: compilation from the researchers' statistical output.

As reflected in Table 6.17, all the items are above the minimum acceptable Cronbach's alpha of 0.70 and the overall score for all items is 0.772, which is good. No items were dropped, and no items were reversed. In the next section, the scores of shopping experience are covered.

6:4:5 Shopping experience (SE)

All the items can shed some light on e-consumer awareness of free data resource exploitation. Figure 6.13 covers the scores of shopping experience followed by the reliability tests.

Figure 6. 13 Shopping experience



Source: compilation from the researchers' statistical output.

Table 6.18 reflects the mean scores and the level of responses.

Table 6. 18 Shopping experience mean scores summary

Item	Mean (SD)	Low	Neutral	High
Always buy from online companies with quality services (n=400)	4.25(0.78)	3.00	9.00	88.00
Benefit from shopping online (n=400)	4.09(0.87)	4.25	16.50	79.25
Online companies provide personalised offers (n=400)	3.91(0.86)	6.00	21.75	72.25
Online companies use our information to offer right products (n=400)	3.87(0.94)	9.50	18.50	72.00
Online companies protect disclosed information (n=400)	3.63(0.96)	10.50	31.75	57.75
Have control over my information online (n=400)	3.52(1.08)	18.75	25.75	55.50
Online companies should use our information for free (n=400)	2.71(1.26)	47.50	23.50	29.00
Overall	**3.71(0.96)**	**14.21**	**20.96**	**64.82**

Source: compilation from the researchers' statistical output.

According to Table 6.18 concerning shopping experience, the overall percentage score of respondents who strongly agree and agree is 64.82% as reflected in Table 6.18 concerning shopping experience. Figure 6.6 reflects that 88% of the respondents strongly agree and agree that they always buy from online companies with better quality services. Hamouda (2021: 2) shares the same view that quality products or services online attract e-consumers to transact online without noticing that they are leaving a trail of browsing data exploited by online shoppers. Respondents transact online for better quality, not realising that they are leaving behind valuable e-consumer data, which is later exploited by online companies for predictions and retargeting, which benefit online companies at the expense of e-consumers, who are the producers of such valuable data resources. Also, 72% of the respondents strongly agree and agree that online companies provide personalised offers. Personalised services prompt e-consumers to transact online, thereby providing online retailers with free online behavioural data.

When online firms provide personalised offers, they tend to engage online, leaving a trail of free data that is exploited by online companies without the awareness of e-consumers who generate the data resources that benefit the company. On the other hand, as indicated in Figure 6.6 pertaining to shopping experience, 48% of the respondents strongly disagree and disagree that online companies should use their data resources for free. This means that once e-consumers become aware that online companies exploit their information for free, it may lead to unrest and deteriorating consumer relations. Table 6.19 lists the reliability tests for the shopping experience.

Table 6. 19 Shopping experience reliability tests

Items	Mean	Item-rest correlation	Alpha-if-deleted
Have control over my information online	3.520	0.501	0.714
Benefit from shopping online	4.093	0.462	0.723
Online companies protect disclosed information	3.635	0.583	0.695
Online companies provide personalised offers	3.908	0.493	0.717
Online companies use our information to offer right products	3.868	0.505	0.713
Online companies should use our information for free	2.715	0.362	0.757

Always buy from online companies with service quality	4.247	0.433	0.730
Overall	**3.712**	**-**	**0.751**
ITEMS DROPPED	Improvement	Items Max Alpha	Overall, Alpha
#N/A	#N/A	#N/A	#N/A
ITEMS SCALE REVERSED	-	-	-
#N/A	#N/A	#N/A	#N/A

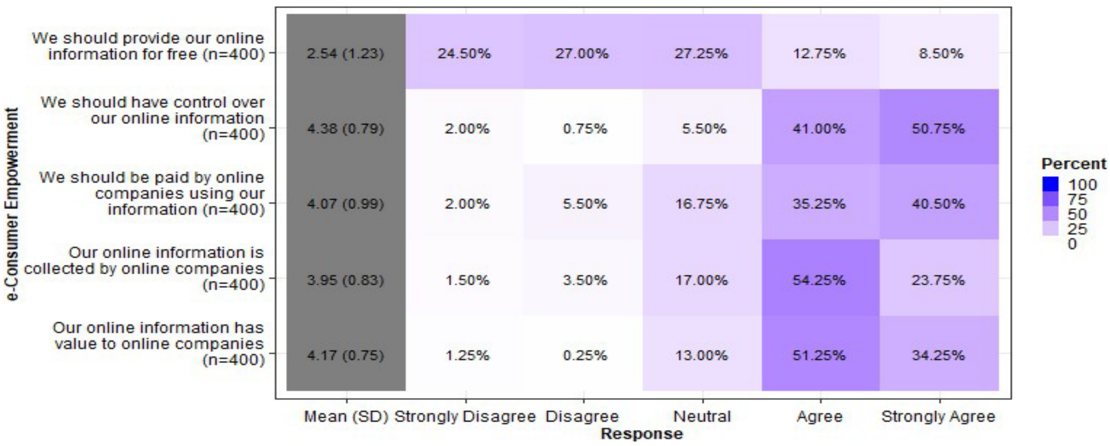
***Source: compilation from the researchers' statistical output**.*

The overall reliability test for the shopping experience construct is 0.751, as shown in Table 6.19, which meets the acceptable level of 0.70 Cronbach's alpha. E-consumer empowerment scores are provided in the next section.

6:4:6 E-consumer empowerment (EE)

To empower e-consumers, the return on exchanging valuable data with online firms must be driven by the economic value that e-consumers will receive in return for the exchange of data (Krafft *et al.* 2021: 139). Questions relating to the recognition of e-consumer data input were carefully designed to obtain the opinions of online shoppers participating in the study. The e-consumer empowerment construct acts as the remediation strategy for free data resource exploitation. Two items from this construct were dropped in order to improve the reliability tests. Figure 6.14 covers the scores of e-consumer empowerments in a graphical format.

Figure 6. 14 E-consumer empowerment



***Source: compilation from the researchers' statistical output**.*

Table 6.20 reflects the mean scores and the level of responses.

Table 6. 20 E-consumer empowerment scores

Item	Mean (SD)	Low	Neutral	High
We should have control over our online information (n=400)	4.38(0.79)	2.75	5.50	91.75
Our online information has value to online companies (n=400)	4.17(0.75)	1.50	13.00	85.50
Our online information is collected by online companies (n=400)	3.95(0.83)	5.00	17.00	78.00
We should be paid by online companies using our information (n=400)	4.07(0.99)	7.50	16.75	75.75
We should provide our online information for free (n=400)	2.54(1.23)	51.50	27.25	21.25
Overall	**3.82(0.9)**	**13.65**	**15.90**	**70.45**

Source: compilation from the researchers' statistical output.

Table 6.20 reflects an overall score of 70.45% of respondents that strongly agree and agree to all the items pertaining to e-consumer empowerment, which implies that respondents have a positive attitude towards all the items. For example, in Figure 6.7, 50.75% of the respondents strongly agree, and 41% agree that they should have control over their data, which is controlled by online firms to make profitable predictions leaving the producers of online data with no control over their data. Bornschein, Schmidt and Maier (2020: 135) concur that e-consumers are powerless and have no control over their data as they shop online. In Table 6.18, 51.50% of the respondents are against supplying their data for free, which means that e-consumers are progressively becoming aware that their data has value to online firms, and they should be rewarded rather than exploited.

As seen in Figure 6.14, 54.25% agree, and 23.75% of the respondents strongly agree that their online information is being tracked by online companies, which means that consumers are becoming aware that their data is collected but are not aware of free e-consumer data exploitation. However, 51.25% agree that their data has value to online companies but are not aware that that value is being exploited by online companies without compensating data producers. Table 6.21 reflects the reliability tests of e-consumer empowerment.

Table 6. 21 E-consumer empowerment reliability tests

Items	Mean	Item-rest correlation	Alpha-if-deleted
Our online information is collected by online companies	3.953	0.446	0.652
We should have control over our online information	4.378	0.516	0.610
Our online information has value to online companies	4.170	0.524	0.609
We should be paid by online companies using our information	4.067	0.455	0.657
Overall	**4.142**	**-**	**0.695**
ITEMS DROPPED	Improvement	Items Max Alpha	Overal l Alpha
We should provide our online information for free	2	0.6955	0.5509
ITEMS SCALE REVERSED	-	-	-
We provide our information for free			

Source: compilation from the researchers' statistical output.

As reflected in Table 6.21, the overall Cronbach alpha is 0.695%, which can be rounded up to the minimum acceptable alpha of 0.70. Since the measurement tool used in the current study is new, the output of the reliability tests is acceptable, and all the items are consistent with each other. Having explained the descriptive statistics, the next section covers exploratory factor analysis to ensure validity.

6:5 EXPLORATORY FACTOR ANALYSIS (EFA)

Due to the fact that the questionnaire used in the current study is new and the volatility is due to the dynamics of the digital phenomenon about this study, EFA is suitable to ensure validity as compared to CFA. It's impractical to confirm a dynamic situation. The EFA is normally used when there is inadequate information concerning the latent structure, while the Confirmatory Factor Analysis CFA requires the researcher to confirm the existing structure in order to ascertain empirical data to fit the structural model (Finch 2020: 6). The wavering digital environment concerning the current study has not been tested before, and therefore, EFA was considered. Table 6.22 reflects the KMO, which deals with the sample adequacy ideal for conducting EFA. To ensure that data is appropriate for factor analysis, the Kaiser-Meyer Okin (KMO) sampling adequacy was used with 0.6 as the minimum value and a p-value at $p \leq 0.01$ level of significance (Dawson 2018: 44).

Table 6. 22: Sample adequacy

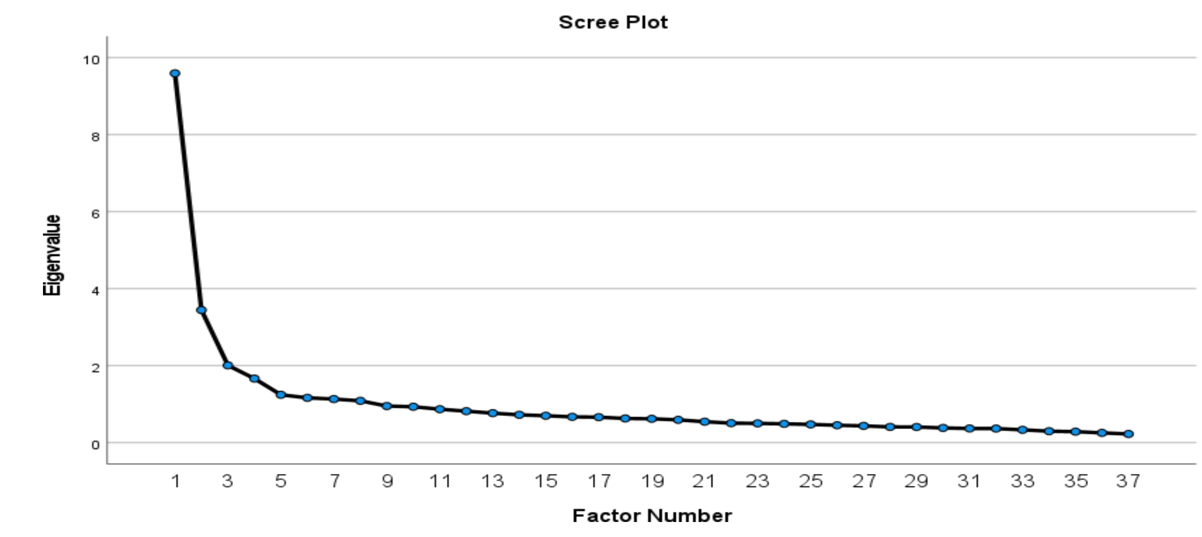
KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.904
Bartlett's Test of Sphericity	Approx. Chi-Square	5654.596
	df	666
	Sig.	.000

***Source: compilation from the researchers' statistical output*.**

As indicated in Table 6.22, the KMO at 0.904 is greater than 0.600, which is the minimum acceptable KMO value, and the *p*-value is <0.01, allowing the continuation of factor extraction. In factor extraction the axes are rotated normally by orthogonal varimax rotation, assuming that all factors are uncorrelated (Dawson 2018: 50). Factor analysis allows the reduction of dimensions by retaining variables with an eigenvalue of 1, thereby extracting factors that are uncorrelated (orthogonal) (Finch 2020: 27).

Eigenvalues are variances of the variables in correlation, with the initial factor having the largest eigenvalue, followed by the others in the sequence (Finch 2020: 27). An eigenvalue indicates how much overall variation there is for each factor, ensuring that each factor contributes to the variation and the cut off eigenvalue is 1, which can be visualised by a scree plot considering all the factors above its cliff edge (Dawson 2018: 45). Figure 6.15 reflects all the extracted factors on the scree-plot, where all factors below 1 are rejected.

Figure 6. 15 Factor extraction



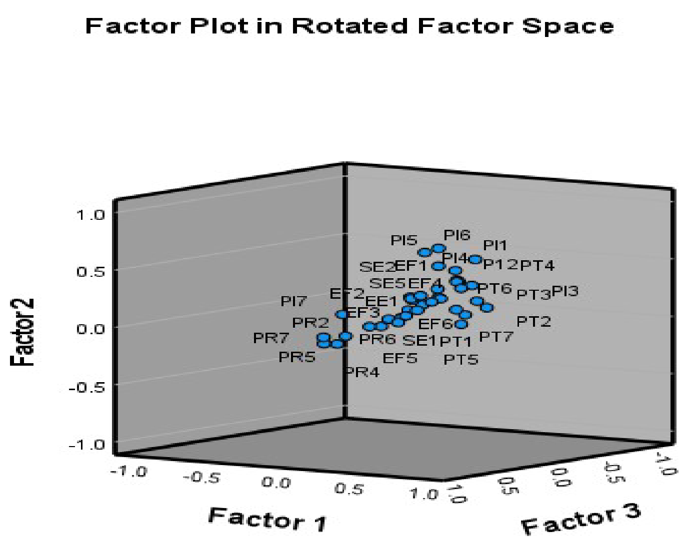
Extraction Method: Principal Axis Factoring.

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	9.593	25.928	25.928
2	3.445	9.310	35.238
3	2.008	5.426	40.665
4	1.664	4.497	45.162
5	1.244	3.361	48.524
6	1.164	3.147	51.670
7	1.133	3.061	54.731
8	1.087	2.937	57.668

Source: compilation from the researchers' statistical output.

As indicated in Figure 6.15, the X-axis reflects the factors extracted, with only 8 factors with an eigenvalue ≥1, but only 6 higher-scoring factors were considered in the study. The eigenvalue of the first factor is 9.593, which reduces as more factors are added, with the 8th factor contributing 1.087 of the eigenvalues making the 8th factor the cut off baseline. The first factor accounts for 25.928% of the variance, while the 8th factor accounts for 2.937% of the variance. Figure 6.16 reflects the visual rotation of the factors.

Figure 6. 16 Rotated factor space



Source: compilation from the researchers' statistical output.

Figure 6.16 indicates that the factors are rotated in a small space and are somehow related to each although they are not correlated. After ensuring validity through factor analysis, Table 6.23 was utilised to show the matching factor groupings based on the responses from data collection.

Table 6. 23: Factor analysis

EFFECTS
EF1. I recommend dependable online companies to my peers
EF2. We provide our free information which is used for profitable predictions by online companies.
EF3. Our previous online records are used by online companies to target us
EF4. Disclosing our information during online shopping is inevitable
PERCEIVED RISK
PR1. I worry about the delivery of my online shopping orders
PR2. I am afraid of disclosing my information to online companies
PR3. Online shopping is risky
PR4. I fear about losing my money when I shop online
PERCEIVED TRUST
PT1. I buy from recommended online companies
PT2. I buy from online companies that protect my privacy
PT3. I shop from credible online websites
PT4. Online shopping saves time
PT5. I only disclose my information to online companies that deserve my loyalty
PT6. I am happy with online customer care
PT7. I regard trust when disclosing my information during online shopping
PT8. I consider price when shopping online
PT9. Online feedback helps to make informed shopping decisions
PT10. I always buy from online companies with quality services
PURCHASE INTENTION
PI1. I am happy with online shopping
PI2. I consider reputable online companies when shopping online
PI3. Online shopping satisfies my preferences
PI4. Online shopping is convenient
PI5. I benefit from shopping online
SHOPPING EXPERIENCE
SE1. I have control over my information online
SE2. Online companies protect our information disclosed while shopping online
SE3. Online companies have to use our information in order for us to get the right products
SE4. Online companies should use our information for free
E-CONSUMER EMPOWERMENT
EE1. Our online information is collected by online companies
EE2. We should have control over our online information
EE3. Our online information has value to online companies
EE4. We should be paid by online companies using our information

Source: Measurement tool designed by the researcher

As reflected in Table 6.23, factor analysis grouped items, and the results of EFA were used to conduct the structural equation modelling discussed in the next section. Table 6.24 represents the reliability tests after the EFA tests.

Table 6. 24 Reliability tests after EFA

Shopping experience	**Perceived trust**
Cronbach's Alpha .695	Cronbach's Alpha .861
Cronbach's Alpha Based on Standardized Items .703	Cronbach's Alpha Based on Standardized Items .864
N of Items 4	N of Items 10
Perceived risk	**Effects**
Cronbach's Alpha .743	Cronbach's Alpha .649
Cronbach's Alpha Based on Standardized Items .746	Cronbach's Alpha Based on Standardized Items .652
N of Items 4	N of Items 4
Purchase intention	**E-consumer empowerment**
Cronbach's Alpha .823	Cronbach's Alpha .677
Cronbach's Alpha Based on Standardized Items .825	Cronbach's Alpha Based on Standardized Items .685
N of Items 5	N of Items 4

Source: compilation from the researchers' statistical output.

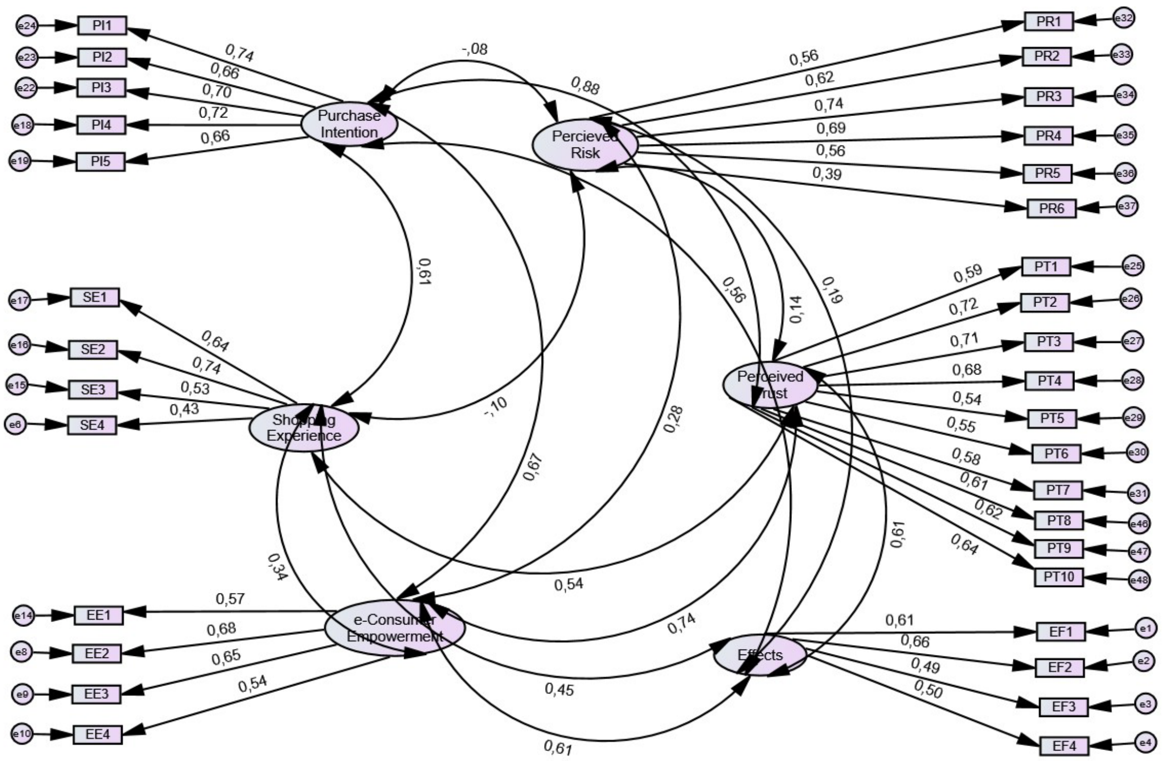
As reflected in Table 6.24, the reliability tests for all the items are good except for effects and shopping experience constructs, which can be rounded to 0.70 to meet the acceptable level. The alpha of 0.70 is okay and 0.60 for a new scale is good (Rouf and Akhtaruddin, 2018: 1503). However, since the measuring tool is new, the level of reliability is okay. Structural equation modelling is conducted in the next section.

6:6 STRUCTURAL EQUATION MODELLING

Structural Equation Modelling (SEM) is a multivariate analysis combining factor analysis with multiple regressions, permitting simultaneous calculations of inter-connected variables and latent constructs (Sandoval and Ramos-Diaz 2018: 1). Validity testing uses either EFA or CFA but not both because EFA and CFA are opposite on the continuum and must never be used in the same study (Finch 2020:

7). EFA and CFA measure validity differently, with EFA exploring and CFA confirming an already existing tool. Six factors were extracted in the EFA calibration sample using a principal axis factoring method with Varimax rotation and *n*=400 sample size. Although CFA is gaining popularity, Exploratory Factor Analysis is a commonly used technique in statistical analysis. Figure 6.17 represents the measurement model of the study from which the correlation estimates were extracted.

Figure 6. 17 Measurement model



***Source: compilation from the researchers' statistical output*.**

Correlation estimates were extracted from the output of the measurement model in Figure 6.17 and the following results in Table 6.25 were obtained.

Table 6.25 Correlation estimates

PI	<-->	PR	-,076
PI	<-->	PT	,876
EF	<-->	PI	,558
EE	<-->	PI	,675
SE	<-->	PI	,612
PT	<-->	PR	,140

EF	<-->	PR	,191
EE	<-->	PR	,285
SE	<-->	PR	-,103
EF	<-->	PT	,609
EE	<-->	PT	,738
SE	<-->	PT	,544
EE	<-->	EF	,610
EF	<-->	SE	,451
EE	<-->	SE	,335

Source: compilation from the researchers' statistical output in Figure 6.17.

As indicated in Table 6.25, Purchase Intention (PI) is inversely correlated with Perceived Risk (PR) at -.076, which means that the more online shoppers develop purchase intentions, the less they perceive online shopping to be risky, thereby exposing e-consumers to free data resource exploitation due to online engagements aroused by purchase intention. When the risk of transacting online is intense, online shoppers will refrain from transacting online, but a low risk attracts online engagement, leading to self-disclosure and free data resource exploitation (Sahin and Gelmez 2020: 2294). On the other hand, the correlation between PI and Perceived Trust (PT) stands at 0.876, which indicates that the more online shoppers develop purchase intentions, the more they trust online shopping.

The trust espoused in online shopping renders e-consumer vulnerable to online self-disclosures associated with free data resource exploitation. Persuasive opportunities like price offers, which are positive effects of data exploitation often appear automatically in the e-consumers' inbox based on the tracking and exploitation of e-consumer profile data (Clarke 2019: 66). For example, the correlation between the Effect (EF) of free data resource exploitation and PI is 0.558, which means that there is a 56% possibility that the more positive the effects of free data exploitation, the more online shoppers develop purchase intentions, thereby leading to online self-disclosures and free data exploitation.

Furthermore, the correlation between Shopping Experience (SE) and PI is 0.612, as reflected in Table 6.12 extracted from the measurement model. This shows that the more online shoppers receive a memorable shopping experience, the more they develop purchase intentions, which lead to online self-disclosures and free e-consumer data resource exploitation. The cognitive affection due to a memorable shopping experience influences e-consumer long-term associations, prompting voluntary data disclosure and free data resource exploitation (Hamouda 2021: 2). The correlation between EF and PT is 0.609, which indicates that there is a 60% likelihood that the greater the effects of free data resource exploitation, the greater the perceived trust, thereby increasing the chances of e-consumer online engagements propelling free data exploitation without the awareness of the online shopper. The correlation between EE and PI is 0.675, indicating that the more e-consumers are empowered, the more they spread purchase intentions online, thereby unwittingly exposing their data to exploitation.

The correlation between EE and PT is 0.738, which reveals that the empowerment of e-consumers increases perceived trust online, which lures e-consumers to engage online, thereby leading to unintended exposure to free data resource exploitation. The correlation between EE and EF is 0.610, which shows a positive relationship between the empowerment of e-consumers and the effects of free data resource exploitation, leading to e-consumer exposure to free data resource exploitation by engaging online in a bid to gain from the positive effects. Puri and Mohan (2020: 1151) affirm that positive perceptions prompt online shopping decisions, leading to self-disclosure and free data resource exploitation. The correlation between SE and PT is 0.544, reflecting that there is an average increase in perceived trust if shopping experience is increased, which in turn improves the chances of online selection due to trust, leading to self-disclosures and free data resource exploitation.

6:6:1 Model fit

The goodness-of-fit test tests whether SEM reflects the data and a poor goodness-of-fit means that the results are unreliable. Therefore, model assessment using the goodness-of-fit indices is a process for interpreting the outcome of SEM (Tan-lei and Lin 2018: 83). Table 6.26 represents a summary of some of the model fit indices.

Table 6. 26: Model fit indices

CMIN					
Model	NPAR	CMIN	DF	P	CMIN/DF

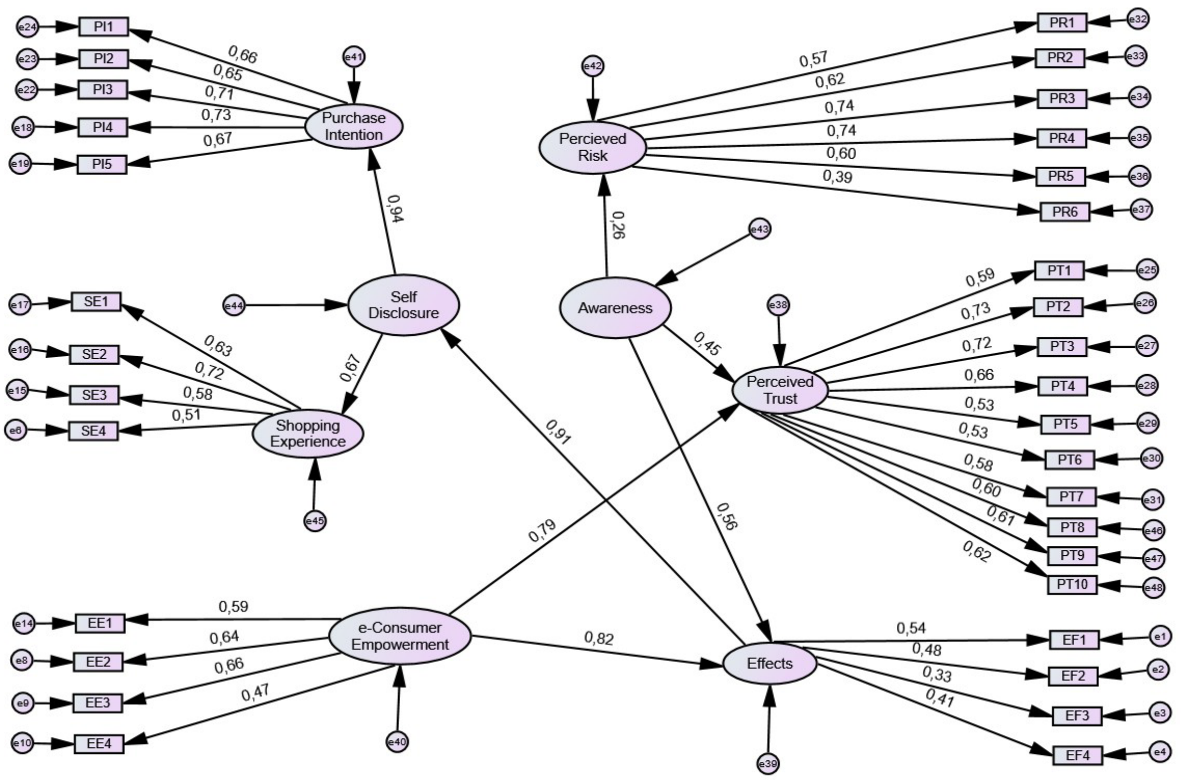
Default model	102	1440,545	492	,000	2,928
Saturated model	594	,000	0	Saturated model	594
Independence model	66	5086,989	528	,000	9,634
Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,717	,696	,794	,777	,792
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000
RMSEA					
Model	RMSEA	LO 90	HI 90	PCLOSE	Model
Default model	,070	,065	,074	,000	
Independence model	,147	,143	,151	,000	Independence model

Source: compilation from the researchers' statistical output.

Table 6.26 reflects the model fit indices. The χ^2/df referred to as minimum chi-square value discrepancy per degree of freedom in the model of fit indices should not be significant, and a CMIN ≤ 3.00 is a good fit, while the RMSEA, which is the Root Mean Square Error of Approximation ≤ 0.08 but >5 is also a good fit (Tan-lei and Lin 2018: 83; Olugboyega and Windapo 2022: 859). Researchers are still discussing the suitability of all the model indices. The results in Table 6.24 indicate that the CMIN is 2,928, which is < 3 and the RMSEA is 0.070, which is < 0.080 meaning that there is a good model fit. Communalities analogous to rr^2 regression analysis consider values ranging from 0 to 1 where scores closer to one reflect a relatively higher indicator accounted for by factors indicating a higher load due to the association (Finch 2020: 26). The CFI in Table 6.26 is 0.792, which is relatively closer to 1, indicating approximately 80% of model fitness.

In fact, the goodness-of-fit deteriorates with smaller samples and in such incidences, interpreting the goodness-of-fit differs, and the goodness-of-fit worsens if the observed variables increase. Nevertheless, the purpose of the SEM is to prove hypothetical assumptions but not to improve model fit. So, the evaluation of a good model depends on statistical significance and coefficient of determination rr^2 values. However, even when the goodness-of-fit is high, you cannot conclude that a model is good if some coefficients are much lower than expected. There are many conflicting model indices that researchers are still debating, but currently we use a few common model indices. Figure 6.18 covers the relationships where the closer the r^2 path values are to 1, the more the positive relationship, and the closer the values are to -1, the more the negative relationship. Figure 6.18 reveals the structural model of the study.

Figure 6. 18 Structural model



Source: compilation from the researchers' statistical output.

Figure 6.18 reflects the direction of relationships between variables and the variance explained (rr^2 values) with the higher values reflecting lower measurement errors (1- RR^2). On average, all the observed indicators are loading well towards their respective latent variables. Based on the standardised output of the structural model, PI has a loading of 0.66, 0.65, 0.71, 0.73, and 0.67, meaning that each observed variable in the group loads well to on the unobserved variable PI. The observed variables for PR load well at 0.57, 0.62, 0.74, 0.74, 0.60, and 0.39, with only one factor loading below 0.50. Also, PT observed variables are loading well at 0.59, 0.73, 0.72, 0.66, 0.53, 0.53, 0.58, 0.60, 0.61, and 0.62, meaning that all the observed factors are loading well above 0.50. The factor loadings for SE 0.63, 0.72, 0.58, and 0.51 load well with the unobserved variable SE, with all the factors loading above 0.50.

The EF factor loadings of 0.54, 0.48, 0.33 and 0.41 are low except for the first two observed variables, which can be rounded to 0.50, while the remaining two factors have a low factor loading. The factor loadings for EE are 0.59, 0.64, 0.66, and 0.47, which can be rounded off to 0.50, meaning that all the factors are loading well with the unobserved variable EE. Therefore, all the observed factors contribute to the construct grouping obtained in the explanatory factor analysis. In the section, hypotheses are covered.

6:7 HYPOTHESES

The hypotheses are extracted from Figure 6.18 pertaining to the structural model. The path among the latent variables has r^2 values that represent the relationship between the latent variables, which include: Purchase intention, Shopping experience, Perceived risk, Perceived trust, E-consumer empowerment, Awareness, Effects, and Self-disclosure. Table 6.27 represents the hypothesis tests derived from the relationships between latent variables.

Table 6. 27 Hypotheses tests

	<0.40 Low	**0.40< <0.60 Moderate**	**0.6< <1 High**
• *H1* E-consumer self-disclosure has a positive influence on purchase intention.			0.94
• *H2* the effects of free e-consumer data resource exploitation has a positive influence on e-consumer self-disclosure.			0.91
• *H3* E-consumer self-disclosure has a positive influence on shopping experience.			0.67
• *H4* E-consumer awareness has a positive influence on the effects of free data resource exploitation.		0.56	
• *H5 E*-consumer awareness of free data resource exploitation has a positive influence on perceived trust.		0.45	
• *H6* E-consumer awareness has a positive influence on perceived risk.	0.26		
• *H7* E-consumer empowerment has a positive influence on perceived trust.			0.79

• *H8* E-consumer empowerment has a positive influence on the effects of free data resource exploitation.	0.82

Source: compilation from the researchers' statistical output.

As reflected in Table 6.27, the following hypotheses are explained.

6:7:1 Purchase intention and self-disclosure

H1. E-consumer self-disclosure has a positive influence on purchase intention, with a high score of 0.94, meaning that online purchase intentions depend on self-disclosure online. There is a 94% support for the hypothesis. E-consumers are trapped in self-disclosures as they seek information from ads on the search engines, which motivate purchase intention, prompting further online disclosures that enable online retailers to harvest free data that is exploited for retargeting (Gauri *et al.* 2021: 44). The more e-consumers increase their disclosures online, the more they develop purchase intentions, leaving a trail of browsing searches and e-consumer data that is exploited by online traders without the awareness of the online shopper.

6:7:2 Effects and self-disclosure

H2. The effects of free e-consumer data exploitation have a positive influence on e-consumer self-disclosure, with a 0.91 high score. There is 91% support for the hypothesis. The tracking and exploitation of free e-consumer data result in a positive effect of mass customisation, guided by harvested data, where the uniqueness of each individual customer excites online shoppers with increased perceived product value, leading to online self-disclosure (Lang, Xia and Liu 2020: 2). E-consumer self-disclosures depend on the effects of free data resources, where, if the effects are positive, online shoppers will engage online, which leads to free data resource exploitation due to online self-disclosure.

6:7:3 Shopping experience and self-disclosure

H3. E-consumer self-disclosure has a positive influence on the shopping experience, with a 0.67 high score. There is 67% support for the hypothesis. The retailer's website friendliness, coupled with customer support and security, usually motivates consumer confidence, prompting a high level of inadvertent online self-disclosures associated with free data exploitation (Jaiswal and Singh 2020: 42). This means that the shopping experience has an influence on e-consumer self-disclosures in that the more online shoppers engage in self-disclosures, the more they enjoy a memorable online shopping experience, which results in e-consumers leaving a trail of data that is ultimately exploited by online traders for targeting.

6:7:4 Awareness and effects

H4. E-consumer awareness has a positive influence on the effects of free data resource exploitation, with a moderate score of 0.56. There is 56% support for the hypothesis. Today, without the awareness of e-consumers, algorithms can handle e-consumer data harvest, identify unique customer insights, and predict consumer purchases by assimilating useful undetectable historical data, which is a positive effect of free data exploitation (Tong, Luo, and Xu 2020: 75). The effects of free data exploitation are felt, but e-consumers are unaware that while they are transacting online, online traders are monitoring their data in order to make precise predictions that benefit the online shopper positively.

6:7:5 Perceived trust and awareness

H5. E-consumer awareness of free data resource exploitation has a positive influence on perceived trust, with a moderate score of 0.45. There is 45% support for the hypothesis. This means that e-consumers' perceived trust depends on their level of awareness of free data resource exploitation. The perceived trust signals e-consumer commitment due to the integrity of e-retailers faith, which lures self-disclosure, leading to free data exploitation without the awareness of the online shopper (Oghazi *et al.* 2020: 2). As consumers become aware of free data exploitation, they tend to lose trust in the online traders. However, e-consumers are apparently not aware of free data resource exploitation. The loss of trust due to e-consumer free data resource exploitation can affect e-commerce due to the sceptic's mindset.

6:7:6 Perceived risk and awareness

H6. E-consumer awareness has a positive influence on perceived risk and a low score of 0.26. The hypothesis has low support of 26%. Perceived risk depends to a small extent on e-consumer awareness of free data resource exploitation, but to a larger extent it does not. Perceived risk renders online shoppers able to constantly search for the useful online information during online shopping, which has resulted in e-consumers unwittingly leaving footprints of free browser behavioural data resources that are exploited by retailers (Manikandan 2020: 135). E-consumer awareness of free data resource exploitation may not alert them to the risks of engaging online andthey may inadvertently continue to engage online, thereby exposing themselves to free data exploitation.

6:7:7 E-consumer empowerment and perceived trust

H7. E-consumer empowerment has a positive influence on perceived trust and high score of 0.79. There is 79% support for the hypothesis. E-consumer empowerment through monetary compensation, loyalty programmes, and tangible rewards has a substantial impact on increasing trust with e-consumer probability of disclosing data free data to be exploited by online traders (Krafft *et al.* 2021: 134). Therefore, e-consumer trust depends on e-consumer empowerment, and once e-consumers are empowered, they are willing to engage in online self-disclosure due to an increase in trust, thereby allowing online traders to optimise e-consumer data resources.

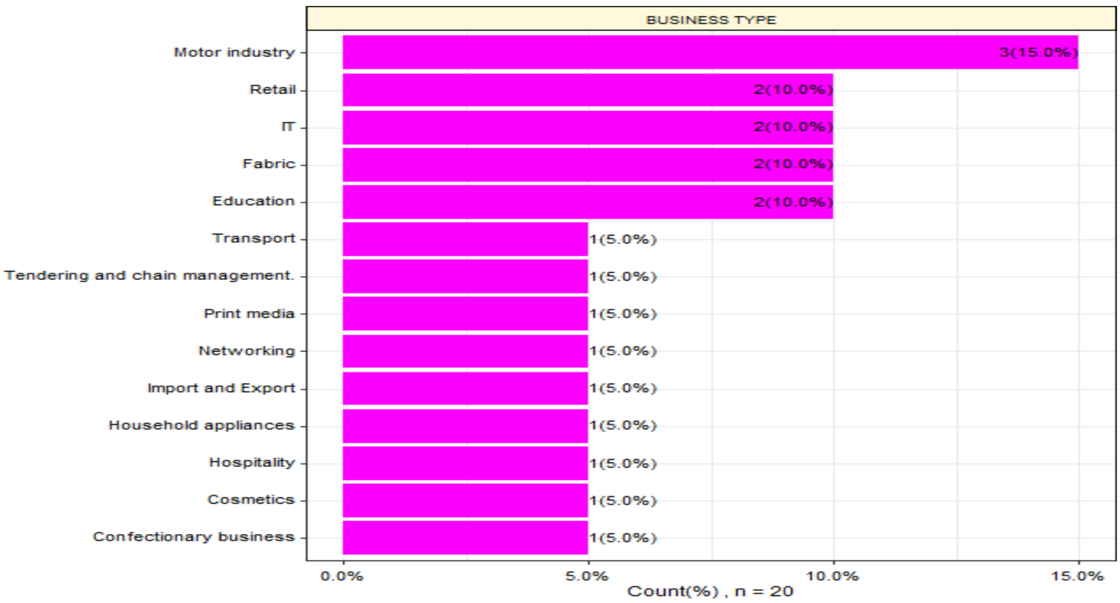
6:7:8 Effects and E-consumer empowerment

H8. E-consumer empowerment has a positive influence on the effects of free data resource exploitation and has a high score of 0.82. There is 82% support for the hypothesis. Ruckenstein and Granroth (2019: 2) articulate that e-consumer autonomy, as a negative effect of data exploitation, is threatened by monitoring, which has rendered e-consumers powerless over digging deep into their social lives and behavioural surplus. This means that if e-consumers are empowered, they will have the ability to control the effects of free data resource exploitation independently, thereby reducing the negative effects.

6:8 FIELD INTERVIEWS

Interviews were conducted after the quantitative survey. Twenty online companies in Durban were selected based judgement sampling until data saturation was achieved. Data saturation is reached when no new ideas are obtained from the continuance of interviews based on the prior data gathered (York 2020: 461). A guideline for the interview is attached in Annexure 3 at the end of this thesis. There are no standard procedures for conducting a qualitative interview, but guidelines and protocols were helpful in the study (Brinkmann and Kvale 2018: 40). A brief introduction informing the participant about sound recording and a debriefing with feedback were conducted. Audio recordings and notes were taken during the interview sessions in order to organise logical transcripts of the data collected in the field. Requests to participate in the interviews along with the letters of information were served to prospective participants, and thereafter interested participants were issued with a consent letter. Participant were allowed to choose the best to be contacted for interviews. A convenient place of interviews was communicated to the participants prior to the interviews. Before the interviews, all the consent letters were duly signed by the participants. Table 6.28 indicates the categories of different online entities that participated in the interviews.

Table 6. 28 business types



Source: compilation from the researchers' NVivo output.

As reflected in Table 6.28, the majority of the online companies selected were in the motor industry followed by retail, information technology, fabric and education. A few participants selected from the cosmetics, household appliances, print media, chain management, import and export, confectionery, transport, and hospitality industries were interviewed. Figure 6.19 reflects the word frequency generated from the transcripts of the data collected from the interviews. The responses from the online traders are interpreted in the subsequent sections.

Figure 6. 19 Word frequency

Source: compilation from the researchers' NVivo output.

A word frequency query was run on the NVivo interface. The results from the word frequency query indicated in Figure 6.19 affirm that the most dominant word is data, followed by consumer, business and online. The study is about consumer data online, which is in line with the frequency chart. Several key terms are embedded in Figure 6.19 like awareness, exploitation, tracking, and customers' data resources, which are covered in the full-scale study. Online consumer or e-consumer data can be visibly seen in bold, which is the core of the study espousing, free e-consumer data exploitation. E-consumer data is explained based on the interviews with online traders.

6:8:1 E-consumer data

Participants were asked how important e-consumer data is to their businesses, and most participants are of the view that e-consumer data is very important. Some participants are of the view that e-consumer data is important for business success, conducting business, promoting business, and smooth business operation. While others believe that e-consumer data is important for conducting business easily. One online retailer was heard saying that, *“customer data is important when I am focusing on business success, where weakness can easily be found”.* Grandhi, Patwa and Saleem (2020: 2) argue that the harvest of e-consumer data provides valuable insights exploited by online retailers to send commercials based on e-consumer browsing behaviour. This means that e-consumer data is exploited principally for the benefit of the online firm, but consumers are not aware of their economic contribution to online firms’ decision-making.

Furthermore, some participants affirmed that consumer data is important for finding gaps, smooth business operation and teamwork. Participants 14, 17 and 18 believed that e-consumer data harvest is used for tendering and outsourcing some of the resources for the smooth running of the business. A participant affirmed that consumer data helps in communicating with clients directly while participants 11, 19, and 20 maintained that consumer data is important for finding gaps, smooth business operations, and teamwork. The surveillance of e-consumer data helps online traders to iron out uncertainties and predict e-consumer behaviour more precisely (Cueller and Huq 2019: 1293). Free e-consumer data resources enable online traders to conduct business smoothly and evaluate the business for better profitable decisions, which largely benefit the online trader at the expense of the e-consumer.

Participants 4 and 12 share the same view that online private schools consider e-consumer data to be important when buying requirements and setting strategies aimed at getting more students. Another participant stated that e-consumer records help in the smooth running of the business and monitoring trends for decision-making. E-consumer data resource exploitation provides individualised online data with identifiable attributes, which helps target offerings to optimise consumer needs satisfaction (Farman, Comello and Edwards 2020: 301). Most participants contend that consumer data is important to keep up with customer needs, target clients in the future and keep promises. Although the feedback helps e-consumers get better services, the positive effects of data tracking benefit the online trader by assisting in stocking the best-selling items, which usually attract enormous profits to the online firm.

Additionally, participants: 1, 6, and 9 agree that e-consumer data is important for identifying and meeting customer needs. While others purport that e-customer data gives them a sense of direction in their businesses. Online traders harvest e-consumer browsing history in order to moderate online behaviour by streaming automated product recommendations along the online shopping journey (Pelau, Niculescu and Stanescu 2020: 829). Another participant expressed that e-consumer data is important for us to keep updated with customer needs, target our clients in the future and keep promises. Consumers are unaware that their online data resources are being exploited by online traders.

On the other hand, participants 15 and 19 were heard saying that e-customer data is important when designing advertisements, new offers, improving stock, and meeting customer needs. Other participants propound that e-customer data gives them a sense of direction in their business. E-consumers normally seek information from ads on search engines without having to travel long distances to the retail outlet, which motivates purchase intention related to online self-disclosures and data exploitation (Gauri *et al.* 2021: 44). Free e-consumer data resources enable online traders to conduct business smoothly and evaluate the business for better profitable decisions, which largely benefit the online trader at the expense of the e-consumer.

The better services rendered, as alluded to by the participants, unknowingly lure e-consumers to part with their valuable data for free. Participants 3, 6, 9, 11, 12, 14 and 15 believe that consumer data is important when buying business requirements and setting strategies. Also, participants 1, 2, 6 and 15 are of the view that clients' data is useful in building friendly relationships, increasing sales, and making contacts for new stock. The exploitation of e-consumer data enables online firms to improve service quality based on behavioural data as technologies facilitate direct interactions with online shoppers (Anica-popa *et al.* 2021: 122). E-consumer shopping experiences can be realised by tracking online consumer data in order to provide excellent services. However, e-consumers are unaware that their data is being exploited by online traders who use e-consumer data for retargeting.

Most participants commented that consumer data is important to keep with customer needs, target our clients in future and keep our promises. Consumer records help in the smooth running of the business and monitoring trends for decision-making. The inbound e-consumer requests are resolved by nudging technology, which deal directlywith the online shopper while harvesting data to enact Recommenders that put forward the desired product in real-time, prompting full data disclosure and free data exploitation (Guha *et al.* 2021: 31). Evaluation of the good services and the fulfilment of promises of excellent service delivery attract purchase intention, which leads e-consumers to engage on the online platform, leaving behind valuable data insights that are harvested by online traders without the awareness of the unsuspecting online shopper.

6:8:2 Targeting E-consumers

In another instance, participants were asked whether they use e-consumer data for targeting, and most of the responses were positive. All the participants, from 1 to 20, are of the view that consumer data is a major source of information for the business. Participant 9 said, *"Yes, I do use consumer data to improve my business".* Another participant clearly commented that *"I use consumer data to alert clients about what's available, and then clients inform other clients".* Unlike conventional targeting using homogenous groups, targeting e-consumers is based on individual-by-individual targeting, which constitutes a high degree of personalisation by matching offers using machine learning algorithms (Ma and Sun 2020: 490). The negative effect of targeting clients with their previously tracked data is that e-consumers often get upset with unsolicited commercials popping up on their devices and miss out on new offers consumer based on their online behavioural patterns where the communication is based on previous data harvests.

Participant 5 is of the view that tracking consumer data is essential for the success of the business. Most of the participants reported that they use customer information to improve their customer services and supply the right products using the marketing tools. Participant 14 commented, *"I use customer data to offer personalised services and customer care for my clients".* By tracking e-consumers based on their browsing history, the information about hidden conditions of e-consumers requires personalised discriminatory marketing practices that automatically match e-consumer needs in real-time (Bornchein, Schmidt and Mairer 2020: 139). The personalised service along with customer care ignites loyalty, which prompts e-consumers to trust online traders by downplaying issues of free e-consumer data exploitation online.

Even B2B online firms monitor the trends of their online customers in order to decide what type of product fetches more profits. Participant 14 was quoted saying, *"I use customer information to target clients[and] to decide on what to offer".* Participant 16 said that *"Every event is different, which makes promotional messages different to different customers".* While Participant 4 was recorded saying that *"We use customer data for communication and keeping them updated about any emergences".* Data exploitation has enabled online retailers to track consumers and open direct communications by eliminating media companies and enabling retailers to optimise the use of powerful in-house e-consumer data for the execution of programmes (Purchase and Volery 2020: 779). The most precise comment about the exploitation of e-consumer data was from Participant 19, who openly said that *"Yes, it is useful for targeting customers differently in order to be precise".*

The participant agrees that e-consumer data is used for the running of the business, while consumers may not be aware that online trader's profit from their data profitably without rewarding e-consumers as the producers of the data. The machine learning online technology groups similar e-consumer behavioural patterns, tastes, locations and movements to reproduce fine-grained behavioural data with algorithms that can automatically predict future possibilities for decision-making (Tong, Luo and Xu 2020: 74). Data producers, referred to as e-consumers, are victims of free data resource exploitation online. The precious data input harvested through tracking consumer data is a valuable data resource online. The participants agree that e-consumer data is used for the running of the business, while consumers may not be aware that online trader's profit from their data profitably without rewarding e-consumers as the producers of the data.

However, online traders' profit from consumer data without rewarding the producers of the useful data input. E-consumers are unaware that their precious data input is obtained for free, yet it is of economic value to online traders. Participant 3 was heard saying that, *"consumer data enables service delivery to the few customers that I have"*. Excellent service quality motivates trust based on the outcomes of online interactions, permitting loyalty to a single e-retailer that compromises online self-disclosure and free data resource exploitation (Qalati *et al.* 2021: 3). Online firms net benefit outweighs that of e-consumers by far. Moreover, some clients are sceptical while, others are open to information disclosure, but if you explain the reason for data collection, clients are more comfortable releasing their information. E-consumers inadvertently disclose their online data after online retailers deliver quality online services, which ultimately leads to free e-consumer data exploitation.

E-consumer data is of economic value to online traders in deciding what to invest in, giving the business undertaking a sense of direction, but e-consumers are unaware that their data resources have economic value, although such data resources are exploited by online traders without compensating the data producers. All the participants strongly believe that e-consumer data is extremely vital for their businesses' success. The digital technology segments similar e-consumer behavioural patterns, locations and online movements in order to reproduce future fine-grained behavioural insights that automatically predict future possibilities for profitable decision-making (Tong, Luo and Xu 2020: 74). Most participants agree that using free e-consumer data resources enables a company to reach out to the customers through advertising and identify current problems. Based on e-consumer data resources, online traders are enabled to stock the right products as long as they keep in touch with the customer. However, e-consumers who own the data resources are not aware that their valuable input is of extreme importance for business performance.

Therefore, e-consumers are left supplying valuable free data input while the online trader generates huge profits from e-consumer data harvesting. The negative effect of targeting clients with their previously tracked data is that e-consumers often get upset with unsolicited commercials popping up on their devices and miss out on new consumer online behavioural patterns where the communication is based on previous data harvests. Sponder and Khan (2018: 44) caution that online retailers track e-consumers' demographics, interests, locations, and behavioural preferences to send precisely targeted online commercials that may be met with discomfort. Online traders always continue to target their clients, even in the long run, surprising online shoppers as to how they can be identified. However, e-consumers are willing to disclose their valuable data resources online, provided that they are updated with their immediate needs.

The participants agree e-consumer data is use for the running of the business while consumers may not be aware that online traders benefit from their data profitably without rewarding e-consumers who are the owners of the data resources. Impractical manual data collection in the digital age giving way to artificial intelligence that can handle huge amounts of e-consumer data resources enabling real-time prediction and decision-making (Kuchta 2020: 36). The consumer online behavioural patterns contribute to free e-consumer data resources, which are exploited by online firms to make predictions. Online transaction self-disclosures initiated by shoppers are monitored by online traders who profit from the valuable data resources owned by e-consumers. E-consumers are unaware that their precious data input is obtain for free, yet it is of economic value to online traders. The targeted commercials are a signal to e-consumers that while they are transacting online, behind the scenes, online traders are harvesting their data without noticing. Therefore, e-consumers are left to be supplying free valuable data input while the online trader generates huge profits from e-consumer data harvesting.

6:8:3 Perception on e-consumer data exploitation

E-consumers who are becoming aware of free data exploitation online are negatively affected by data monitoring, while others take up some level of risk to disclose their online data, provided that the risks are eased. Participant 5 was quoted saying that *"customers do not trust data collection; however, an important level of knowledge of the purpose of collecting information ensures confidence in showing information"* and added that *"but, if you explain the purpose of data collection, they are comfortable".* Moreover, there is a psychological tendency among online shoppers to consider online retailers to compel e-consumers to reveal personal data when completing the online purchase, which is met with scepticism (Li *et al.* 2020: 90). Perceived trust due to service delivery and the confidence obtained after the online trader explains the purpose of data tracking enable e-consumers to unwittingly disclose their valuable data resource without compensation.

Furthermore, participant 11 was heard saying that *"some e-consumers feel fine, but most clients need enough explanation to understand why we need consumer data, although they lack computer education".* Online retailing necessitates harvesting e-consumer data to function competitively in today's data-driven economy, and therefore, e-consumers face a data usage security risk where the assurance of security prompts data disclosure, leading to exploitation (Dabrynin and Zhang 2019:

17). Depending on the risks perceived online, e-consumers are left with the task of taking a risk by engaging online, which is accompanied by online self-disclosure or avoiding online shopping, thereby reducing the incidence of falling prey to free data resource exploitation. Most participants assert that e-consumers feel okay with data harvesting but e-consumers who feel okay may not know that their data has value, which is exploited by online traders tracking the browsing data.

The participants accept that they use e-consumer data to identify gaps, which eventually lead to better profitable decisions. Most participants say that it requires time to explain the reasons for data monitoring in order for the customers to trust and accept self-disclosures. Participant 16 believes that *"some customers have issues and are sceptical, but it is a good thing to record consumer data"*. But those who are suspicious positively perceive data tracking to be risky and do not engage online, thereby limiting their exposure to free data resource exploitation. E-consumers who agree with data harvesting are looking in the direction of an excellent shopping experience, unaware that the same data resources profit the online trader to a greater extent, yet e-consumer data input is exchanged at virtually zero marginal cost incurred by the online trader. The online shopping experience is enjoyable and simply requires e-consumers to click on the website, which gives immediate access to a variety of products in real-time, allowing self-disclosure, leading to free data exploitation (Ayodele and Chigbata 2021: 3). A memorable online shopping experience prompt re-purchase intention online, which increases the chances of falling prey to e-consumer data resource exploitation.

Once trust is built, e-consumers can comfortably unleash their precious data resources for free. Ultimately, e-consumers develop trust, which renders them vulnerable to exploitation as they give away free data that largely benefits the online trader. Online shoppers might feel happy because online traders are willing to predict consumer demand based on behind-the-scenes online data monitoring. However, the tracking of consumers poses some risks, making e-consumers unhappy about online data harvesting. Nevertheless, based on the calculus of perceived risk against perceived benefits, the e-consumer inadvertently discloses data online in pursuit of better services. Online shoppers faced with choices withstand the dilemma of trust by seeking enormous amounts of choice-related information about the product by searching several digital platforms for better decisions, leading to unintended self-disclosure and data exploitation (Kumar *et al.* 2019: 140). Depending on how e-consumers perceive the risk of transacting online, the lower the perceived risk, the more trust they perceive to disclose personal data online. On the other hand, those who feel that it is not confidential unintentionally restrict online self-disclosure.

6:8:4 E-consumer data exploitation effects

Participants were recorded saying that *"e-consumer data is useful in business improvement"; "consumer data is beneficial for the success of my business as mentioned earlier"; "consumer data is useful when we need to make changes, knowing what is missing, and finding course requirements"; "e-consumer data assists in offering different product to the clients"; e-consumer data helps in accessing further information about the client"; e-consumer data helps in finding the quality that is beneficial to the customer"; and "the recording of the most required items to help in shelf-life requirements".* Online retailers have embraced artificial intelligence, which has led to machine learning technology extracting e-consumer behavioural browsing data for digital marketing analyses (Petrescu, Krishen and Bui 2020: 676). Although e-consumer data tracking has positive effects for both the online trader and the consumer, the online trader to a greater extent benefits profitably while the consumer merely benefits from quality products, which come at a cost.

Furthermore, Participant 15 is of the view that *"consumer data also helps in easy communication"* and that *"I benefit tremendously from consumer data".* Cuellar and Huq (2019: 1290) argue that behavioural surplus is harvested to guide automated predictions that benefit consumers, defending the view that data harvesting largely benefits automated predictions. E-consumer data is obtained by online traders for free, but the economic value that comes with it is diverse. As much as the consumer receives better products due to online data monitoring, product innovations come at a cost to the consumer and highly benefit the online trader. The product changes lure e-consumers to do away with their precious online data for free.

Participants are of the view that educated e-consumers, especially those who are computer literate, tend to trust online activities and often ignore the issues of data harvesting as they continue to engage online on a daily basis, which makes them vulnerable to data exploitation. Furthermore, the level of income as well as education influence e-consumer engagement on the digital platforms in that high-income groups tend to have good education involving computer literacy, thereby engaging on the internet with ease while having access to smart devices and internet connectivity (Chipp, Ismail and Meiring 2017:117). Participants were quoted saying that *"consumer data is essential when I need to improve performance, "tracking customers in a given period", and "helping to run the advertisement campaign".* Due to the improved shopping experience associated with improved performance, e-consumers end up disclosing their valuable data resources, which are used to target and retarget clients, thereby exploiting the consumer for economic gains.

Most participants agree that data monitoring is essential to tracking clients in order to run a profitable advertisement campaign, but due to their shopping experiences, they downplay data tracking as long as they enjoy the online shopping experience. The effective use of online consumer monitoring technology speeds up the decisions to sustain fast e-consumer expectations with increased satisfaction while building online consumer relationships (Ameen *et al.* 2021: 1). While online traders make huge profits from the use of e-consumer data resources, e-consumers who generate the data input are not rewarded for their economic contribution in the form of e-consumer data resources. E-consumer data can guide online traders to send targeted ads while the online shopper is searching for the product online, and the data is also vital for online traders to invest in stocks that e-consumers normally search for. Online firms multiply their turnover and profit based on the e-consumer data harvest that is exploited without rewarding the data owners.

Participant 16 as quoted saying that *"we use consumer data when sending offers, in preparing for small functions, continuing to contact our clients for further business, and not to forget our clients".* While another participant was heard saying that *"I make more sales if I use customer data to target them with the right appliances".* Online retailer websites are utilised to monitor online shoppers' trends in a bid to develop keywords and content that can optimise visibility online, thereby maximising top viewership and getting higher returns by targeting consumers based on their popular searches (Sponder and Khan 2018: 24). E-consumers perceived as beneficiaries of data harvesting do not know that online traders make enormous profits from their free data input. The re-targeting based on e-consumer data attracts the consumer to unknowingly engage in self-disclosure online activities with the trusted online trader, thereby generating a trail of data that is harvested relentlessly to upscale business.

E-consumers ought to be considered producers of data resources that lead to the prosperity of online business dealing. The use of e-consumer data resources for free is sometimes in conflict with the principles of customer care. Online traders use e-consumer data to improve their businesses by identifying strengths and weaknesses to make profitable decisions such as personalised services, which also benefit e-consumers but at a cost. E-consumer data preferences, especially search browsing behaviour data, is exploited to lock in consumers during the purchase journey by connecting previous purchases to allocate personalised offers in real-time (Chipp, Ismail and Meiring 2017: 13). When e-consumers transact online, they are unaware that behind the scenes, their browsing data is monitored by online traders, who economically use it to improve stock and make targeted offers that profit the online trader.

As much as targeted services enable a personalised touch, online traders’ economic gains outweigh the that benefits e-consumers recoup from personalised services. With the surveillance of e-consumers, attractive opportunities often automatically appear in e-consumers inboxes like price specials that are allocated based on e-consumer profile (Clarke 2019: 66). In fact, e-consumer data is the new oil that is progressively gaining value day by day in the exponentially growing digital market. When e-consumer data is harvested, online shoppers can be served with a better-quality service experience, which ignites purchase intentions that may generate revenue and more data to harvest for re-targeting.

When e-consumers transact online, they are unaware that behind the scenes, their browsing data is monitored by online traders, who economically use it to improve stock and make targeted offers that profit the online trader. As a requirement, online shoppers are obliged to register with their emails during online shopping, and the emails are later used for monitoring without the consumers' knowledge (Van Heerde, Dinner and Neslin 2019: 425). E-consumers ought to be considered producers of data resources that lead to the prosperity of online business dealings. E-consumer data should be equated to any other raw materials or resources online traders require to run their businesses smoothly. However, online consumers are left to be data providers while the capitalists are making huge profits out of e-consumer data resources.

6:9 CONCLUSION

This chapter covered the results, analyses, and interpretation of the study. The study is espoused in a mixed method design where the sequence favours the quantitative stance followed by the qualitative stance. Firstly, descriptive statistics were conducted, and the majority of respondents in the online survey were males at 65.2% out of a sample of 400 participants. Secondly, Exploratory Factor Analysis (EFA) was conducted, and then Structural Equation Modelling was executed. Due to the newness of the measuring instrument and the dynamics of the phenomenon of digital nature, some cut-off values were rounded up, but the structural model still fits the data. The qualitative interviews covered online traders from different sectors of e-commerce. Although some e-consumers are aware of free data resource exploitation, most online shoppers are not aware of the phenomenon of free e-consumer data exploitation. A detailed discussion of the findings is covered in Chapter 7, the final chapter.

CHAPTER 7. CONCLUSIONS, RECOMMENDATIONS, LIMITATIONS, AND FUTURE STUDY

7:1 INTRODUCTION

This chapter provides a summary of the study and is organised into nine sections. Section 7.1 provides the chapter outline. Section 7.2 provides a review of the study, outlining the summary of the theoretical study. Section 7.3 outlines a summary of the empirical study. In Section 7.4, the achievement of the objectives is discussed. Section 7.5 covers the implications of the study. Section 7.6 covers the study's contribution for future studies. Section 7.7 discusses the recommendations. The limitations of the study are acknowledged in Section 7.8 and finally, the chapter provides the overall conclusion to the study in Section 7.9. Therefore, this chapter focuses on providing a broad understanding of the empirical study in relation to the theoretical study, with a focus on illuminating the implications of the study in order to suggest recommendations that may assist in pursuing further studies. A summary of the theoretical study is discussed in the next section.

7:2 THEORETICAL STUDY SUMMARY

The theoretical summary from the perspective of the objectives of the study covers the effects of digital consumerism concerning e-consumer free data resource exploitation. Then the theory about e-consumers' perceived risk followed perceived trust. Also, in this section, e-consumer purchase intentions along with shopping experiences are discussed summarily. The summary of the theoretical study is reflected in Chapters 2, 3, and 4 of this study. But first, the summary of the effects of free data resource exploitation is discussed in the next sub-section.

7:2:1 Effects of e-consumer data exploitation theory

In Chapter 2, the effects of digital consumerism concerning free e-consumer data exploitation are covered. The effects can be summarised as positive and negative, where the negative effects discourage e-consumers from transacting online while the positive effects encourage e-consumers to shop online. Ghosal *et al.* (2020: 1401) are of the view that all theoretical influences faced by online consumers are centred on the technology acceptance model (TAM) because e-consumers must accept technology in order to transact online. However, Farman, Comello and Edwards (2020: 299) argue that digital marketing tactics involving surveillance have exposed e-consumers to targeted advertising, which has negative effects. E-consumer awareness of free data resource exploitation can nonetheless be answered by empirical evidence.

Furthermore, impractical manual data collection is now progressively being replaced by digital monitoring, handling vast amounts of free e-consumer data resources, enabling real-time decision-making (Kuchta 2020: 36). Nevertheless, e-consumer autonomy is threatened by data harvesting rendering online shoppers powerless due to constant monitoring of digital behavioural surplus. Based on this theoretical study, e-consumers are unaware of free data resource exploitation. In the next sub-section, a summary of perceived risk theory is discussed.

7:2:2 Online Perceived risk theory

In the current study, perceived risk theory (PRT) determines how risk influence e-consumer awareness of free data resource exploitation (Mwencha and Muathe 2019: 172). Individual practical reasoning and decision tend to downplay the cognitivist interpretations even when there are repercussions of the decision (Rabinoff 2018: 100). Perceived risk prompts the expansion of browsing search in order to discover the less risky online shopping websites allowing e-consumers to inadvertently scatter free data resources browsing footprint exploited by e-retailers. Also, e-consumers can evaluate risks in a bid to make decisions based on judgement built from the consequences of transacting online using cognitive probabilistic beliefs (Li *et al.* 2020: 77). Ultimately the online shopper is inadvertently exposed to free data resource due to the overlooking of the risks. Online retailers have to provide sufficient information in order to lessen the perceived risk issues, which leads to e-consumer high level approval enabling self-disclosure and eventual free data exploitation. In the next sub-section, a summary of perceived trust theory is discussed.

7:2:3 Online Perceived trust theory

Perceived trust is a psychological motivation of certain beliefs gained through learning, which shapes attitude towards deciding (Sharma 2019: 1163). Trust motivates e-consumers to make online purchase decisions that facilitate free data resource exploitation without e-consumer knowledge. Nonetheless, the trust that there is adequate built-in online security interface drives online shopping decisions (Carstens, Ungerer and Human 2019: 5). Unsuspecting e-consumers with a strong perceived trust find themselves engaging online, which can lead to an increased appetite for online retailers to exploit e-consumer data to make profitable decisions. Shoppers on the online platforms unwittingly share their trusted preferences allowing online retailers to harvest the digital footprint that is eventually exploited by e-retailers to match likes with different online shoppers

On the other hand, the value-attitude-behaviour tendency is central to perceived trust to transact online. For example, hedonic products whose value is based on emotional pleasure forces e-consumers to ignore perceived trust issues (Nghia, Olsen and Trang 2020: 546). While utilitarian online shopping value attract product-centric evaluation requiring sufficient information of product attributes in order to develop trust (Irshad and Ahmad 2019: 93). As a result, e-consumers engage in a wide scope of searches on the browser that are eventually exploited to predict demand. Purchase intention theory is discussed in the next section.

7:2:4 Online purchase intention theory

Online purchase intention is often shaped by perceived usefulness and perceived ease of technology (Harrigan *et al.* 2021: 4). Online shoppers accept online shopping depending on how easy and how useful technology to them is, which exposes them to free data exploitation online. As they develop purchase intentions, e-consumers searching for products while they are intercepted by invisible algorithms that create desirable short cuts prompting purchase intention based on the tracking of browsing behaviour (Liao and Sundar 2021: 2). When developing purchase intention, e-consumers inadvertently leave a trail of trackable behaviour online without e-retailers' request as the prospective online trader passively observe online shoppers' intentions for precise targeting. E-consumers are therefore unaware that while they are developing purchase intentions online, online traders are tracking and exploiting their data for profitable targeting.

Qatali *et al.* (2021: 5) allude to the fact that purchase intention is normally mediated by how online shoppers perceive the risks of dealing online to complete their purchases. As e-consumers develop online purchase intentions, tracking hidden algorithms connect to recommender systems and filter all the browsing behaviour in order to match products to preferences, thereby prompting data disclosure and exploitation (Liao and Sundar 2021: 2). Real-time communication improves the willingness of online shoppers to develop purchase intentions where e-consumers unwittingly fall prey to e-retailers who monitor behavioural intentions online for targeting. Purchase intention usually lure e-consumers into online self-disclosure through the online engagements, which provide insights that are monitored and exploited for prediction and targeting. The next sub-section discusses a summary of online shopping experience theory.

7:2:5 Online shopping experience theory

Generally, shopping experience is espoused by hedonic and utilitarian aspects where hedonism is enjoyment while utilitarianism is product or service functional quality (Cachero-Martinez, Vazquez-Casielles (2019: 596). The emotional, digital, and the pragmatic experience give e-consumers a feeling of affection. Online shopping experience boosts the cognitive state of feeling in response to high-speed interactions, aesthetics, control, perceived benefits, and interconnectedness (Jaiswal and Singh 2020: 43). The experience enjoyed online attract e-consumers to unknowingly disclose data and is later exploited by online retailers. Once e-consumers enjoy the memorable experience, there is a propensity of repeat business, which attract self-disclosures linked to e-consumer free data resource exploitation.

E-consumers pleased with the online services throughout the complex purchase journey enjoy the online shopping experience attracting repurchasing. The cognitive aspect of affection pre-occupies e-consumer memory with indefinite association to the online retailer. Constantly, e-consumers remain attracted to the online trader prompting unintended data disclosure, leading to free data resource exploitation. Surely, what encompasses online shopping experience is still unknown because of a multiplicity of new digital experiences. Ultimately, due a positive online experience, e-consumers leave a trail of behavioural browsing data, which is exploited by online traders without e-consumers knowledge. Although some online shoppers are getting aware of free data resource exploitation, some e-consumers are unaware. In the next section, a summary of the empirical study is discussed.

7:2:6 E-consumer empowerment theory

E-consumers are losing control of their online data resources and are contemplating trade-off of their data (Draper and Turow 2019: 1826). Bornschein, Schmidt and Maier (2020: 137) caution that e-consumers have no power to resist behind the scenes data harvest while transacting online. Normally, online shoppers are willing to engage in online activities that compel self-disclosures as long as there is some economic benefit. Data ownership is the starting point to settle data exchange issues. The recognition of e-consumer data ownership and assigning a measure of data value can propel self-disclosure. E-consumer awareness of data value is crucial in the growing data-driven economies requiring e-consumer empowerment. Once e-consumers are empowered strategically, online firms can then e-economically optimise data usage without exploiting the data producer. With the summarised discussion of the theoretical study, a summary of the empirical study is compared in the next section.

7:3 EMPIRICAL STUDY SUMMARY

The empirical study was positivist and interpretivist, while the positivist study was analysed using descriptive and inferential statistics. The interpretivist study was analysed using pattern matching and coding. The summary of the empirical data started with the positivists and ended with the interpretivist study. The online survey for the quantitative study constituted a sample of 400 respondents, while the interview stance considered a sample of 20 participants. A five-point Likert-type scale was used to collect the continuous data. The data was later analysed, and a summary of the empirical study is discussed in the next sub-sections, beginning with the demographics.

7:3:1 Demographics summary

Data regarding the frequency of online shopping indicates that 44% of the respondents purchase monthly, while 30.8% purchase weekly. This reflects a regular frequency of online shopping, which exposes a total of 74.8% to a high incidence of online self-disclosure, leading to the inadvertent free e-consumer data exploitation discussed in the theoretical study. Another aspect of the demographics was gender with a 65.2% of the respondents being male. This indicates that males are innocently exposed to free data resources due to their high likelihood of engaging online compared to females. Females are thus sceptical of shopping online and are less vulnerable to free data resource exploitation due to low online self-disclosure. When e-consumers shop online, they do not realise that they leave a trail of browsing data while completing their online purchase, which puts them at a high risk of free data resource exploitation.

Furthermore, a score of 52% constitutes respondents who are fully employed meaning that the respondents can afford enough time to engage online, thereby unknowingly leaving a large portion of browsing behavioural data that is later exploited by online traders for retargeting. Evidence also shows a 42.5% score of respondents between the ages of 25 and 34, implying that the youth are technologically savvy with computer skills, enabling them to shop online in large numbers without realising that while they transact online, their data is being harvested and exploited for economic predictions that largely benefit online retailers. Another demographic variable of interest is race, where 62.8% of the respondents were blacks, which is simply a reflection of the population characteristics. Blacks are naively vulnerable to free data resource exploitation.

As for the marital status variable, single respondents have a score 68.2%, meaning that they are more likely to fall prey to free data resource exploitation due to their online shopping engagements. As for dwellings, 55.8% reside in the suburbs, which implies that over half of the respondents shop online, leading to online self-disclosures and free data resource exploitation. In addition, 68.2% of the respondents are at tertiary level with regard to the education variable, while 43.2% of the respondents earn below R10 000 according to the income grouping. High income earning consumers can afford to purchase goods and services online because they have extra cash for paying online shopping related expenses. Due to their high rate of online shopping linked to online self-disclosure, the highly educated are vulnerable to free data resource exploitation. They shop online due to their ability to perform online transactions with ease. The next sub-section summarises the effects of data resource exploitation.

7:3:2 Empirical study about effects

The items measuring the effects had an overall Cronbach's alpha of 0.74 where 71% of the respondents agreed with the statements for all items. The fact that they agree with all the statements implies that they are affected by the effects of free data resource exploitation. In light of that, respondents are not aware that their free data resources are conduits for the effects of free data resource exploitation. While some of the effects are positive for the respondents, other effects are negative. Respondents agree that they provide their data to online retailers during shopping, but they are not aware that the free data they provide is exploited by online traders to make economic predictions and precise re-targeting. For example, the item stating that disclosing our data online is inevitable had a score of 59.25%, which means that online shoppers have no option but to provide their data in order to complete the online transaction, but they are not aware that that information is used for targeting them.

Furthermore, 82% of the respondents agree that they recommend online products to their peers, which allows online retailers to monitor electronic word-of-mouth behind the scenes and exploit e-consumer data history in order to target particular online shoppers based on their recommendations. In addition, 78.50% of the respondents agree that online retailers use their data to improve their products but do not realise that although they are offered an improved product, they are not aware that their free data is exploited at the benefit of the online retailers and at a cost to e-consumers, who are the producers of the highly valuable data resources. On the flipside, 60.25% of the respondents agree that they provide free data to online traders who profit from it after making calculated predictions. This implies that well more than half of the respondents are becoming aware that online companies are profiting from their free data resources. The more e-consumers become aware of free data resource exploitation, the more the relations between online retailers and shoppers worsen. The perceived risk empirical study summary is discussed in the next sub-section followed by a summary of the effects.

7:3:3 A summary of perceived risk empirical study

The reliability test for the items pertaining to perceived risk had a score of 0.71, with 59.17% of the respondents on the agree side of the Likert scale, 20.83% on the disagree side, and 20% remaining neutral. Although 59.17% perceive online shopping to be risky, 20.83% have no issues with transacting online and are thus vulnerable to online self-disclosures, leading to free data resource exploitation, while 20% of the respondents are completely unaware of the risks of transacting online and may fall prey to free data exploitation once the need for transacting online arises. However, the 59.17% who perceive online shopping to be risky may not transact online and therefore escape the risk of exposure to free data resource exploitation. Contrary to this, 79.75% of the respondents shop at popular online companies to minimise risks instead of abstaining from online shopping altogether. But nevertheless, online shoppers transacting online, whether they are dealing with popular companies or not, are innocently propelled into online self-disclosures, aiding free data resource exploitation.

The respondents who disagree are unaware that while they are transacting online, online companies are harvesting their data to target them with unwelcome ads, while the 30% who are neutral can easily fall prey to online self-disclosures without realising that there are hidden algorithms tracking their data for the online retailers to exploit for profitable predictions. However, 45.25% of the respondents perceive online shopping to be risky and may escape the incidence of free data resource exploitation if they refrain from the risky online shopping. E-consumers will always try to avoid or minimise the risks of transacting online and develop trust. Thus, a summary of the empirical study on perceived trust is discussed next.

7:3:4 Perceived trust empirical study summary

The reliability test for perceived trust has an overall Cronbach's alpha of 0.82, and 83.68% of the respondents agree with the items representing perceived trust. Evidence shows that 89.25% of the respondents buy from credible websites or recommended online traders, which indicates a high level of trust, prompting online shoppers to downplay online risks by disclosing valuable data that is later exploited by online firms. It is also indicative that online traders who protect privacy gain much trust from e-consumers who are trapped in online self-disclosures as long as they are protected. Certainly, 86.25% of the respondents buy from online companies that protect their privacy, but without noticing, they expose e-consumers to free data resource exploitation.

Also, the empirical evidence shows that 72.25% of the respondents disclose their information to online traders who deserve loyalty. Notably, e-consumers developing loyalty usually trust online shopping, which renders them vulnerable to innocently disclosing valuable data that is later exploited by online firms to make economic decisions that highly benefit online traders. Moreover, 75.25% of the respondents buy from online companies with good customer care, which lures innocent e-consumers to willingly disclose their precious data without noticing that online traders are harvesting it for targeting and to make valuable predictions. Due to the fact that online shopping saves time compared to going to a brick-and-mortar store, 91.50% of the study sample agreed that they do online shopping because it saves time. Therefore, perceived trust unknowingly exposes e-consumers to free data resource exploitation. But once there is trust, e-consumers develop purchase intentions, which are discussed in the next subsection.

7:3:5 A summary of purchase intention empirical study

All items reflecting purchase intention have 0.77 reliability test results based on Cronbach's alpha and 83.71% agree with the items. The empirical study indicates that 91% of the respondents consider price when shopping online. Online firms attract shoppers by lowering prices, which in turn attracts e-consumers to develop purchase intentions that involve web searches, allowing e-consumers to scatter valuable browsing behavioural data that is exploited without e-consumers knowledge. The statement "online feedback helps to make informed shopping decisions" has a score of 87.50% agreement. Online firms send real-time feedback to browsing customers, and the feedback prompts potential online shoppers to release more data.

Furthermore, 87.75% of the respondents are happy with online shopping and are not aware that while they are transacting online, their valuable data resources are being monitored and exploited by online firms for strategic decision-making. The data indicates that 80.25% of the respondents agree that online shopping satisfies their preferences. As long as online shoppers are satisfied with their preferences; they will continue shopping online. The respondents show a 62% score that they consider the dangers of online shopping when shopping online. But while they browse for products, online, firms are tracking the movement of the cursor. In the next sub-section, an empirical summary of online shopping experience is discussed.

7:3:6 Shopping experience empirical study summary

The items pertaining to the online shopping experience indicate an overall reliability alpha value of 0.75, and 64.85% of the respondents agree with the statements overall. The data shows that 88% of the respondents agree that they buy from online companies with quality services, without realising that as they admire quality online, they are leaving a trail of browsing behavioural data that is exploited by online traders for their economic benefit. Additionally, 72.25% of the respondents enjoy personalised offers provided by online traders. The personalised offers are facilitated by prior e-consumer browsing behavioural data harvesting without the awareness of the online shopper. Once e-consumers accept the personalised offers, they are willing to engage with the online trader frequently without realising that the personalised offers that come at a cost are facilitated by e-consumers' free data resource exploitation.

Moreover, 47.50%, or nearly half of the respondents, disagree that online companies should use e-consumer data for free. While e-consumers continue to transact online, with 79.25% of respondents accepting that they benefit from online shopping, online shoppers are unaware that they provide their valuable data for free. Also, 55.50% of the respondents agree that they have control over the data they disclose online, not knowing that while they try to exact control, their browsing behaviour is being monitored and exploited to recommend products in line with their browsing behaviour. Furthermore, 72% agree that online traders use their data to offer the right product. For now, e-consumers do not realise the value of the data resources they give away in order to be targeted with the right products. The empirical summary of e-consumer empowerment is discussed in the next sub-section.

7:3:7 Summary of e-consumer empowerment empirical study

For all the items constituting e-consumer empowerment, a Cronbach's alpha of 0.695 was calculated with 70.45% of the respondents agreeing to all the items thereof. The majority of the sample (91.75%) of the sample agrees that they should have control over their online data. So, e-consumers should be empowered on the online platforms so that their data is valued, which can boost deliberate self-disclosures, benefiting the online firms and e-consumers not only in providing personalised services but also in valuing data. Also, 85.50% of the respondents believe that their online data has value to online retailers. Therefore, as the digital environment is developing, online shoppers are becoming aware that their free online data has huge benefits for online firms, but they are not rewarded for the production of the valuable data input, which generates revenue. In fact, 75.75% of the respondents disagree that they should provide their online data for free, while the rest are not aware that they are providing valuable online data to online traders who are exploiting it for decision-making. In the next section, the achievement of the objectives is discussed.

7:4 ACHIEVEMENT OF THE OBJECTIVES

The aim of this study is to evaluate e-consumers' awareness of digital consumerism involving free data resource exploitation, with the following objectives:

- To assess e-consumers' awareness of the effects of digital consumerism,
- To determine the influence of perceived risk on e-consumers,
- To determine the influence of perceived trust on e-consumers,
- To investigate the influence of e-consumer purchase intention,
- To investigate the influence of the e-consumer shopping experience.

In the next sub-sections, the achievement of the objective relating to the effects of digital consumerism concerning free data resource exploitation is discussed.

7:4:1 Awareness of the effects of data exploitation

The awareness of the effects depends on online purchase intention in that there is a 0.558 level of correlation where the more respondents develop purchase intentions, the more they become aware of digital consumerism concerning free e-consumer data exploitation. So, e-consumers frequently shopping online are aware of the effects of free data resource exploitation, while irregular buyers are unaware of it. Also, there is an association between trust and awareness of the effects of free data resource exploitation, where a score of 0.609 indicates a 60% probability that an increase in trust increases the level of awareness of the effects of free data resource exploitation.

However, based on the findings of the study reflected in Table 6.25 in Chapter 6 page 221 the effects of e-consumer free data exploitation positively influence online shoppers into self-disclosure. For example, the effect of personalised offers positively influences e-consumers into online self-disclosure without realising free data exploitation. This main objective was therefore achieved after the findings revealed that the positive effects unwittingly attract online engagement, leading to free data resource exploitation, while the negative effects discourage online shopping, thereby reducing the incidence of exposure. Perceived risk is discussed in the next sub-section.

7:4:2 Influence of perceived risk

Based on the findings reflected in Table 6.25 in Chapter 6, page 221, there is an inverse relationship between perceived risk and online purchase intention, with a score of -0.76 reflecting that e-consumers are not willing to develop purchase intentions due to the risks involved in online shopping. Perceived risk therefore reduces purchase intentions and the possibility of being prey to free data resource exploitation, but as e-consumers try to minimise the online risks, they unknowingly engage in information searches that lead to a trail of browsing behavioural data resources that are ultimately exploited by online traders without their awareness.

Furthermore, perceived risk has an inverse association with shopping experience, with a score of -0.103, meaning the more risks online the worse the shopping experience. Therefore, perceived risk reduces online engagements that facilitate shopping experiences, leading to self-disclosure and free data exploitation. Moreover, the findings reflected in Table 6.25 in Chapter 6, page 221 reveal that e-consumer awareness of free data exploitation is positively influenced by perceived risk at the 0.26 level, which means that to some extent, perceived risk controls e-consumer awareness of free data exploitation. This objective was fulfilled after the findings indicated that online shoppers are sceptical of transacting online due to the enormous online risks, but once the risks are minimised, e-consumers transact online, which unintentionally exposes e-consumers to free data exploitation. A discussion on perceived trust follows in the next sub-section.

7:4:3 Influence of perceived trust

The findings in Chapter 6, Table 6.25 on page 221, indicate that perceived trust has a significant relationship with e-consumer purchase intentions with a score of 0.876, which reflects that the more e-consumers develop trust online, the more they develop online purchase intentions without realising that while they deal online, their precious data resources are being harvested and exploited by online traders who use it for economic predictions. Also, perceived trust has an influence on e-consumer awareness of free data resource exploitation based on a 0.609 correlation. E-consumers who trust online shopping continue to transact online without noticing that their data resources are being monitored and exploited for the benefit of the online trader. Therefore, these findings, leading to the achievement of this objective, reveal that trust has a substantial influence on e-consumers' willingness to shop online without realising retailers' activities of free data exploitation. The attainment of purchase intention objective is discussed in the next sub-section.

7:4:4 Purchase intention influence

Based on the findings in Chapter 6, Table 6.25 on page 221, there is a 0.558 association between purchase intention and the effects of free data exploitation, which indicates that the more the greater the effects, the more the intention to purchase online. As a result, the positive effects propel e-consumers to inadvertently disclose personal data to online retailers who exploit this valuable data without rewarding the producers of the data. The is a correlation of 0.612 between purchase intention and shopping experience, reflects that, once e-consumers are pleased with online shopping, they develop online purchase intentions based on past experiences, making them susceptible to unintended free data resource exploitation.

With a 0.94 regression score, online self-disclosure is a prerequisite to online purchase intention, which in turn exposes e-consumers to free data resource exploitation by online traders waiting to harvest e-consumer online data insights. E-consumers are unaware that while they develop online purchase intentions, they are leaving behind valuable data. The findings pertaining to the influence of purchase intention on e-consumers ultimately reveal that once online shoppers develop purchase intentions, they unknowingly leave a trail of free product search behavioural data that is exploited for retargeting. Even the shopping experience discussed in the next sub-section alludes to discussions of purchase intention.

7:4:5 Influence of shopping experience

The findings in Chapter 6, page 221, Table 6.25 show that shopping experience and purchase intention have a relationship with a correlation value of 0.612 indicating that, as long as there is a good online shopping experience, online shoppers will develop purchase intentions that lead to online disclosures and free e-consumer data exploitation. Likewise, e-consumers may not attain an outstanding online shopping experience without an initial purchase intention. Therefore, purchase intention has an influence on the shopping experience. However, shopping experience is inversely related to perceived risk with a correlation value of -0.103, which reflects that perceived risk presents a bad shopping experience, preventing e-consumers from shopping online and escaping vulnerability to free e-consumer data exploitation.

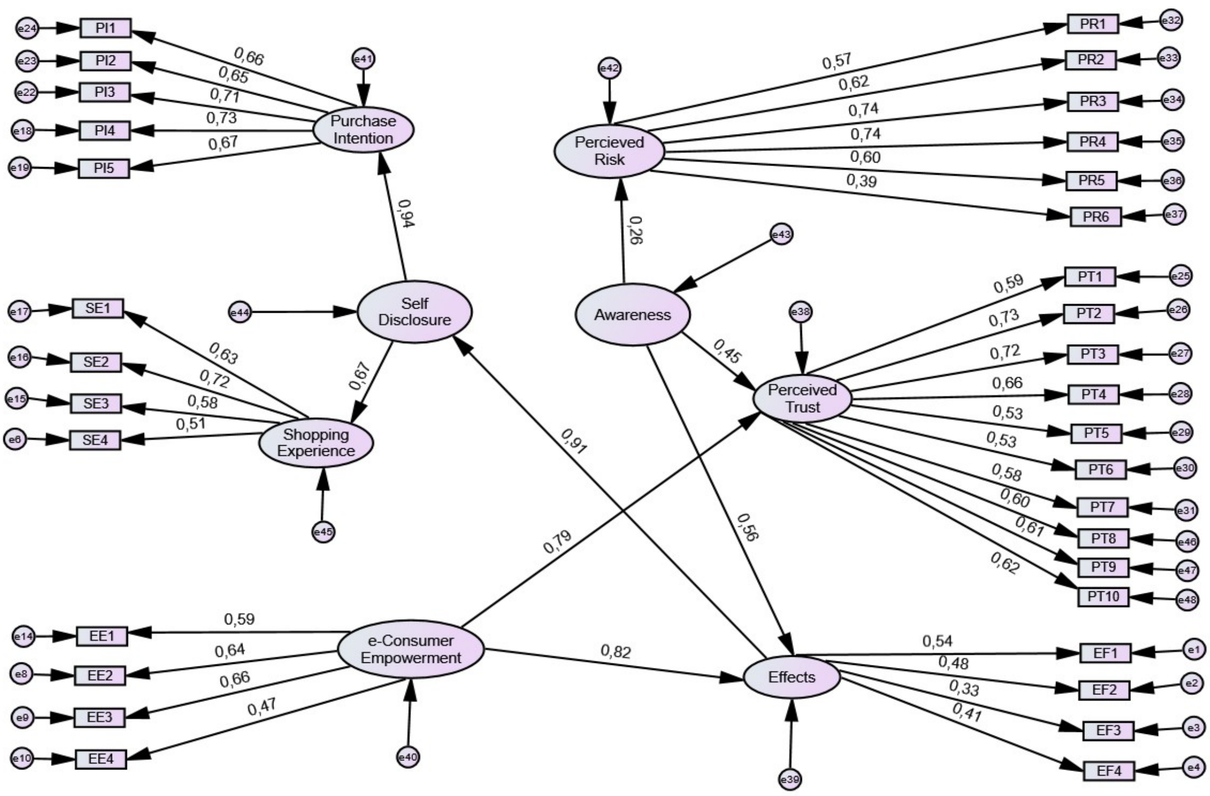
The findings in Chapter 6, Table 6.25. page 221, reflect that self-disclosure has a positive influence on shopping experience, with a factor loading of 0.67 reflecting that the more e-consumers enjoy a memorable shopping experience, the more they unwittingly engage in the online behaviour, leading to free e-consumer data exploitation. A good shopping experience is therefore a recipe for e-consumers' online shopping desires. This objective concerning the influence of shopping experience on e-consumers was achieved after the findings divulged that a memorable shopping experience attracts repurchase intentions, allowing e-consumers to innocently downplay the resultant effect of free data resource exploitation. Having attained the objectives of the study, it is imperative to envisage the empirical implications pertaining to this current study.

7:5 IMPLICATIONS

The free e-consumer data exploitation model in Chapter 6, Figure 6.18 on page 226, reflects three important implications, which include e-consumer empowerment, self-disclosures, and awareness, affecting the objectives of the current study. The findings imply that the empowerment of e-consumers in the growing digital age requiring consumer online data for digital marketing is important to enable e-consumers to willingly supply data resources for the equal benefit of online traders and e-consumers. Online shoppers are trapped in online self-disclosures once they enjoy the positive aesthetic effects of digital consumerism concerning free data resource exploitation. Online shoppers' perceptions in terms of online risks and online trust influence online self-disclosures, leading to free data resource exploitation.

Also, the intention to purchase online involves shoppers searching online for clues about the product or service desire, which inadvertently results in e-consumers online self-disclosures that are harvested for targeting. Once e-consumers start to enjoy the online shopping experience, they are unaware that their data resources disclosed online are a valuable resource for online traders who harvest and exploit them for predictions, decision-making, and targeting. For clarity, Figure 7:1 relating to free e-consumer data resource exploitation is utilised in order to discuss thoroughly the implications based on the visual display.

Figure 7. 1 Free e-consumer data exploitation model



Source: Statistical calculations by the researcher

As reflected in Figure 7.1, there is a 91% likelihood that the effects of digital consumerism concerning free data resource exploitation influence self-disclosures, leading to free data exploitation. Positive effects motivate shoppers to self-disclose, which then leads to personalised offers that fulfil their online shopping needs. Targeting e-consumers based on prior free e-consumer data exploitation helps online traders the offer the very product or service online shoppers prefer. Consumer awareness has a positive influence on e-consumer perceptions of free data exploitation. Since this study contributes to how managers should use e-consumer data optimally without engaging in free data exploitation, it is ideal to discuss managerial implications in the next sub-section.

7:5:1 Managerial implications

Managers in the growing digital environment are focusing on expanding e-consumer data optimisation mechanisms by monitoring and harvesting rich e-consumer data. Little is considered about the usage of e-consumer data input, but more emphasis is vested in harvesting as much free data as possible from e-consumers. Online traders use sophisticated technology to monitor e-consumer data resources in order to predict and target online shoppers based on their browsing behavioural history. E-consumers are unaware that their precious online data resources are being exploited by online retailers. To beat competition in the digital environment, managers use e-consumer data to make real-time decisions in order to keep pace with the dynamics of a volatile online landscape. However, empirical evidence indicates that e-consumers are progressively becoming aware of the exploitation of their data, which is met with discomfort. Notably, it is important for online traders to seek out new strategies that can remediate free data exploitation in order to have a healthy relationship with e-consumers, who are the owners of the data resources.

In order to optimise the usage of e-consumer data, this current study implies that online traders have to reward e-consumers through empowerment, which ultimately leads to trust and increased online self-disclosures. Figure 7.1 reflects that e-consumer empowerment has a 79% influence on perceived trust, which is used as a conduit to free e-consumer data exploitation. Furthermore, e-consumer empowerment has a positive relationship with awareness of the effects of free data resource exploitation, with an 82% probability reflecting that, by empowering e-consumers, online shoppers get to know the importance of their data resources and eventually increase their levels of online data disclosures that can be optimised by the online trader on a give-and-take basis. E-consumer empowerment can increase the level of online self-disclosures that can be harvested to boost the business based on e- consumer data. Therefore, the more managers empower e-consumers, the more they perceive online shopping with trust, eventually leading to unrelenting e-consumer online data harvest, benefiting both the online trader and the e-consumer.

Along with e-consumer empowerment, creating awareness can ultimately build online shopping trust and increase e-consumer data harvest. There is a 45% chance that if awareness is boosted, e-consumers will increase their level of perceived trust, thereby enabling online engagements that lead to rich data utilised in predictions. Also, awareness increases the level of perceived risk by a small margin of 26%, implying that awareness does not greatly hinder online shoppers from taking risks to transact online. Awareness opens many options for e-consumer to decide on transacting online, provided that e-consumers are empowered, thereby increasing the level of online self-disclosures that facilitate free data optimisations. There is a 94% possibility that online self-disclosures positively influence purchase intentions, meaning that once managers encourage self-disclosures, there will be more intentions to purchase online, thereby increasing the volume of e-consumer data, which helps with decision-making. In the next sub-section, future research is discussed.

7:6 FUTURE STUDIES

Research is not an event but a recurring exercise of curiosity. Figure 7.1 reflecting the tested model, contributes to the pursuance of further studies pertaining to the phenomenon of e-consumer free data resource exploitation. This current study's objectives were restricted to e-consumer awareness of the effects of digital consumerism concerning free data exploitation and the influence of perceived risk, perceived trust, purchase intention, and shopping experience on e-consumers. During the study, related literature revealed e-consumer empowerment as a remediation strategy for free e-consumer data exploitation and online self-disclosure as the main conduit towards free data exploitation based on the study objectives. The relationship between e-consumer empowerment, awareness, and online self-disclosures has not received much attention in the current study. Also, the use of Confirmatory factor analysis is recommended to confirm the new measurement tool developed by the researcher. Based on the model in Figure 7.1, further research on this study's phenomenon in consideration of self-disclosure is needed. The next section suggests recommendations.

7:7 RECOMMENDATIONS

Based on the results of this current study, it has been realised that e-consumer data is a new class of raw materials that is a major resource for online business prosperity. Notably, e-consumer data should be assigned its economic value by intensifying e-consumer empowerment through equivalent rewards to acknowledge e-consumer data input just like any other raw material valued for business. For example, a fairly consensual economic exchange of data should be taken into consideration by online traders.

Not only e-consumers should be made aware of the tracking algorithms behind the scenes, but also online shoppers should be sensitised about the value of their data input in the expanding data-driven digital economy. In order to build a very strong relationship with online shoppers, it is recommended that online companies seek a way of acknowledging e-consumer data's contribution to the growth of e- commerce and consider e-consumers as suppliers of a valuable resource for the success of online retailers. A standard mechanism to assign a fair value to e-consumer data resources ought to be debated in order to recognise the appropriate return on e- consumer data.

As e-consumers become exponentially aware of the value of their data resources, time will come when e-consumers defect from online shopping due to the negative effects of free e-consumer data exploitation. Online traders are sitting on a ticking bomb because more consumers may rebel in the future if they become fully aware of free data resource exploitation. Due to the fact that online trade is dependent on e-consumer data, apart from empowering e-consumers in order to optimise e-consumer data, managers should seek out tactical strategies that enable online self-disclosures in order to generate rich data from e-consumers, thereby boosting perceived trust and minimising perceived risks in online shopping. In the next section, the limitations of the current study are discussed.

7:8 STUDY LIMITATIONS

This study was proposed a few months before the outbreak of the deadly Corona virus (COVID-19) in South Africa in 2020. The lockdown due to COVID-19 rendered accessing the resources needed for the research difficult. Moreover, the COVID-19 restrictions were exacerbated by disturbing power outages, extending the study from three to four years. Also, since the measurement tool of the quantitative stance was fairly new, and the changes in the digital environment from which data was collected were frequent, only exploratory factor analysis was employed. Furthermore, most of the available literature on this current study was conducted in the Asia-Pacific countries although there are a few South African studies. Finally, the conclusion of this study is presented in the next section.

7:9 CONCLUSION

This chapter aimed to discuss the findings of the study in relation to the theoretical background from a broad perspective and then focus on the South African context. Specific issues discussed in the chapter include a summary of the theoretical study, a summary of the empirical study, how objectives were achieved, implications, further studies, recommendations, limitations, and the conclusions of the study. This chapter also explained how e-consumer online data harvesting is practised in South Africa. Results of this study provide statistical evidence from the structural equation modelling that indicates that the effects of free e-consumer data exploitation have a positive influence on e-consumer self-disclosure. On the other hand, there is a positive relationship between self-disclosure and shopping experience on the other hand. Also, e-consumer awareness has a positive influence on the effects of free data resource exploitation. Awareness of free data resource exploitation is positively influenced by perceived trust. On the flip side, the empowerment of e-consumers positively influences perceived trust, and in turn, e-consumer empowerment positively influences the effects of free data resource exploitation.

The literature review conducted in this study further revealed that online shoppers are unaware that their online data is exploited by online retailers. It emerged that while digitalisation is in its infancy in South Africa, online retailing companies are using conventional brick-and-mortar data collection, while simultaneously slowly progressing to online consumer behavioural data collection. The findings of the study revealed that the majority of online shoppers are unaware that while they are transacting online, their data is being harvested by online traders. The chapter further indicated that there are still significant challenges besetting online retailers in recognising the value of online consumer data and how to reward e-consumers for their data input through e-consumer empowerment remediation strategies. The challenges include a low level of digital transformation and inadequate digital literacy in South Africa in managing e-consumer data optimisation.

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ANNEXURES

ANNEXURE 1. ETHICAL CLEARANCE

Institutional Research Ethics Committee

Research and Postgraduate Support Directorate
2nd Floor, Berwyn Court
Gate 1, Steve Biko Campus
Durban University of Technology
P O Box 1334, Durban, South Africa, 4001
Tel: 031 373 2375
Email: lavishad@dut.ac.za
http://www.dut.ac.za/research/institutional_research_ethics
www.dut.ac.za

18 August 2021
Mr A Serubugo
703 Salbany House
48 Albany Grove
Durban
4001

Dear Mr Serubugo

E-consumers awareness of digital consumerism concerning free data resource exploitation
Ethical Clearance number IREC 035/21
The Institutional Research Ethics Committee acknowledges receipt of your final data collection tool for review.

We are pleased to inform you that the data collection tool has been approved. Kindly ensure that participants used for the pilot study are not part of the main study.
Please note that FULL APPROVAL is granted to your research proposal. You may proceed with data collection.

Any adverse events [serious or minor], which occur in connection with this study and/or, which may alter its ethical consideration must be reported to the IREC according to the IREC Standard Operating Procedures (SOP's).

Please note that any deviations from the approved proposal require the approval of the IREC as outlined in the IREC SOP's.
Yours Sincerely,

Prof J K Adam
Chairperson: IREC
Institutional Research Ethics Committee

ANNEXURE 2. QUESTIONNAIRE AFTER PILOT STUDY

AMENDED ONLINE QUESTIONNAIRE FOR FULL SCALE SURVEY

F1. I have read the information about this academic research survey, and I consent to participate in this survey. VIEW LETTER OF INFORMATION AND CONSENT before
you answer.
Yes
No

F2. I am a Durban resident
Yes
No

F3. I do my online shopping

Daily
Weekly
Monthly
Yearly
Any time
I do not shop online

DEMOGRAPHICS

D1. What is your gender?

Male
Female

D2. What is your employment status?

Full-time employment
Part-time employment
Unemployed
Self-employed
Homemaker
Student
Retired

D3. What is your age group?

18-24
25-34
35-44
45-54

55-64
Above 64
D4. What is your race/ethnicity?

Black
Coloured
Indian
White

D5. What is your marital status?

Married
Single
Divorced
Widowed

D6. Where do you live?

City Centre
Location
Suburb
Farmland

D7. What is your level of education?

Tertiary
Matric
Below Matric

D8. What is your monthly income group in Rand?

Between 0 and 10,000
Between 10,001 and 20,000
Between 20,001 and 30,000
Between 30,001 and 40,000
Over 40,000

Feel free to give your opinion from the scale of: Strongly Disagree, Disagree, Neither Disagree nor Agree, Agree, Strongly Agree.

To what extent do you Disagree or agree with the following statements?
Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**
1. I am comfortable with online shopping
2. Our online information is monitored by online companies
3. Our online information is used by online companies to predict our needs
4. Online shopping is convenient
5. I enjoy shopping online
6. I post online compliments about online companies with quality offers

To what extent do you Disagree or agree with the following statements?

Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**

1. Our online information benefits online companies targeting us
2. I worry about the delivery of my online shopping orders
3. I only buy from popular online companies
4. I am afraid of disclosing my information to online companies
5. Online shopping is risky
6. I receive unwelcome adverts online
7. I fear about losing my money when I shop online

To what extent do you Disagree or agree with the following statements?
Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**

1. I buy from recommended online companies
2. I buy from online companies that protect my privacy
3. I shop from credible online websites
4. Online shopping saves time
5. I only disclose my information to online companies that deserve my loyalty
6. I am happy with online customer care
7. I regard trust when disclosing my information during online shopping

To what extent do you Disagree or agree with the following statements?
Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**

1. Online companies offer good products
2. Shopping online is cheaper
3. Before I buy online, I consider comments about online companies
4. I consider reputable online companies when shopping online
5. Online shopping satisfies my preferences
6. I regard convenience I am shopping online
7. I think of online shopping dangers when I am shopping online

To what extent do you Disagree or agree with the following statements?

Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**

1. I have control over my information online
2. I benefit from shopping online
3. Online companies protect our information disclosed while shopping online
4. Online companies provide personalised offers
5. Online companies have to use our information in order for us to get the right products
6. Online companies should use our information for free
7. I always buy from online companies with quality services

To what extent do you Disagree or agree with the following statements? Strongly Disagree:**1**, Disagree:**2**, Neither Agree nor Disagree:**3**, Agree:**4**, Strongly Agree:**5**

1. I recommend dependable online companies to my peers
2. We provide our free information, which is used for profitable predictions by online companies
3. Our previous online records are used by online companies to target us
4. Our online information is helpful to online companies
5. Disclosing our information during online shopping is inevitable

STATEMENTS OF CHANGES MADE ON THE FINAL TOOL

I, Ayub Serubugo the Principal Researcher, hereby acknowledge that I have made changes to the tool in the proposal after the PILOT SURVEYhttps://ayubserubugo.questionpro.com

The questions have been re-shuffled to fit with reliability and validity tests conducted on the data output from the PILOT STUDY. Filter questions have been added at the beginning of the survey together with three additional questions. This is my FINAL TOOL intended for full-scale online survey.

Signature of the Researcher: ……………………………………………………………..

ANNEXURE 3. SEMI-STRUCTURED INTERVIEWS

Online traders were interviewed in order to collaborate the findings of the online consumer survey. Prior to the onset of the field study, the following questions laid the basis for the line of questioning during the actual stage of interviewing and follow up questioning.

- What kind of business are conducting?
- How important is online shoppers' data to you?
- Do you use online shoppers' data to target them?
- How do online shoppers feel when you use their data?
- What challenges do you face when using online shoppers' data?
- Do you benefit from online shoppers' data?
- How do you identify online shoppers?
- Are your customers willing to disclose their online information?
- Are your online shoppers happy when you collect their online data?
- How should online shoppers be compensated for the use of their data?