Understanding the Mechanism of Consumer Resistance to Innovation:
The Moderating Role of Consumption Values

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Abstract

Although previous research has established different types of barriers that lead to consumer resistance to innovation, little has been done to understand the effects of some scarcely researched barriers and how these different barriers can be mitigated. Further, there is scant empirical research examining the detrimental impact of resistance to innovation. Therefore, drawing on prospect theory and innovation resistance literature, this study develops and tests a conceptual framework to address the above-noted gaps in the literature. The key aims of the study are to understand: 1) the mechanism of consumer resistance in the context of smart payment services; 2) the development of consumer resistance to smart payment services due to different barrier perceptions; 3) the detrimental impact of consumer resistance to smart payment services by empirically establishing its consequence in the form of negative word of mouth (NWOM); 4) the role of consumer resistance to smart payment services as an underlying mechanism that explicates the translation of perceived barriers into NWOM; and 5) the role of perceived consumption values in buffering the effects of barrier perceptions on consumer resistance to smart payment services. Based on an online survey, data from n = 356 consumers (laggards) were collected and analysed in the context of smart payment services. The findings revealed that although most barriers from the extended Ram and Sheth framework influence resistance, the effects of the commonly investigated value and tradition barriers are, surprisingly, not found to be significant. Resistance is found to mediate the relationship between most barriers and NWOM, implying resistance is the key underlying mechanism that explicates why laggards who perceive barriers spread NWOM about smart payment services. Most importantly, consumption values are found to buffer the effects of some of the perceived barriers on resistance, which extends our understanding of the mechanism of resistance. Based on these results, theoretical and managerial contributions are discussed.

Keywords: Consumer Resistance to Innovation, Barriers, Consumption Values, Negative Word of Mouth, Smart Payment Service

Publications

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List of Abbreviations

AI	Artificial intelligence
AIR	Active innovation resistance
AVE	Average variance extracted
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CMB	Common method bias
CR	Composite/construct reliability
EFA	Exploratory factor analysis
e.g.	for example
GOF	Goodness of fit
HIT	Human Intelligence Task
i.e.	that is
IoT	Internet of Things
KS	Kolmogorov-Smirnov (test)
MOOC	Massive open online course
MTurk	Amazon Mechanical Turk
NFC	Near-field communication
NWOM	Negative word of mouth
PIR	Passive innovation resistance
POS	Point of sale
RMSEA	Root mean square error of approximation
SD	Standard deviation
SEM	Structural equation modelling
TAM	Technology Adoption Model

TAP	Technology adoption propensity (index)
TLI	Tucker-Lewis index
UK	United Kingdom
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance inflation factor

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Chapter 1 – Introduction

In the present digital world, consumers come across a variety of technologically advanced innovations in their day-to-day domestic as well as professional lives in terms of entertainment, business transactions, retail, and social networking. These trending technological innovations consist of personal computing devices (e.g., mobile technologies – smartphones, wearable technologies and smartwatches), search technologies (e.g., voice recognition-based search), analytical computing technologies (e.g., artificial intelligence – AI and cloud computing), and connectivity technologies (e.g., Internet of Things – IoT), which are categorized under the name 'smart products/services' (Kannan and Li, 2017). Hence, it is important to understand how consumers respond to these smart products/services (Verhoef et al., 2017).

As innovations in the digital world, smart products/services possess a variety of characteristics, such as relative advantage, compatibility, trialability and observability (Rogers, 2003), communicability (Rogers and Shoemaker, 1971), amenability to modification (Zaltman et al., 1973), usefulness and ease of use (Davis, 1989). Smart innovations also possess unique capabilities, termed smartness characteristics, such as autonomy, adaptability, reactivity, multifunctionality, ability to cooperate, human-like interaction and personality (Hultink and Rijsdijk, 2009; Lee and Shin, 2018; Rijsdijk and Hultink, 2003), which differentiate these from traditional technological innovations. As such, these factors (characteristics) drive the adoption of these innovations by consumers. In addition to these characteristics, innovations are also adopted if they increase the social image and status of the consumer (social value), allow consumers to enjoy the innovations to their fullest potential (emotional value), and may even arouse curiosity in the consumers to keep trying the existing and novel forms (epistemic value) of innovations (Sheth et al., 1991).

Although these innovations may have numerous advantages, they also pose various challenges (e.g., associated risks) that are likely to inhibit their adoption by consumers, resulting in their failure (Heidenreich and Handrich, 2015; Sheth, 1981). Examples include the discontinuation of the Samsung Galaxy Note 7 smartphone due to functional failure; lack of success of Google Glass in satisfying personal use; removal of the digital newspaper app The Daily from the App Store due to high subscription prices; and the Microsoft Zune, which proved to be an unsuccessful alternative to the Apple iPod (Altman, 2015; Eadicicco et al., 2017; Rosoff, 2012; Titcomb, 2016). It is argued that a major reason for such innovation failures in the consumer market is the resistance shown by consumers towards these innovations (Heidenreich and Handrich, 2015; Ram and Sheth, 1989). Ram and Sheth (1989, p. 6) defined consumer resistance to innovation as "the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure".

Therefore, as innovations involve a significant change in the behaviour of the consumers, which can upset the status quo, such changes might not be considered beneficial and hence consumers show a negative attitude towards innovations, often in the form of resistance (Heidenreich and Spieth, 2013; Ram, 1987; Ram and Sheth, 1989). In other words, consumer resistance to innovation explains why consumers are unwilling to accept the novelty/change brought by an innovation (Ram, 1989). It has also been elaborated that the ultimate adoption or rejection of innovation is decided only after the consumers have overcome their initial passive resistance (Ram, 1987; Talke and Heidenreich, 2014). Thus, the perspective of innovation resistance plays a significant role in understanding the innovation decision process, from the time consumers first confront an innovation until their final decision regarding that innovation (Talke and Heidenreich, 2014). In particular, if consumers show considerable resistance towards an innovation, the innovation is ultimately rejected and there is no adoption (Ram, 1987; Talke and Heidenreich, 2014). Furthermore, when consumers have more power, they may also express resistance by opposing the innovation as well as the company that is offering it (Kleijnen et al., 2009).

Consumers resist innovations if they perceive that the innovation will not meet their current needs and/or the innovation attributes are unfavourable, leading to the perception of various innovation-specific barriers (Talke and Heidenreich, 2014). Further, the same innovation can be resisted by different consumers for different reasons in terms of functional barriers (e.g., associated risks and complexity) and psychological barriers (e.g., image and tradition conflicts or anxiety about using technology and technological dependence) (Mani and Chouk, 2018; Ram and Sheth, 1989).

The introduction of innovations in a consumer market fosters high investments in research and development activities (e.g., Berry et al., 2006). Since consumer resistance to innovation can be a significant cause of innovation failure, and as failures represent futile investments (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014), return on these high expenditures can only be achieved by a successful introduction and fast diffusion of the innovation among consumers (Montaguti et al., 2002). Consequently, studies have emphasized investigating various strategies (e.g., communication, product, pricing, market and coping strategies) to reduce consumer resistance to innovation (e.g., Ram and Sheth, 1989). However, empirical research on these grounds is still limited (Heidenreich and Kraemer, 2016); for instance, investigation of the effectiveness of value perceptions derived from innovations in mitigating the effects of barriers on resistance has been neglected.

Therefore, studying the complex phenomenon of consumer resistance to innovation can guide scholars and practitioners to understand the factors driving this phenomenon, as well as in developing and implementing targeted instruments for controlling resistance and thereby reducing the failure rate of innovations. In the following sections, this chapter presents the research problem, outlines a summary of research gaps (see the detailed discussion in Chapter 2) and states the study objectives. Next, the innovation context of the study is elaborated, which includes an understanding of 'smart payment services' as a service innovation and the relevance of the present study in the context of smart payment services. Further, the importance of the study is discussed in terms of its prospective theoretical contributions and managerial implications. Last, the thesis structure is outlined to provide a brief outline of the other chapters.

1.1 Research problem

a) Factors influencing consumer resistance to innovation

In innovation research, scholars have extensively studied 'innovation adoption' in the context of various technological products/services to investigate their adoption intention, purchase intention, continuance use intention and related attitudes and behaviours, as well as factors influencing these attitudes/behaviours (e.g., Herz and Rauschnabel, 2018; Mamonov and Benbunan-Fich, 2020; Yee et al., 2017; Yu et al., 2016). This is because innovations are generally considered successes over their predecessors and bring benefit to the lives of those consumers adopting them (Åstebro and Michela, 2005). Innovation research also highlights the failure of innovations in a way that emphasizes 'innovation resistance' by consumers due to factors such as complexity in usage (Rogers, 2003), associated risks (e.g., performance, social, physical, and economic risk along with perceived adverse side effects) (Ram, 1987; Sheth, 1981) and the potential to bring abrupt changes to the existing habits (Sheth, 1981) of the consumers. However, studies on the 'resistance paradigm' of innovation research are still limited compared with those on the 'innovation adoption' paradigm (Heidenreich and Handrich, 2015; Mani and Chouk, 2018).

When organizations offer innovations in the consumer market, they aim to provide something novel to consumers (Ram, 1987). However, this newness may be unacceptable to some consumers because the innovation might have the potential to change the satisfactory status quo and/or to be in conflict with the belief structure of the consumers, thereby resulting in innovation resistance (Ram and Sheth, 1989). Hence, consumers show resistance to innovations due to their unfavourable evaluation of innovation characteristics, which is reflected in the form of various barrier perceptions such as functional and psychological barriers (Mani and Chouk, 2017, 2018; Ram and Sheth, 1989; Touzani et al., 2018). Furthermore, consumers might not even evaluate the potential of the innovations and resist them because of irrational personal preferences about currently owned products/services (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014). Much research has been done to understand functional and psychological barriers (Ram and Sheth, 1989) and how these lead to consumer resistance to innovation (e.g., Borraz-Mora et al., 2017; Chouk and Mani, 2019; Juric and Lindenmeier, 2019; Laukkanen, 2016; Mani and Chouk, 2018). However, more investigation is required of those barriers that are specific to revolutionary technology-based products/services (e.g., technology vulnerability barriers), consumers' personal convictions against innovations (e.g., Mani and Chouk, 2018) and the factors related to consumers' predisposition to resist innovation (e.g., Heidenreich and Handrich, 2015), as very little is known about the impact of such factors or barriers on consumer resistance to innovation (e.g., Chouk and Mani, 2019; Talke and Heidenreich, 2014).

b) Consequences of consumer resistance to innovation

The innovation literature argues that, conceptually, innovation-resistant consumers shape the opinions of those with whom they have direct ties (e.g., friends and family members) by acting as diffusion mechanisms of unfavourable information about a particular innovation (e.g., Hietschold et al., 2020). Such unfavourable information (e.g., negative word of mouth – NWOM) can have a detrimental impact on newly introduced innovations, as it has the potential to drive away potential customers (Jahanmir and Cavadas, 2018). For instance, negative feedback received from peers about a product/service can lead to the development of negative feelings (e.g., brand hate and betrayal) among the existing consumers of that product/service, resulting in future avoidance of that product/service (Jabeen et al., 2022). A study by Azemi et al. (2020) also demonstrates that aggressive consumers experiencing a poor or failed recovery of service failure engage in severe electronic NWOM and amplify the influence of such negative comments on various platforms by paying others with the express intention to damage the service provider's reputation. Furthermore, to create more harm in response to the grievance caused by the innovation provider/brand, anti-brand internet hate sites are created by vengeful consumers for sharing vindictive posts and comments about the innovation and brand (de Campos Ribeiro et al., 2020).

However, little is known about such consequences of consumer resistance to innovation (Heidenreich and Handrich, 2015; Heidenreich and Kraemer, 2015) besides intention to adopt or use intention (e.g., Kim and Park, 2020; Kladkleeb and Vongura, 2019). As unfavourable information about innovation has enormous potential to discourage prospective consumers from adopting the innovation in future (Jahanmir and Cavadas, 2018), which can be extremely deleterious to the success of the firm offering the innovation (Van Tonder, 2017), more empirical research is required to provide a deeper understanding of the nature and extent of the detrimental impact of consumer resistance to innovation by empirically establishing its consequence in the form of NWOM.

Furthermore, recent studies have demonstrated direct relationships between barrier perceptions and the spreading of NWOM about an innovation to fellow consumers (e.g., M. Talwar et al., 2021, S. Talwar, Dhir et al., 2021). However, these studies have reported equivocal findings. For instance, M. Talwar et al. (2021) found a positive relationship between barrier perceptions and NWOM, Kaur, Dhir, Ray et al. (2020) reported a positive relationship between barriers and WOM, and Kaur, Dhir, Singh et al. (2020) found a neutral relationship between barriers and intention to recommend. Hence, to clarify these inconsistent findings, a thorough investigation is required to understand if consumer resistance to innovation is an underlying mechanism that explains how and why barrier perceptions lead consumers to spread NWOM.

c) Mitigation of consumer resistance to innovation

In addition to investigating the barriers that lead to consumer resistance to innovation and its detrimental consequences, it is essential to investigate how the effect of such barriers can be reduced. This is because innovators must not only make innovations beneficial, but also devise strategies to deal with the various barriers perceived by consumers in their decision-making process. Research has highlighted various marketing strategies that can mitigate the effects of barriers and consequently reduce consumer resistance to innovation (e.g., Laukkanen et al., 2009; Reinhardt et al., 2017; Rodríguez Sánchez et al., 2020; Yeatts et al., 2017). However, understanding of how resistance can be mitigated is rather limited (Heidenreich and Kraemer, 2016), to, for instance, optimizing the perceived value of innovations to consumers.

Parallel developments in the field of innovation adoption literature underscore the pivotal role played by consumption values in consumer decision making (e.g., H. Liu et al., 2021; Sheth et al., 1991; Tan et al., 2022). These consumption values mainly comprise functional value i.e., a product/service's ability to offer enhanced performance and quality; emotional value i.e., a product/service's ability to generate feelings or affective states (e.g., comfort, security and passion); social value i.e., a product/service's ability to enhance one's social self-concept (e.g., social image and status-seeking); and epistemic value i.e., a product/service's ability to arouse curiosity and fulfil exploratory motives (e.g., novelty and variety seeking and satisfying the desire for knowledge) (Alba and Williams, 2013; Sheth et al., 1991; Sweeney and Soutar, 2001). As consumers consider both benefits and risks when evaluating any innovation (Chiu et al., 2014; Kahneman and Tversky, 1979), they are likely to perceive both barriers (risks) and consumption values (benefits) simultaneously. As such, consumption values perceived by consumers are likely to mitigate the effects of the perceived risks or barriers that build their resistance towards such innovation because when the consumption decision is driven by consumption values, consumers are less likely to be concerned about associated barriers that may affect their consumption decision (Cocosila and Trabelsi, 2016; Groß, 2018). However, little is known about how perceived barriers and consumption values may interact to influence consumer resistance to innovation.

d) Selection of service innovation as the study context

Service innovations form a significant portion of the global economy as these novel and enhanced intangible offerings are developed with an intention to benefit consumers, thereby driving the economic growth of a firm as well as a nation (Dotzel et al., 2013). However, Storey et al. (2016) stated that service innovations can be risky since services are intangible and, therefore, demonstrate inconsistent delivery performance, which makes it difficult for companies to fully anticipate consumers' reactions to service innovations (Kuester et al., 2013). Moreover, the majority of existing innovation research on service innovation emphasizes the adoption process (e.g., Choudrie et al., 2018; Evanschitzky et al., 2015; Klein et al., 2022) and success factors (e.g., Kuester et al., 2013; Storey et al., 2016). Limited attention has been paid to innovation resistance research in the context of service innovation (e.g., Claudy et al., 2015; Mani and Chouk, 2018). O'Cass et al. (2013) also highlighted that there is inadequate understanding of service-specific issues, especially how value is created for consumers via service innovation. Therefore, research is required to understand consumers' responses to smart services under the paradigm of innovation resistance to advance our understanding of the phenomenon of resistance in the services context (i.e., barriers influencing resistance, the consequences of resistance and how resistance can be mitigated).

To address the above-noted research gaps in the literature, this study aims to:

1. understand the mechanism of consumer resistance in the context of service innovation (i.e., smart payment services).
2. understand the development of consumer resistance to smart payment services due to different barrier perceptions;
3. provide a deeper understanding of the detrimental impact of consumer resistance to smart payment services by empirically establishing its consequence in the form of NWOM;
4. understand the role of consumer resistance to smart payment services as an underlying mechanism that explicates the translation of perceived barriers into NWOM;
5. understand the interplay of perceived barriers and consumption values in the formation of consumer resistance to smart payment services by investigating the role of perceived consumption values in buffering the effects of barrier perceptions on consumer resistance to smart payment services, as well as the resulting NWOM.

The next section provides a detailed overview of the research context of the study (i.e., smart payment services).

1.2 Research context

To achieve the above-stated study objectives within the context of smart payment services, it is essential to understand the application of such services in the context of innovation resistance research. Therefore, this section first establishes smart payment services as a 'service innovation' and then discusses the relevance of the present study to the context of smart payment services.

1.2.1 Smart payment services as a service innovation

Innovation can generally be classified into three forms: it may include improvements in the currently available characteristics of a product/service; it may involve the introduction of novel characteristics into an existing product/service; or it might give rise to the introduction of an entirely new product/service. Specifically, innovations that consist of changes to existing products/services are generally termed *continuous innovations* or *incremental innovations*; whereas those that are entirely novel products/services are termed *discontinuous innovations* or *radical innovations* (Bagozzi and Lee, 1999). Hence, in order to consider smart payment services as a 'service innovation', it is essential to understand the term 'service innovation' and how its definition can be related to the context of this study.

When considering 'services' as the context of their studies, scholars in innovation research define service innovation in different ways. For instance, Toivonen and Tuominen (2009, p. 893) defined service innovation as

> a new service or such a renewal of an existing service which is put into practice, and which provides benefit to the organization that has developed it; the benefit usually derives from the added value that the renewal provides the customers. In addition, to be an innovation the renewal must be new not only to its developer, but in a broader context, and it must involve some element that can be repeated in new situations i.e., it must show some generalization feature(s).

Further, based on the three perspectives of assimilation, demarcation and synthesis laid down by Coombs and Miles (2000) that define how innovation research should be studied when 'services' are considered as the context instead of 'products', Witell et al. (2016) suggested that service innovation can simply be interpreted as a 'new service (offering)' and hence, each and every organization developing a service innovation is to some extent innovative. The term 'service innovation' has also been used interchangeably with new service development and service design to explain the process of developing novel or improved services (Biemans et al., 2016). Recently, Gustafsson et al. (2020) argued that the concept of service innovation should be something beyond the development process and they defined service innovation as a new process or offering that can be put into practice such that it is adopted by one or more stakeholders as it creates value for all of them.

Smart payment services take the advantages of different communication technologies (e.g., the internet and near-field communication – NFC) and help consumers to carry out various transactions at point-of-sale (POS) terminals in retail stores, as well as payments for digital content (e.g., news, music and games), transport fares, bills and invoices via their own mobile or smart devices (e.g., smartphones and smart watches) (Dahlberg et al., 2008). Further, smart payment services offer characteristics such as connectivity (i.e., communication protocols to ensure information exchange between users and devices as well as among different connected devices), ubiquity (i.e., the ability to be used with the help of any connected device anywhere and at any time) and intelligence (i.e., analysing previously captured data related to the user), thereby providing a smooth and continuous user experience when making payments, online as well as offline (Mani and Chouk, 2017). For instance, smart payment services, such as Apple Pay, Google Pay and Samsung Pay, allow consumers to pay in physical stores via *connectivity* technologies (e.g., NFC); on-demand and continuous network accessibility provide a *ubiquitous experience* to pay electronically; and the facility to capture multiple credit/debit card data within smart devices makes smart payment services *intelligent*, allowing consumers to perform quick payments both online and offline (Leong et al., 2020). As a result, smart payment services have revolutionized the digital financial services industry by making outstanding applications for mobile devices (e.g., smartphones and smart watches) as they can replace physical wallets by eliminating the need to carry multiple credit and debit cards and membership and loyalty cards (Sharma et al., 2018).

In conclusion, in acknowledging the definitions of service innovation and the concept of smart payment services discussed above, smart payment services can be considered a ‘new service’ or ‘service innovation’ as they provide benefits to their various stakeholders (i.e., consumers and the firms offering the service) in the form of derived value that allows them to perform all kinds of essential monetary transactions, including consumer-to-business, consumer-to-consumer, consumer-to-machine, consumer-to-online and business-to-business payments, directly through smart devices (Shin, 2009).

Further, in addition to smart mobile devices and wearables, smart payment services also have the advantage of being integrated with different IoT environments, such as connected cars and smart home electronics. For instance, in a smart home environment, an app called Groceries™ enables consumers to do online grocery shopping using their Samsung Family Hub smart refrigerator and purchasing groceries easily via the embedded smart payment service (Mastercard, 2015). In the case of connected cars, Mastercard's smart payment service (Masterpass) allows drivers and passengers to make payments for goods and services directly from their General Motors car's AI-powered infotainment system – OnStar Go (BusinessInsider, 2016). However, despite these numerous advantages and the wide use of smart payment services in different IoT environments, these applications are considered challenging because they may disrupt the behavioural patterns of consumers (e.g., Kaur, Dhir, Singh et al., 2020). This is further supported by evidence that consumers in many countries, and specifically the USA, have shown reluctance towards using smart payment services (e.g., Lulic, 2020; McKee, 2019). This suggests that there might be valid reasons for resisting smart payment services and hence these issues need to be addressed by understanding consumers' resistance to this service innovation.

The next section provides a detailed discussion of the relevance of the present study in the context of smart payment services, supported by industry information and statistical data.

1.2.2 Relevance of the present study in the context of smart payment services

Recent announcements have reported that AI is increasingly being applied within the finance and insurance industry, for example, where it has played a major role by combining with internet-connected devices to make automated payments (Huber, 2020). The tech and e-commerce giants are also focusing on POS innovations. Just as retailers had brought the physical experience of in-store shopping into online shopping, the tech giants have brought the same touch-free experience as that of online shopping into the physical stores with the implementation of smart payment services. These touch-free technologies include Apple Pay, Google Pay, and similar types of smart payment services that are transforming consumers' digital wallet use in different ways (Magats, 2020). For instance, Google is partnering with banks in the USA to allow Google Pay users to access their checking and savings accounts (managed by the banks concerned) in order to boost digital banking (Gross, 2020). The introduction of Amazon One in Amazon Go stores in Seattle allows consumers to perform contactless payments via biometric authentication (in the form of a palm wave) (Mintel, 2019a). Further, to increase the use of Apple Pay, Apple and Goldman Sachs have collaborated to introduce an innovative credit card, known as the Apple Pay Card, which allows consumers to track their spending goals and manage balances (Mintel, 2019b). More globally, the European Central Bank and the Bank of England are making efforts in analysing various scenarios to assess the risks and rewards of issuing digital currency to the general public (Kalifa, 2020; Sandbu, 2020). It was also predicted that the market size of global contactless payments was expected to grow from $10.3 billion to $18 billion in the next five years, as retailers applying for the implementation of digital POS financing platforms are receiving handsome offers from multiple lenders without much paperwork required (Lulic, 2020).

However, despite smart payment services having been prominent in retail consumer markets for the past decade, such services have not yet gained much traction (Hoek, 2017). Prior research has also indicated that, despite being beneficial, smart payment services were still far from being adopted widely, other than among a few early adopters (Zhou, 2013). Reports have suggested that consumers in the USA were still inactive in the adoption of proximity mobile payments (29% of smartphone users) (Forbes, 2020). Regarding the use of Amazon One scanners, consumers were still uncomfortable about financial companies storing their biometric data (Mintel, 2020a). Other analysis by 451 Research, conducted in the USA, reported that even after heavy investment in digital wallet development, hardware instalment in brick-and-mortar retail stores, and extensive consumer marketing, the use of smart payment methods (e.g., Apple Pay and Google Pay) was very poor and accounted for less than 2% of US brick-and-mortar retail sales (McKee, 2019). It has been observed that this issue of a reluctance to accept smart payment services is prevalent both in developed and emerging economies, as the global statistics regarding the use of smart payment technologies are not promising. A recent study by RTi Research reported that 30% of consumers had tried contactless payments for the very first time, and this was actually due to the recent global pandemic. However, it was still uncertain that such consumers would continue to use smart payment methods after the pandemic ended (Reville, 2020). According to a two-phase McKinsey survey conducted in the USA, UK, Germany and France regarding shopper preferences for retail technologies, the first-phase findings were that more than 35% of shoppers showed no interest in in-store technologies such as mobile contactless payments. In the second phase of the survey, a limited proportion of shoppers (only 30%) showed their intention to use such technologies in the store (Periscope by McKinsey, 2020). Further, according to recent Mintel Trends statistics, above 50% of consumers in countries such as the USA, UK and India own smartphones. However, consumers are still suspicious of using smart payment methods. For instance, 53% of US consumers rely more on cash spending as they feel uncomfortable leaving their houses without cash, 66% of Canadian consumers stated that digital payment systems can never replace face-to-face customer service, and only 10% of Indian consumers had accessed digital wallets while shopping online (Mintel, 2020b). Another digital consumer survey, conducted by Euromonitor International (2020), revealed that Western countries continued to have a slow adoption rate of smart payment services compared with countries in the Asia Pacific region. For instance, the survey found that consumers in the USA and Europe were still reluctant to shift their preferences to smart payment services as they found the use of plastic cards and cash to be more digitally anonymous, widely accepted in stores, and an authentic way of making payments (Euromonitor, 2020). Statista (2020) reported that from 2015 to 2018, the percentage of merchants worldwide accepting smart payment services as a payment method had increased from 24% to 29%. Further, as of 2021, during the pandemic, less than 47% of smartphone users worldwide had used contactless smart payment services at POS terminals (eMarketer, 2021).

Thus, smart payment technology allows easy purchasing on the part of consumers, thereby allowing brands to push impulse purchases to them. Hence, retailers should make sure that they are keeping pace with these payment technologies; otherwise, they might see a decline in consumers who are already using these payment services. However, the transition from conventional payment systems to smart payment services has yet to fully take place, as some consumers are slow to change their payment habits for a number of reasons and resist such payment technologies or services. Therefore, brands (offering these payment services) and retailers (implementing these payment services) should ensure that consumers feel comfortable with using smart payment services in order to provide a seamless purchasing experience, thereby reducing their resistance towards such services and technologies (Mintel, 2020b).

Furthermore, extensive empirical research has been carried out to examine consumer behaviour towards smart payment services which focuses on the factors motivating their adoption. For instance, Johnson et al. (2018) revealed perceived ease of use, relative advantage, and visibility to be factors driving consumers' usage intentions of smart payment services. Kaur, Dhir, Bodhi et al. (2020) found that relative advantage, compatibility, and observability were associated with use intentions of smart payment services. Morosan and DeFranco (2016) suggested that performance and consumers' habits in relation to using mobile payments also influenced their use intentions towards NFC-based smart payment services. Therefore, various studies (e.g., Chatterjee and Bolar, 2019; Chawla and Joshi, 2019; Shaw, 2014; Singh et al., 2017) have applied key innovation adoption theories to explain consumers' reasons for using smart payment services, including the Technology Acceptance Model (TAM; Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and the UTAUT2 (Venkatesh et al., 2012).

However, studies investigating smart payment services from the innovation resistance perspective are very limited. Table 1 below summarizes the empirical research on consumer resistance to innovation in the context of smart payment services.

Table 1: Summary of consumer resistance to innovation research in the context of smart payment services

Reference	Theoretical underpinning	Empirical research
Cham et al. (2021)	Innovation resistance theory	• Impact of functional, psychological and risk barriers on elderly people's resistance towards using mobile payment services. • Impact of stickiness to cash as a moderator on the relationships investigated.
Chung and Liang (2020)	Self-determination theory; innovation resistance theory	• Influence of complexity, image, and risk barriers on usage intention of mobile payments. • Examining the extent of consumers' self-determination (i.e., their autonomy, competence, and relatedness) in their barrier perceptions.
Eriksson et al. (2021)	Innovation resistance theory	• Identification of potential barriers to a wider adoption of mobile in-store payments.
Kaur, Dhir, Singh et al. (2020)	Innovation resistance theory	• Influence of functional and psychological barriers on use intention and recommendation intention of mobile payment solutions.
Khanra et al. (2021)	Innovation resistance theory	• Influence of functional and psychological barriers on adoption postponement of mobile payment services. • Examination of moderating effect of security concerns on the relationships between different barriers and consumers' adoption postponement.

Leong et al. (2020)	Innovation resistance theory	• Influence of functional and psychological barriers on mobile wallet resistance. • Influence of perceived novelty and demographic variables (age, education, and income) on mobile wallet resistance.
Y. Liu et al. (2021)	Innovation resistance theory	• Influence of privacy-related factors, such as effectiveness of privacy policy, privacy control, privacy concerns and privacy risk, on resistance to facial recognition payment.
Migliore et al. (2022)	Innovation resistance theory; UTAUT2	• Influence of both drivers and barriers on behavioural intention to adopt mobile payment. • Moderating influence of cultural dimensions of individualism, uncertain avoidance, power distance, and long-term orientation.
Pitari et al. (2020; 2021)	Innovation resistance theory; innovation diffusion theory	• Influence of relative advantage, complexity and compatibility; as well as five resistance factors (value barrier, usage barrier, tradition barrier, risk barrier, image barrier) on willingness to adopt NFC mobile payments. • Influence of resistance on intention to adopt mobile payment
Kladkleeb (2019); Sivathanu (2019)	Innovation resistance theory	• Influence of functional and psychological barriers on resistance to use digital payment systems. • Influence of resistance on actual usage of digital payment systems.
M. Talwar et al. (2021)	Dual factor theory	• Investigation of how inhibitors and enablers of m-wallet use are associated with positive and negative word of mouth. • Investigation of how positive and negative word of mouth may, in turn, influence continued m-wallet usage intention.
S. Talwar, Talwar et al (2021)	Innovation resistance theory	• Influence of functional and psychological barriers on rejection, postponement, and opposition to m-payments.

Although smart payment services are a technologically advanced innovation that is likely to disrupt consumers' status quo satisfaction (Ram and Sheth, 1989), consumers might, on the other hand, derive consumption values from these services that are also likely to play a critical role in mitigating resistance towards this service innovation. For instance, smart payment services are likely to provide well-designed and efficient payment platforms that enhance the performance quality of the service (Chemingui and Ben lallouna, 2013; Zhang et al., 2019);

allow consumers to gain social status and prestige among others through conspicuous consumption (de Kerviler et al., 2016); reinforce emotional attachment (e.g., pleasure) as consumers are likely to experience surprising visual or vocal interfaces with the smart payment services used in various mobile shopping apps (de Kerviler et al., 2016); and invoke curiosity among consumers to explore using the different financial services available on smartphones (Omigie et al., 2017).

Overall, in acknowledging the above references and trends, this calls for a study to understand the phenomenon of consumer resistance to innovation in the context of smart payment services, as an investigation of other possible barriers (e.g., technology vulnerability, ideological and individual barriers; Mani and Chouk, 2018) that may drive consumer resistance towards smart payment services, the detrimental effect of such resistance and possible strategies that may reduce such resistance remain unexplored.

1.3 Prospective study contributions

This study aims to address the above-stated research gaps, contribute theoretically to the literature on innovation diffusion and innovation resistance, and suggest various managerial implications for organizations, managers, and innovators offering smart payment services.

1.3.1 Prospective theoretical contributions

The majority of the existing research in the literature on consumer resistance to innovation has been done to understand the functional and psychological barriers and how these lead to resistance (e.g., Borraz-Mora et al., 2017; Chaouali and Souiden, 2019; Kaabachi and Obeid, 2016; Laukkanen, 2016; Leong et al., 2020; Ram and Sheth, 1989; Sivathanu, 2019; Yu and Chantatub, 2016; Yu et al., 2015) (see Table 5, Chapter 2). By addressing the first aim, this study intends, in addition to functional and psychological barriers, to explore the effects of sparsely investigated barriers on consumer resistance to smart payment services, which have been recently added by Mani and Chouk (2018). These sparsely investigated barriers include *factors related to consumers' predisposition to resist innovations* and *consumers' personal conviction towards the innovations and barriers specific to technologically advanced services*.

Next, empirical research exploring the detrimental consequences of consumer resistance to innovation has been surprisingly scarce, specifically in the context of smart payment services. Hence, by addressing the second and third aims (i.e., investigating NWOM as a direct detrimental consequence of consumer resistance to smart payment services), this study intends to validate the influence of consumer resistance to such services on NWOM as well as to shed light on the novel mediating role of consumer resistance to smart payment services to explicate the relationship between perceived barriers and NWOM. Furthermore, by exploring these relationships, this study intends to contribute to the innovation diffusion literature by providing new insights into the opinion leadership nature of laggards (Rogers, 2003) of smart payment services.

Finally, as prior research has documented marketing strategies that help in the reduction of consumer resistance to innovation (e.g., Laukkanen et al., 2009; Ram and Sheth, 1989; Rodríguez Sánchez et al., 2020), understanding how the effects of perceived barriers on consumer resistance to innovation (e.g., smart payment services) can be mitigated is rather limited. For instance, the perceived value offered by smart payment services to consumers could be used as a strategy to mitigate the effect of perceived barriers. Hence, by addressing the third aim of investigating the buffering role of consumption value perceptions (Sheth et al., 1991), this study intends to contribute to the innovation resistance literature with a new set of mitigation strategies that may buffer the impact of barrier perceptions on consumer resistance to smart payment services. This study also intends to contribute to the innovation resistance literature by understanding the application of a novel theoretical underpinning (i.e., prospect theory; Kahneman and Tversky, 1979) in investigating the joint effects of perceived consumption values and barriers on consumer resistance to smart payment services.

1.3.2 Prospective practical contributions

A major concern of companies offering an innovation is to reduce consumer resistance towards it by implementing multiple strategies in order to avoid innovation failure in the consumer market. This study intends to explore the various barriers that are perceived by consumers and lead to their resistance towards smart payment services and the resulting detrimental consequence of NWOM. Based on these prospective findings, this study intends to propose managerial implications emphasizing how innovators and marketing managers can minimize perceived barriers to reduce resistance towards smart payment services and the subsequent NWOM of resistant consumers.

Further, this investigation also proposes to explore the role of perceived consumption values that can be extremely helpful in mitigating the effects of barrier perceptions on consumers' resistance towards smart payment services as well as minimizing the resulting NWOM. Hence, based on these proposed findings, this study intends to advise practitioners to maximize the consumption values that can be offered by smart payment services, thereby reducing consumers' resistance and the consequent NWOM about this service innovation.

1.4 Thesis structure

The thesis is structured into six chapters, with the first being this Introduction. The rest of the chapters are as follows.

Chapter 2 – Literature Review – This chapter provides a detailed conceptualization of consumer resistance to innovation as well as its types and forms. Next, the theoretical background on the factors that influence consumer resistance to innovation and those that can mitigate consumer resistance to innovation is discussed. Prior empirical research is discussed under each section, based on which research gaps are identified in the current literature. Based on the research gaps identified, the required theoretical frameworks are discussed, together with the rationale for their selection.

Chapter 3 – Research Hypotheses and Conceptual Framework – This chapter starts with the development of individual hypotheses for direct effects, mediating effects, moderating effects, and moderated mediation effects. These hypotheses are developed based on past empirical evidence as well as the theoretical underpinnings highlighted in Chapter 2, which include the extended Ram and Sheth model (Mani and Chouk, 2018), prospect theory (Kahneman and Tversky, 1979) and the theory of consumption values (Sheth et al., 1991). At the end of the chapter, the conceptual framework of the research is provided, highlighting all the proposed hypothesized relationships.

Chapter 4 – Research Methodology – To test the hypothesized relationships developed in the previous chapter, this chapter presents the methodology adopted for this study. This chapter discusses the various philosophical paradigms, research approaches, and research designs that have been laid down in business and management research, based on which a suitable research philosophy, approach, and design were adopted that led to the selection of a quantitative study approach. Last, the quantitative study objectives, sampling procedure, ethical considerations, and data collection tools used in the study are discussed.

Chapter 5 – Quantitative Data Analysis – This chapter presents the quantitative analysis and results regarding the proposed hypothesized relationships. The quantitative analysis consists of a preliminary examination of the collected data followed by factor analyses and descriptive statistics of the latent constructs of this study. Last, the path analysis results are discussed, which include the direct effects, mediating effects, moderating effects, and, finally, the moderated mediation effects.

Chapter 6 – Discussion and Managerial Implications – This chapter consolidates the study findings derived from the quantitative results. The final section discusses the theoretical and practical contributions of the study.

Chapter 7 – Limitations, Future Research and Conclusion – This chapter outlines the limitations of this study, based on which future research directions are proposed. This is followed by the conclusion of the entire study.

Chapter 2 – Literature Review

This chapter presents a detailed discussion on the conceptualization of 'consumer resistance to innovation', together with the factors that influence this phenomenon. It also discusses the factors that are likely to mitigate consumer resistance to innovation.

The literature review has been structured into two main sections: 1) Consumer resistance to innovation; and 2) Mitigating consumer resistance to innovation. The first section provides a detailed conceptualization of consumer resistance to innovation, highlighting its various types and forms. Next, the research background is provided on various factors that influence consumer resistance to innovation, together with an overview of previous empirical research. Similarly, the second section provides the research background on the factors that can mitigate consumer resistance to innovation.

Finally, research gaps are outlined based on the literature review. The chapter concludes with a literature review table summarizing the publication information, antecedents, moderators, mediators and consequences of consumer resistance to innovation.

2.1 Consumer resistance to innovation

The phenomenon of 'consumer resistance to innovation' is defined by Ram and Sheth (1989, p. 6) as "the resistance shown by consumers to an innovation, either because it poses potential changes from a satisfactory status-quo, or it conflicts with their belief structure". The literature further highlights that this phenomenon exists along a continuum, initiated in a general reluctance to innovation (passive resistance) due to various personal reasons (e.g., cultural factors) that may further lead to consumers perceiving that innovation as too risky to adopt at that particular point of time (active resistance) (Heidenreich and Spieth, 2013; Ram and Sheth, 1989). In addition, if consumers perceive an innovation to be highly unsuitable, they may take steps to harm the innovation provider (Van Tonder, 2017). Consumer resistance also varies with the continuity of the innovation, such that highly discontinuous innovations (or radical innovations) involve a great degree of change in behaviour among consumers that can lead to higher resistance when compared with that of continuous innovations (or incremental innovations). However, even continuous innovations can also face resistance from consumers if their existence conflicts with their belief structure (e.g., Heidenreich and Handrich, 2015; Heidenreich and Kraemer, 2016; Ram and Sheth, 1989).

2.1.1 Resistance by laggards

The phenomenon of consumer resistance to innovation also varies with the time of the innovation adoption and has been associated with five categories of consumers: innovators (showing no resistance at all), early adopters, early majority, late majority, and laggards (showing the highest resistance) (Ram and Sheth, 1989; Rogers, 2003). Laggards are further highlighted as those who do not show any opinion leadership as they are fearful of the change to be brought by an innovation that is likely to disrupt their status quo and traditional norms (Rogers, 2003). Laggards also give importance to traditional values and are highly suspicious of innovations. As a result, these characteristics slow their innovation adoption process (Rogers, 2003). Hence, laggards are generally resistors to innovations as they will stick to their currently owned product. However, they often have a tendency to skip several generations of a product and then upgrade to a superior and technologically advanced generation of that product type (Goldenberg and Oreg, 2007). This implies that it is possible to encourage laggards to adopt innovations after the necessary modifications are applied. Hence, studying the factors that encourage laggards to resist an innovation can assist firms to identify the shortcomings of their innovations. This might help innovators and managers to design strategies to overcome or reduce such shortcomings and the resulting resistance. Moreover, it has been suggested that involving laggards in the new product development process could be fruitful for the companies concerned because the insights drawn from them can help in the exploration of emerging trends and ways of creating value that can be derived from the innovation (Jahanmir and Lages, 2015). *Therefore, it is important to understand what factors cause laggards to resist innovations and how such factors can be mitigated.*

2.1.2 Types and forms of consumer resistance to innovation

Although the majority of the empirical studies have examined consumer resistance to innovation as a unidimensional construct (see Table 5), pioneering researchers in the fields of innovation and technology studies have approached the concept from various perspectives, including different types and forms of resistance, which are discussed below.

The literature has highlighted that consumers exhibit two types of resistance towards innovation based on their stage of innovation evaluation: passive innovation resistance (PIR) and active innovation resistance (AIR) (Heidenreich and Spieth, 2013; Talke and Heidenreich, 2014). The complex phenomenon of consumer resistance to innovation can also be delineated into three forms depending on how individual consumers express resistance towards the innovation as determined by their cognitive style (i.e., the manner of information processing, decision making and problem solving). Therefore, consumers may express resistance to innovation in the form of rejection, opposition, and/or postponement (e.g., Chen et al., 2019; Kleijnen et al., 2009; Szmigin and Foxall, 1998). The following sections present a discussion of these different types and forms of consumer resistance to innovation.

a) Passive innovation resistance and active innovation resistance

Passive innovation resistance (PIR) is consumers' tendency to resist an innovation even before evaluating it, which results from the individual's inclination to resist change and degree of status quo satisfaction (Heidenreich and Handrich, 2015). Conservative consumers who possess negative innovative behaviour mainly show PIR, thereby reducing their willingness to seek novel and varied products (Heidenreich and Kraemer, 2015; Van Tonder, 2017). PIR can be further classified into four types: *dual passive resistance*, which occurs when the consumer is highly satisfied with his/her current situation, as well as showing a high tendency to resist changes from pre-established routines; *low passive resistance*, which occurs when a consumer shows low levels of inclination to resist change, as well as status quo satisfaction; *cognitive passive resistance*, which is due to a consumer's high inclination to resist change but low status quo satisfaction; and, finally, *situational passive resistance*, which occurs as a result of a consumer's high status quo satisfaction but a lower tendency to resist change (Talke and Heidenreich, 2014).

Among the different types of PIR, dual passive resistance is found to be the most crucial in inhibiting adoption (Heidenreich et al., 2016). Moreover, cognitive passive resistance is also termed *habit resistance* because such resistance is a result of changes in a consumer's established habits developed from using a current product and cognitive biases such as loss aversion, regret avoidance and omission of action bias (Ram, 1989; Sheth, 1981; Stryja and Satzger, 2019).

On the other hand, *active innovation resistance (AIR)* is shown by consumers in the post-evaluation stage (i.e., when consumers form a negative attitude because of an unfavourable evaluation of the innovation attributes) (Nabih et al., 1997; Talke and Heidenreich, 2014). Further, AIR can result from cognitive and emotional factors. When consumers cognitively evaluate innovation attributes, unfavourable evaluations result in the formation of innovation-specific barriers (functional and psychological barriers) that contribute to *cognitive active resistance* (Castro et al., 2019; Ram and Sheth, 1989; Talke and Heidenreich, 2014). In addition, unfavourable evaluations of innovation attributes may generate negative emotions (e.g., anger, anxiety, fear and sadness) that lead to emotional barriers (e.g., pleasure barrier, arousal barrier, and dominance barrier), resulting in *emotional active resistance* (Bagozzi and Lee, 1999; Castro et al., 2019). Castro et al. (2019) further suggest that the combination of cognitive active resistance and emotional active resistance can lead to four types of active resistance scenarios. High levels of both cognitive and emotional active resistance can result in *dual resistance*, whereas low levels of both cognitive and emotional active resistance can lead to *low active resistance*. Further, the presence of high levels of cognitive active resistance and low levels of emotional active resistance result in *cognitive-dominant resistance,* whereas high levels of emotional active resistance and low levels of cognitive active resistance cause *emotion-dominant resistance* (Castro et al., 2019).

b) Postponement, opposition and rejection

The innovation resistance literature has also presented the construct of 'consumer resistance to innovation' in three different forms: <u>rejection, postponement, and opposition</u> (i.e., how consumers express their resistance towards innovation).

Rejection is defined as "the active decision to not at all take up an innovation" (Kleijnen et al., 2009, p. 352). This form is generally shown when the consumer has already processed the available information and, based on that information, perceives that the innovation lacks relative advantage over its alternatives (Szmigin and Foxall, 1998). The decision to reject an innovation refers to the decision not to adopt it after an active evaluation (Talke and Heidenreich, 2014); however, if appropriate modifications are incorporated into the innovation, this may result in a positive response (i.e., acceptance) (Szmigin and Foxall, 1998). Further, conservative consumers (i.e., those who prefer their status quo) can show rejection even prior to the evaluation of an innovation. In such cases, any modifications and updates are unlikely to change the consumer's decision to reject innovation (Van Tonder, 2017). Furthermore, a temporary form of rejection has been highlighted in the literature that is termed the 'leapfrogging effect'. In this case, consumers resist a new product/service innovation, skip several generations of that innovation, and, finally, upgrade to a technologically advanced generation of the product/service. Consumers generally show an intention to leapfrog when they perceive that successive generations of product innovation do not offer any significant benefits or the innovation offers poor value for money against the currently owned innovation (Goldenberg and Oreg, 2007; Heidenreich et al., 2022).

Postponement is a situation-based response that is defined as "an active decision to not adopt an innovation at that moment in time" (Kleijnen et al., 2009, p. 352). Consumers may delay their final decision as they prefer to monitor the developmental progress of the innovation and collect more information about it, even if they are aware of its advantages and disadvantages (Szmigin and Foxall, 1998). Moreover, the literature has highlighted two classifications of postponement: trial postponement and adoption postponement (Nabih et al., 1997). Whenever a consumer is unsure whether to try an innovation or not, a trial postponement occurs. Adoption postponement, on the other hand, refers to a state in which a consumer is unable to decide whether to continue the trial of an innovation or abandon it completely. Hence, adoption postponement can also result in a delayed final purchase decision due to the presence of situational constraints, such as a high price or product unavailability (Nabih et al., 1997).

Finally, opposition refers to the "active behaviour directed in some way towards opposing the introduction of an innovation" (Kleijnen et al., 2009, p. 353). Consumers are likely to oppose an innovation when they are unable to see any differential advantage in it (Szmigin and Foxall, 1998). Opposition may also arise when consumers' established habits are likely to be disrupted by an innovation (Sheth, 1981; Szmigin and Foxall, 1998). Opposition has been found to be the most aggressive form of consumer resistance to innovation as this form has been suggested as being associated with adverse activities (e.g., protest activities) against the innovation (Kleijnen et al., 2009). Therefore, opposition is particularly detrimental to both the innovation and to the innovation provider (Chen et al., 2019). Cavusoglu et al. (2010) also found that consumers opposing an innovation focus on increasing the number or size of opposition groups as they strive to restrain the adoption of the innovation by negatively influencing the innovation's diffusion process. Research also suggests that opposition can be expressed either passively (i.e., not accepting the change) or actively (i.e., engaging in combat or rebellion against the innovation and/or innovation provider) (Roux, 2007).

Table 2 provides a summary of the conceptualization of the types and forms of consumer resistance to innovation.

Table 2: Types and forms of consumer resistance to innovation

Types and forms of CRI	Conceptualization	Further classification
PIR	Negative attitude shown as a result of no evaluation on the part of consumers due to their general tendency to resist change and preference for the status quo.	Dual Passive, Cognitive Passive, Situational Passive, Low Passive resistance
AIR	Negative attitude shown as a result of active evaluation on the part of consumers generally arising from their perception of innovation-specific factors.	Cognitive Active and Emotional Active resistance (Castro et al., 2019)
Rejection	Active decision to not at all take up an innovation.	Active and passive rejection, temporary rejection (leapfrogging effect)
Postponement	Active decision to not adopt an innovation at that moment in time.	Trial postponement and Adoption postponement
Opposition	Active behaviour directed in some way towards opposing the introduction of an innovation	Active and passive opposition

Note: AIR = active innovation resistance; CRI = consumer resistance to innovation; PIR = passive innovation resistance.

The next section discusses the different types of factors that influence consumer resistance to innovation.

2.1.3 Innovation resistance theory

Innovation resistance theory explains the formation of consumer resistance to innovation as being due to three factors: *innovation-related factors*, *consumer-related factors*, and *market-*

related factors (Ram, 1987). This theory was later modified by Ram and Sheth (1989) to explain that innovation resistance is a negative consumer response towards the changes that are likely to be brought by an innovation which could disrupt the status quo and be in conflict with the belief structure of those consumers. Therefore, Ram and Sheth (1989) proposed a theoretical framework of two categories of barriers: the functional barriers and psychological barriers that influence consumer resistance to innovation. The next section discusses two factors in detail: innovation-related factors and consumer-related factors, as these are relevant to the present study.

a) Innovation-related factors

Not all the innovations introduced to the consumer market are equal. Each innovation has its own individual set of characteristics/attributes that explain the consumer attitude towards that innovation (Rogers, 2003). According to Ram (1987), innovation characteristics, such as relative advantage, compatibility, trialability, divisibility, communicability, complexity, reversibility, realization and amenability to modification, influence consumer resistance to innovation.

Research has also highlighted that the risks associated with innovations are one of the dominant innovation characteristics responsible for consumer resistance to innovation. Consumers perceive risks as a result of the uncertainties associated with innovations (Sheth, 1981). As such, higher risk perceptions can lead to an increase in consumer resistance to innovation (Ram, 1987). Further, it has been suggested that consumers perceive high risks in the case of discontinuous or radical innovations (vs continuous or incremental innovations), as these are revolutionary technological advancements over their predecessors and hence are likely to be associated with a high level of uncertainty (Sheth, 1981). Table 3 provides a summary of the conceptualization of different innovation characteristics that influence consumer resistance to innovation.

Table 3: Summary of the conceptualization of innovation characteristics

Innovation characteristics	Concept
Associated risks	The perception of aversive physical, social, or economic consequences and uncertainties related to performance which vary based on the type of innovation (i.e., continuous or discontinuous innovation) (Ram, 1987; Sheth, 1981).
Relative advantage	The degree to which an innovation is perceived to be superior to its predecessor as well as over its existing substitutes (Ram, 1987; Rogers, 2003).
Compatibility	The perception that innovation is consistent with existing values, norms, past experiences, needs of the consumers and traditional and cultural values (Ram, 1987; Rogers, 2003).
Trialability	Relates to whether the innovation can be tried or experimented with before taking the final decision of purchase or non-purchase (Ram, 1987; Rogers, 2003).
Divisibility	Closely related to trialability (i.e., the feasibility of the innovation being tried or experimented with in stages) (Ram, 1987).
Communicability	The degree to which the results and tangible benefits of the innovation can be disseminated by the marketers to the consumers (Ram, 1987; Rogers and Shoemaker, 1971).
Complexity	The degree of the perception that the innovation is difficult to understand and to be implemented or used by consumers (Rogers, 2003).
Reversibility	The perception that the innovation offers the option to be discontinued temporarily if desired by the consumer (Zaltman et al., 1973).
Realization	The rate at which consumers expect to receive benefits from the use of the innovation (Zaltman et al., 1973).
Amenability to modification	The feasibility and flexibility of innovation modification according to the consumers' satisfaction level (Zaltman et al., 1973).

The literature also highlights that consumer resistance to innovation can occur as a result of another set of innovation-related factors, commonly termed barrier perceptions. These barriers generally arise when consumers perceive innovation characteristics as dysfunctional or unfavourable for personal needs (Talke and Heidenreich, 2014). For example, risk perceptions can be perceived as a risk barrier, innovation complexity can be perceived in the form of a usage barrier, incompatibility issues can be related to a tradition barrier, and high price as well as lack of relative advantage can be perceived as a value barrier (Mani and Chouk, 2018; Ram and Sheth, 1989). A detailed conceptualization of these barriers is discussed in section 2.1.4.

The next section provides an overview of empirical investigations that highlights the role of innovation characteristics in influencing consumer resistance to innovation.

Empirical research on innovation characteristics

Many empirical studies have investigated the influence of different innovation characteristics on consumer resistance to innovation. For instance, innovation characteristics such as complexity, lack of relative advantage, associated risks, high price, poor novelty, and other unfavourable characteristics can lead to consumer resistance to innovation (e.g., Abbas et al., 2017; Cruz et al., 2010; Kaabachi and Obeid, 2016; Kim and Bae, 2020; Kim, Lee, et al., 2017; Kim et al., 2016; Lee, 2013; Mani and Chouk, 2017; Mohammadi, 2015; Patsiotis et al., 2013). However, if an innovation is compatible with consumers' past experiences and if they are offered an innovation trial before making a final decision, this is likely to reduce their resistance to the innovation (Chemingui and Ben lallouna, 2013; Yoo et al., 2021). Furthermore, based on innovation characteristics, such as risk, lack of innovation trial, difficulty in understanding the technological interface (complexity), and price, previous studies have suggested various profiles of non-adopters of innovation (e.g., Chamaret et al., 2020; Nazzaro et al., 2019; Patsiotis et al., 2012; Wiedmann et al., 2011). For example, Patsiotis et al. (2012) suggested three types of resistant consumer profiles, whereby 'advanced users' had the fewest concerns about risks and lack of trial, the 'concerned majority' were more concerned about these factors when compared to those in the first group, and the 'unconcerned majority' showed more concern about the complexity of the innovation rather than the risks and lack of innovation trial.

Further, extensive research has been carried out to examine the influence of risk perceptions on consumer resistance to innovation (e.g., Herbig and Kramer, 1994; Kim et al., 2016). Consumer resistance to innovation was also found to be influenced by different types of risk perceptions, such as financial, performance, physical, time, social, psychological, network quality, privacy, information privacy and intrusion concerns, lack of group cohesion, business reputation risks, first-mover risks, control, and transparency risk (e.g., Hirunyawipada and Paswan, 2006; Hong et al., 2020; Kang and Kim, 2009; Kim, Park, et al., 2017; Maduku, 2020; Mani and Chouk, 2019; Rodríguez Sánchez et al., 2020; Wiedmann et al., 2011). The effect of risk perceptions on consumer resistance to innovation may also vary due to other factors. For instance, due to cultural variables (e.g., fatalism, religious commitment and traditionalism), the degree of perceived risk was found to be the highest among fatalistic consumers (those with a belief in fate) in contrast to those with religious commitment and a sense of traditionalism (Tansuhaj et al., 1991).

b) Consumer-related factors

Resistance towards any newly introduced innovation is influenced by the psychological characteristics of the consumers that correspond to their willingness to innovate (Ram, 1987). According to Ram (1987), these psychological characteristics consist of consumers' perception, personality, previous experience with an innovation, attitudes and beliefs about an innovation, and motivation.

The characteristic of 'motivation' is related to consumers' habits, which are of paramount importance in the innovation resistance literature. Consumer resistance to innovation emerges due to changes in habit because individuals have a tendency to maintain consistency in their established routines/habits (i.e., status quo maintenance) instead of developing new routines. Being consistent with established habits refers to all behavioural activities in the form of selecting, acquiring, and consuming a particular product/service (Sheth, 1981). Hence, consumers are likely to be less motivated to adopt an innovation when consistency with established habits is disrupted by any change brought by the innovation, resulting in resistance towards that change (Ram, 1987; Sheth, 1981). Furthermore, when consumers are quite satisfied with a current product and potential change in established habits to be brought by innovation is perceived as unfavourable, performing additional cognitive processing to evaluate the benefits of that innovation can lead to resistance towards that change (Ram, 1989).

Table 4 provides a summary of the conceptualization of different psychological characteristics of consumers that influence consumer resistance to innovation.

Table 4: Summary of the conceptualization of consumers' psychological characteristics

Psychological characteristic	Concept
Perception	Refers to the consumer's perception of the need for innovation. The lack of need for any innovation is likely to cause consumer resistance to innovation. Moreover, even after the adoption of innovation, if the need for the innovation is perceived as unfavourable, resistance is likely to occur (Ram, 1987).
Personality	Refers to lack of self-confidence and high dogmatism. Consumers with low *self-confidence* are likely to show high resistance to innovations. Low self-confidence can arise due to the lack of innovation trial and hence consumers are likely to suspect the performance of the innovation, resulting in their resistance (Ram, 1987). *Dogmatism* refers to consumers' discomfort with the change that the innovation is likely to bring. Therefore, if a consumer is uncomfortable and anxious about a change, resistance towards the innovation is likely to occur (Ram, 1987).
Previous experience with an innovation	Consumers' *previous experience with an innovation* greatly influences the consumer attitude towards a presently available innovation of a similar type. Thus, an unfavourable previous experience will influence the current attitude of the consumer towards a similar newly introduced innovation, thereby contributing to higher innovation resistance (Ram, 1987).
Attitude and beliefs about innovation	Characteristics related to consumers' attitudes towards and beliefs about innovation also have an impact on their level of resistance. For example, having a positive attitude of seeking more information from others about an innovation before its adoption helps in lowering the resistance towards the innovation (Ram, 1987).
Motivation	Changes in established habits lower the motivation of consumers to adopt the innovation. The resistance so formed is also termed habit or cognitive resistance (Ram, 1987; Sheth, 1981).

Last, consumers' characteristics related to their ability to innovate depend on their demographic variables. For instance, consumers with a low income, lack of proper education or who are older may have a decreased ability to innovate, leading to an increase in their resistance towards innovation (Ram, 1987).

The next section provides an overview of empirical investigations that highlight the role of consumer-related factors influencing consumer resistance to innovation.

Empirical research on consumer-related factors

Studies have shown that consumer characteristics, such as self-efficacy, motivation to use a new product and consumer innovativeness decreased the degree of innovation resistance, leading to positive attitudes towards an innovation (Abbas et al., 2017). Research has also reported that lack of innovativeness and a poor previous experience increased perceptions of risk, thereby leading to a negative consumer attitude (Mainardes et al., 2019). Studies have also explored various profiles of resistant consumers based on consumer characteristics such as lack of trust in a company, negative attitude, lack of innovativeness and a lack of motivation to use the innovation (e.g., Adigüzel et al., 2018; Jahanmir and Cavadas, 2018; Nazzaro et al., 2019; Patsiotis et al., 2012). Similarly, research has also reported a type of resistor known as dispositional resistors, who skip several generations of a product/service (innovation) so as to adopt the latest generation of that product/service because of their tendency to resist change (Goldenberg and Oreg, 2007).

Furthermore, changes in established habits have been suggested as a major factor responsible for consumer resistance to innovation (Sheth, 1981). The empirical findings in this respect show that habits are responsible for inhibiting the use of new products by consumers, causing them to revert to using existing products (Labrecque et al., 2017). Established habits also generate inertia (i.e., an individual's persistence in using or status quo satisfaction with the incumbent system; Polites et al., 2012), which was found to have a direct positive impact on consumer resistance to innovation (e.g., Kim et al., 2017; Mani and Chouk, 2018). Research also found that the impact of inertia on consumer resistance to innovation can be reduced by favourable consumer characteristics, such as trust in technology (Sharma, 2020), greater experience with an innovation (Nel and Boshoff, 2019) and high self-efficacy (i.e., the person's ability to perform a task; Ellen et al., 1991). However, satisfaction with the currently owned product/service can cause more inertia, leading to an increase in resistance towards innovations (Ellen et al., 1991). Research has also highlighted a barrier termed the 'individual barrier', which corresponds to inertia (i.e., maintaining the status quo) (Heidenreich et al., 2016; Heidenreich and Kraemer, 2015; Heidenreich and Spieth, 2013; Mani and Chouk, 2018).

The above review of the role of consumer-related factors in influencing consumer resistance to innovation suggests that little has been done to understand the impact of inertia or the individual barrier on consumer resistance to innovation and, as such, more research is required in this respect.

2.1.4 Ram and Sheth's (1989) theoretical framework and its extension

Ram and Sheth's (1989) theoretical framework categorizes barriers that can be used to explain the formation of consumer resistance to innovation into <u>functional barriers</u> and <u>psychological barriers</u>. Functional barriers mainly arise when consumers perceive that adopting an innovation will lead to significant changes in their behaviour due to alterations in usage patterns, associated risks, and the value of the innovation. As far as psychological barriers are concerned, these are related to inconsistencies with traditions and norms or the perceived image of the innovation. According to this theoretical framework, functional barriers are further classified into three types of barriers: <u>usage barrier, value barrier and risk barrier;</u> and psychological barriers are further classified into <u>tradition barrier and image barrier</u> (Ram and Sheth, 1989). A detailed description of these barriers is given below.

- **Perceived usage barrier –** Consumers perceive a usage barrier when the innovation is incompatible with their current workflows. Thus, innovations that are likely to change consumers' usage patterns unexpectedly require more time for acceptance by those facing this barrier.

- **Perceived value barrier –** A perceived value barrier occurs when the consumer evaluating a particular innovation perceives that the innovation has a lower performance-to-price ratio than the currently owned product/service or that of other alternatives. Therefore, the consumer considers the innovation less worthy of adoption and resists it.

- **Perceived risk barrier –** When consumers perceive that the innovation under consideration poses some uncertainty or may have adverse side effects, they are more likely to resist it. Ram and Sheth (1989) also highlighted four main types of risk that consumers take into account: physical risk, economic risk, functional risk and social risk. *Physical risk* is perceived by consumers when potential harm related to an individual's health or property is likely to be caused by an innovation. *Economic risk* relates to the high cost associated with an innovation and the uncertainty surrounding that costly innovation. *Functional risk* is perceived by consumers when they are uncertain whether an innovation will deliver the performance they expect, or if they perceive the innovation to be functionally unreliable. *Social risk* is associated with the disapproval of the innovation by a relevant social group, such as peers.

- **Perceived tradition barrier –** This barrier creates consumer resistance if the adoption of an innovation is perceived to be in conflict with traditional norms, values, and cultures. The more extreme the change or the conflict with tradition is perceived to be, the greater the resistance.

- **Perceived image barrier –** If consumers perceive unfavourable associations with a certain brand, country, industry or product class, and the innovation originated from any of these factors, they develop an unfavourable image of that innovation that leads to an image barrier. This type of barrier generally arises from the stereotyped thinking of the consumer.

All the above barriers are also considered to be innovation-specific because they are perceived after a deliberate evaluation of the innovation characteristics by consumers (Talke and Heidenreich, 2014). However, according to recent literature, this theoretical framework of five barriers suffers from the limitation that it does not take into account the individual variables that might explain individuals' predisposition to prefer the current situation (Mani and Chouk, 2018; Talke and Heidenreich, 2014). Moreover, Ram and Sheth's (1989) theoretical framework also does not consider those barriers which are related to individuals' predisposition to prefer and maintain the current situation, particular to advanced technological innovations of the current digital age, and factors that correspond to consumers' personal convictions against an innovation (Mani and Chouk, 2018). These barriers include individual barrier (defined in terms of inertia), technology vulnerability barriers (technological dependence and technology anxiety) and ideological barrier (defined in terms of general scepticism). Since the context of this study is an advanced technological payment service (i.e., smart payment services), the consideration of these additional barriers is necessary in this study and are further illustrated below.

- **Perceived technology vulnerability barrier –** As consumers interact with one or more types of technology in different areas of their lives and during various tasks, the amount of interaction between them and machines (innovations) increases, which may result in questions regarding the vulnerability of that technology. The vulnerability to a particular technology may appear in the form of *technology anxiety* and *technological dependence*.

Technology anxiety refers to consumers' apprehension or fear about using the technology (Venkatesh, 2000), whereas technological dependence refers to consumers' perception of becoming extremely dependent on the technology for their objectives and consequently losing control/autonomy over their tasks because of excessive technology use (Mani and Chouk, 2018).

- **Perceived ideological barrier –** This barrier has been conceptualized by Mani and Chouk (2018) in the form of general scepticism. However, scepticism can be regarded as a predisposed trait or context-based situation (Morel and Pruyn, 2003). This study considers general scepticism based on the latter concept (i.e., a context-based approach), the occurrence of which can be due to the consumer's confrontation with new market stimuli such as new product/service innovations. In other words, this barrier represents consumers' doubts regarding the truthfulness of discourses and companies' claims about innovations and the benefits they promise. These discourses include marketing discourse, such as advertisements promoting the innovations; prescriptive discourse, such as videos demonstrating the functioning and technical features of innovations; and prospective discourse, such as reports describing the economic potential of innovations (Mani and Chouk, 2018).

- **Perceived individual barrier –** This barrier considers individuals' predisposition to prefer and maintain the current situation (i.e., status quo satisfaction) (Talke and Heidenreich, 2014). Status quo bias theory explains the decision of an individual to do nothing or to maintain the current situation (Samuelson and Zeckhauser, 1988). Under the mechanism of rational decision making, this theory further suggests the presence of status quo inertia due to uncertainty in decision making. Moreover, in the context of decision making about new information systems, status quo maintenance is considered in terms of inertia, meaning attachment to existing behaviour or an incumbent system, even if the new system offers benefits and is superior to the existing one (Polites et al., 2012). Based on these concepts, this barrier has been defined in terms of inertia as an individual attitude of preferring the current situation (status quo) in response to the perceived uncertainties that may arise as a result of a change in habit (Mani and Chouk, 2018).

Empirical research on perceived barriers

Many empirical studies have focused their research on investigating the effects of perceived barriers on consumer resistance to innovation (e.g., Arif et al., 2020; Khanra et al., 2021; Nel and Boshoff, 2020, 2021). Studies have highlighted that consumers can be differentiated into adopters or non-adopters of innovations based on the differences in barrier perceptions, such as usage, image, value, risk, and tradition barriers. For instance, in an online shopping context, the adopters of online shopping perceived fewer of these barriers compared with the non-adopters (e.g., Lian and Yen, 2013; Rudolph et al., 2004). Studies have also investigated significant differences in the barriers encountered by each non-adopter category; that is, among postponers, opponents and rejectors (e.g., Elbadrawy and Abdel Aziz, 2011; Kleijnen et al., 2009; Laukkanen et al., 2008; Mzoughi and M'Sallem, 2013). The majority of these studies found that the risk barrier had the greatest effect on resistance compared with the other barriers. However, contrasting results were found by Laukkanen (2016), in which the value barrier was revealed to be a major barrier among the non-adopter categories (i.e., rejectors and postponers) but risk barrier did not have any influence on the resistance shown by these non-adopters.

There has also been research investigating the relative influences of barrier perceptions with regard to those factors that contribute to innovation adoption (e.g., Dhir et al., 2021; Gupta and Arora, 2017a, 2017b; Pillai and Sivathanu, 2020; Sivathanu, 2018). Some studies have shown that the factors driving innovation adoption have a stronger influence on the innovation adoption intention than the barriers (e.g., Claudy et al., 2015). Nevertheless, some studies revealed contrasting results in that barriers had a stronger (negative) impact on innovation adoption intentions, as opposed to the factors that drive innovation adoption (e.g., Gupta and Arora, 2017a).

Empirical research has also highlighted that perceptions of barriers may vary depending on consumers' demographic characteristics, such as age and gender. For instance, barrier perceptions differ according to the age of the consumers, with mature or older consumers facing more risk and image barriers compared with younger consumers (Laukkanen, 2016; Laukkanen et al., 2007; Lian and Yen, 2014). However, research has also reported contrasting results regarding the impact of age, whereby younger consumers showed more resistance to innovation (due to the perception of more barriers) than older consumers (She et al., 2017). In addition to the influence of actual age on the effect of perceived barriers, another age factor, known as cognitive age (i.e., self-perceived age, which is different from actual birth age), also influences the impact of barriers on innovation resistance such that cognitively old consumers perceive more barriers compared with cognitively young consumers (Chaouali and Souiden, 2019). Cognitively young consumers, however, are more sensitive to change because they seek a high degree of novelty in their innovations and can, therefore, be resistant to innovations that they consider to be less novel compared with their expectations (Chaouali and Souiden, 2019). In considering the effect of gender, men were found to be more sensitive towards the value barrier, whereas women's resistance was affected more by the usage barrier (Borraz-Mora et al., 2017). Other studies, in online banking contexts (e.g., Laukkanen, 2016), revealed that women were more likely to reject innovation than men.

In addition to demographic variables, some other individual- and context-specific factors were also found to vary (increase or decrease) the effect of barriers on consumer resistance to innovation. These factors include the information and guidance about the innovation provided by the firm (Laukkanen and Kiviniemi, 2010); product involvement and ecological awareness

(Wiedmann et al., 2011); subjective norms, perceived image, self-efficacy and personal innovativeness (Mohammadi, 2014); consumers’ e-lifestyle (Yu et al., 2015); perceived stimulation (Heidenreich and Kraemer, 2015); user-perceived service quality (Park et al., 2016); task-service fit (Fang, 2017); structural autonomy (Borraz-Mora et al., 2017); social influence (normative and informative) from members of society (Matsuo et al., 2018); satisfaction with offline services and environmental concerns (Chen, Tsai, et al., 2018); emotions (Rieple and Snijders, 2018); consumer experience (Nel and Boshoff, 2019); and consumer stickiness to old product (Sivathanu, 2019).

The above review of the literature highlighting the role of perceived barriers in influencing consumer resistance to innovation suggests that little has been done to investigate these recently explored barriers (e.g., technology vulnerability barriers and ideological barriers). As such, this study investigates the effects of these barriers on consumer resistance to innovation, together with the extensively researched functional and psychological barriers (e.g., Ram and Sheth, 1989).

2.1.5 Consequences of consumer resistance to innovation

The literature suggests that individuals who oppose the change brought by an innovation to the social system share negative opinions about the innovation with other consumers (Rogers, 2003), thereby demoralizing them with regard to adopting the innovation and turning them into late adopters (Jahanmir and Cavadas, 2018). Individuals who spread NWOM have been termed negative opinion leaders and resistance leaders (Hietschold et al., 2020). Hietschold et al. (2020) further highlighted that negative opinion leaders spread unfavourable information to their direct social ties; this is in contrast with resistance leaders, who act against innovation at a societal level (i.e., reaching beyond their personal connections). In addition, spreading negative information even reduces the effectiveness of firm-controlled propagation mechanisms (e.g., advertisements) about innovations (Moldovan and Goldenberg, 2004). It has also been conceptually argued that when conservative consumers fear that their preferred nostalgic products/services can be replaced by newly introduced innovations, they not only actively oppose the potential change likely to be brought by the innovation's introduction into the consumer market, but may also spread NWOM about that innovation, consequently damaging the reputation of the innovation provider (Van Tonder, 2017).

Empirical studies have investigated some of the consequences of consumer resistance to innovation, such as actual usage of innovation (e.g., Sivathanu 2019); intention to use (e.g., Rahman et al., 2021); participation intention (e.g., Kang and Kim, 2009); adoption intention (e.g., Hong, 2020); and related attitudes and intentions (see Table 5 in section 2.4).

The above review of the literature suggests that the current research still lacks a proper empirical investigation of the detrimental consequences of consumer resistance to innovation. Therefore, as resistant consumers are likely to spread unfavourable information about an innovation, this study examines NWOM as a key consequence of resistance to innovation.

2.2 Mitigating consumer resistance to innovation – theoretical background

In the consumer resistance to innovation literature, scholars have always emphasized suggesting various strategies that can be devised by businesses to reduce the effect of perceived barriers on consumer resistance to innovation. Research on these grounds has highlighted strategies, such as communication, product, pricing, market and coping strategies (e.g., Ram and Sheth, 1989). As such, empirical research has explored strategies such as product modifications (Rodríguez Sánchez et al., 2020), communicating positive feedback and benefits about an innovation from peers and innovation leaders (Laukkanen et al., 2009), price incentives (Yeatts et al., 2017), allowing trials and demonstrations of the innovation for consumers (Reinhardt et al., 2017), and making the innovation socially and traditionally acceptable (Bagozzi and Lee, 2005). *However, the understanding of how resistance can be* *mitigated is rather limited (Heidenreich and Kraemer, 2016), such as addressing this by optimizing the perceived value of innovations to consumers.*

It is important to incorporate beneficial characteristics in an innovation that can entice consumers, reducing their resistance towards it (Claudy et al., 2015; Ram, 1987; Rogers, 2003). In line with this, the research has highlighted certain factors that may inhibit innovation resistance, such as usefulness, ease of use, performance expectancy, and effort expectancy (e.g., Im et al., 2014; Lee, 2013; Sivathanu, 2019). In this sense, usefulness, ease of use, and relative advantage have been considered desirable attributes of an innovation that are likely to provide '*value*' in terms of benefits such as higher performance at relatively low cost, convenience, and financial benefits, which may reduce consumer resistance to innovation (e.g., Claudy et al., 2015; Kladkleeb and Vongurai, 2019; Ram, 1987). Therefore, if consumers perceive that innovations can provide some kind of *value*, these value perceptions could be considered useful strategies that might reduce the effect of barrier perceptions on consumers' resistance towards the innovations. The next section provides a detailed conceptualization of perceived value.

2.2.1 Perceived value

The literature has highlighted that the nature of '*perceived value*' can be either unidimensional or multidimensional. From the unidimensional perspective, the first conceptualization of perceived value was developed based on the concept of utility; that is, in terms of the *price-quality tradeoff* (Dodds et al., 1991).

From the same perspective, the second research stream conceptualizes perceived value in terms of a bidirectional *tradeoff between benefits and sacrifices*, which is termed the Zeithaml approach (Gutman, 1982; Zeithaml, 1988). Zeithaml (1988) also provided four distinct definitions of perceived value: value defined in terms of low price; in terms of what the consumer wants from his/her product; in terms of the quality received in exchange for a price; and in terms of what the consumer receives in exchange for something.

From the multidimensional perspective, the first conceptualization developed is termed the *Customer-Value Hierarchy,* which consists of three hierarchical value levels: attributes, consequences, and goals and purposes (Woodruff and Gardial, 1996). Later, Woodruff (1997, p. 142) also defined 'perceived value' as

> customer's perceived preference for an evaluation of those product attributes, attribute performances, and consequences arising from use that facilitate (or block) achieving the customer's goals and purposes in use situations.

A second two-dimensional value scale was conceptualized to measure consumers' evaluation of the shopping experience in terms of *utilitarian* and *hedonic values* (Babin et al., 1994). Here, utilitarian value is defined in terms of task accomplishment, necessary work to be fulfilled, or the value resulting from consumers' involvement only in information collection without the goal of purchasing anything (Babin et al., 1994). In contrast with utilitarian value, hedonic value refers to the shopping tasks arising from various emotions, such as fun, playfulness, enjoyment, and pleasure. Hedonic value may also be derived from impulse purchases and bargained purchases (Babin et al., 1994).

A third multidimensional conceptualization explains perceived value as axiology or value theory, which includes *extrinsic value* (reflecting the utilitarian aspect of the consumption of a product/service); *intrinsic value* (indicating the emotional appreciation and feelings derived from the consumption of a product/service); and *systemic value* (implying the logic or rationale behind the purchase or use of a product/service) (Hartman, 1967, 1973).

A fourth conceptualization was presented by Holbrook (1996, 1999), which includes an eight-celled typology of customer value based on three combinations: extrinsic versus intrinsic value, self-oriented versus other-oriented value, and active versus reactive value. The eight types of perceived value include efficiency, play, excellence, aesthetics, status, ethics, esteem, and spirituality, which occur simultaneously during a particular consumption situation at different levels.

Finally, a fifth multidimensional conceptualization of perceived value is presented by the *theory of consumption values* (Sheth et al., 1991), which consists of functional, social, emotional, and epistemic values. Further, based on the theory of consumption values, the PERVAL measurement scale was developed by Sweeney and Soutar (2001) and measures the value perceptions of consumer products in terms of functional value (quality and value for money), social value (enhancement of social self-concept) and emotional value (feelings or affective states).

In conclusion, the literature has suggested various conceptualizations of perceived value that have an impact on consumers' attitude towards a product/service. This study adopts Sheth et al.'s (1991) conceptualization of perceived values because of its multifaceted nature.

The next section presents a discussion on the different consumption values posited under the theory of consumption values (Sheth et al., 1991).

2.2.2 Theory of consumption values

The theory of consumption values (Sheth et al., 1991) is among the typologies of perceived values that take a multidimensional perspective to explain consumption decisions in relation to a particular product/service. Specifically, this theory explains the reasons for purchasing or enhancing the purchase intention of a particular product/service or a product/service type or brand over its alternative (Sheth et al., 1991). This section discusses the value dimensions: functional, social, emotional, and epistemic values.

- **Functional value –** A specific product/service is said to have acquired this value if it has the ability for functional, utilitarian, or physical performance with the help of its attributes, such as reliability, durability and price. This value is generally considered the primary value driving the consumer choice of products/services.

- **Social value –** This value defines the ability of a product/service to be associated with one or more positively or negatively stereotyped socioeconomic, cultural-ethnic, and demographic groups. The product and service choices that are highly visible to others and have the ability to enhance the social image and class of their owner are said to possess social value.

- **Emotional value –** This value is acquired by that product/service that has the ability to trigger emotions, affective states and feelings in the consumer making the choice. This value is mainly associated with provoking feelings, such as comfort, security, passion, fear and anger.

- **Epistemic value –** The product/service under consideration with an ability to provoke curiosity, novelty, an entirely new experience, or a change of routine or daily habit and can provide satisfaction in acquiring desired knowledge is believed to possess this value.

Empirical research on consumption values

Research on consumption values (Sheth et al., 1991) has focused on explaining and influencing different attitudes towards products/services directly and indirectly. Instances include explaining the choice of products/services based on consumer preferences (N. Chen et al., 2018; Jiang and Kim, 2015); the formation of a beneficial image of a service by the consumers (Tapachai and Waryszak, 2000); the formation of consumer trust (Choi et al., 2018; Moliner et al., 2007); increasing satisfaction with the products/services leading to the use intention of these products/services (Ledden et al., 2007; Moliner et al., 2007; Zainuddin et al., 2013); variation in the brand image of products (Park and Rabolt, 2009); influencing the relationship quality and behavioural loyalty of consumers to a brand (Papista and Krystallis, 2013); predicting consumers’ buying behaviour (Gonçalves et al., 2016); and influencing consumer beliefs regarding products (Jung et al., 2016). Consumption value dimensions have also been explored as mediators in the relationship between cultural values and brand image (Park and Rabolt, 2009), as well as in foreign brand purchasing intentions (Xiao and Kim, 2009).

Furthermore, consumption value dimensions have been extensively explored within the context of technological innovations. For instance, consumption values together form an integrated value dimension that has been used to explain consumer purchase intention of online game items (Park and Lee, 2011). Within the same context, when consumers perceived different consumption values after playing online games, these value dimensions contributed to increasing consumers’ willingness to repurchase and play the online games again, even at a premium price (Rezaei and Ghodsi, 2014; Teng, 2018). In the context of social media sites and similar platforms, the theory of consumption values has been used as a framework to categorize the various activities carried out on Facebook, resulting in the development of a new Facebook usage construct known as Gravitating towards Facebook (Aladwani, 2014). Another interesting study measured consumption values as outcomes resulting from various value co-creation activities that consumers perform in online innovation communities (Akman et al., 2018). Other studies within the same context have measured the use intention of SoLoMo services (Yang and Lin, 2017); purchase intentions of digital items in social networking communities (Kim et al., 2011); stickiness towards Facebook (Yang and Lin, 2014); and the use intention of Twitter (Cocosila and Igonor, 2015), based on the consumption values perceived by the consumers or users. Moreover, the perception of consumption values (functional and social values) also differentiated male and female online purchasers and non-purchasers (Andrews et al., 2007).

In the case of smart products/services, however, research investigating consumer perceptions of consumption values is limited. For instance, consumption values have been used to explain the consumer purchase and continued use intentions of home robots and smart wearables, with emotional value having the strongest impact (Hur et al., 2012; Wang et al., 2022). Further, in a smartphone context, consumption values were evoked due to customer readiness to use novel technology; however, only functional and emotional values were found to have influenced the use intention of the smart product by the customer (Poushneh and Vasquez-Parraga, 2019). Consumption values have also been used to explore the mechanism of consumer use intentions of a smartphone due to product smartness dimensions of autonomy, adaptability, reactivity, multifunctionality, ability to cooperate, and humanlike interactions, further revealing functional and emotional values as the drivers of new usage behaviour of a smart product (Park and Lee, 2014).

In conclusion, previous research has investigated the antecedents and mediating effects of consumption values in predicting consumer attitudes towards a product/service, implying that consumption values have been researched extensively within the innovation/technology adoption literature. Therefore, this study contributes to a better understanding of the moderating role of consumption values in the innovation resistance literature.

Further, to provide theoretical support for the rationale behind the interplay between perceived barriers and perceived consumption values in influencing consumer resistance to innovation, a theoretical underpinning deemed to be suitable for this study is elaborated in the next section: prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

2.2.3 Prospect theory

Prospect theory, proposed by Kahneman and Tversky (1979), suggests that people make decisions based on the calculated utility of various alternatives under uncertain and risky situations. The alternatives are evaluated depending on the outcomes and are perceived as either *'gains'* or *'losses'*, relative to a reference point. According to this theory, people tend to be psychologically *loss averse*; that is, they regret a loss more significantly than they value a gain of equal amount under uncertain conditions (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). This theory demonstrates a *possibility effect*, which suggests that when the outcome of a risky option has a low probability, people overestimate small probabilities over moderate or high probabilities and the above-stated risk preferences are reversed (Kahneman and Tversky, 1979). Hence, people become risk seeking in the case of low probability gains (with the hope of achieving larger gains) and risk averse for low probability losses (due to fear of larger losses).

Therefore, applying the tenets of prospect theory to the study context of smart payment services, the reference point for consumers is defined by the status quo formed due to their utilization of conventional payment methods. The migration to a new and unfamiliar payment service (i.e., smart payment services) would cause a change in the behaviour of the consumers currently using conventional payment services, thereby creating risk situations. Further, in line with the 'possibility effect' of prospect theory (Kahneman and Tversky, 1979), switching to an unfamiliar innovation (i.e., smart payment services) is perceived as a loss relative to the stated reference point, thereby making the consumers risk averse and hence they perceive different barriers, leading to their resistance towards smart payment services (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014).

The possibility effect of prospect theory also states that consumers tend to be risk seeking when they perceive a chance of acquiring gains (Kahneman and Tversky, 1979). Hence, it can be argued that resistant consumers might show a risk-seeking attitude if they perceive that gains can be acquired from smart payment services, which may help to reduce the perception of barriers and the resulting resistance towards such services. Based on these arguments, prospect theory was deemed to be suitable for understanding the role of perceived values in mitigating the effects of perceived barriers on consumer resistance to smart payment services.

2.3 Research gaps

Based on the literature review discussed above on consumer resistance to innovation and the factors that might mitigate it (i.e., perceived consumption values), this study aims to address the following research gaps.

First, according to the literature on consumer resistance to innovation, much research has been done to understand the direct effects of innovation-specific functional (i.e., usage, value, and risk barriers) and psychological (i.e., image and tradition barriers) barriers on consumer resistance to innovation as proposed under innovation resistance theory (Ram and Sheth, 1989). However, little has been done to understand the effects of certain factors or barriers on consumer resistance to innovation. These factors or barriers include consumers' tendency to maintain the status quo (termed individual barrier) (e.g., Mani and Chouk, 2018; Talke and Heidenreich, 2014), barriers that are relevant to technologically enhanced innovations, such as technology vulnerability barriers (technological dependence and technology anxiety) and ideological barrier that corresponds to consumers' personal convictions against innovations (scepticism towards the truthfulness of companies' discourses and the promised benefits of innovations) (e.g., Chouk and Mani, 2019; Mani and Chouk, 2017, 2018). Morevoer, research investigating joint effects of functional and psychological barriers together with consumer- and situation-specific factors on consumer resistance to innovation is scarce (e.g., Heidenreich and Spieth, 2013; Mani and Chouk, 2018). Previous research has also failed to show a significant effect of some of the newly explored barriers (e.g., technology vulnerability barriers) on consumer resistance to innovation (e.g., Mani and Chouk, 2017, 2018). As such, due to these limitations in the extant research, a deeper understanding of the effects of these under-researched barriers on consumer resistance to innovation is required. Therefore, this leads to:

Research gap 1 – There is limited research that adopts an integrated approach to investigating the effects of rarely researched barriers (e.g., technology vulnerability barriers, ideological barrier, and individual barrier) together with extensively researched functional and psychological barriers on consumer resistance to innovation.

Second, research has suggested that negative opinion leaders and resistance leaders showing resistance towards innovations negatively influence their social ties by spreading unfavourable information about an innovation (Hietschold et al., 2020). However, empirical research examining the detrimental impact of consumer resistance to innovation remains surprisingly scarce. In other words, little has been done to empirically understand the consequences of consumer resistance to innovation (Heidenreich and Handrich, 2015; Heidenreich and Kraemer, 2015). Some recent studies have shown direct links between barriers (e.g., poor customer service contributing to a negative image about a service, perceived costs, and risks) and the spreading of WOM/NWOM about an innovation to other consumers (e.g., Kaur, Dhir, Ray et al., 2020, Kaur, Dhir, Singh et al., 2020; M. Talwar et al., 2021, S. Talwar, Dhir et al., 2021). However, the findings of these studies have been equivocal. For instance, M. Talwar et al. (2021) reported that privacy and financial risks associated with innovation can lead consumers to spread negative information about an innovation in order to warn their friends and relatives. Kaur, Dhir, Singh et al., (2020) did not find any significant relationships between image and tradition barriers and consumers' recommendation intentions, and Kaur, Dhir, Ray et al. (2020) found unexpected results that consumers' perception of a value barrier encouraged them to recommend innovations. These conflicting findings suggest that some underlying mediating mechanism that may explain the transformation of barrier perceptions into NWOM spreading has been ignored (e.g., M. Talwar et al., 2021). These inconsistent findings need to be clarified. Therefore, a proper investigation is required that highlights consumer resistance to innovation as an underlying mechanism to provide a better understanding of how and why barrier perceptions lead consumers to spread NWOM. Therefore, this leads to:

Research gap 2 – There is a lack of proper empirical investigation into exploring NWOM as a detrimental consequence of consumer resistance to innovation.

Research gap 3 – There are equivocal findings on the relationship between perceived barriers and NWOM, suggesting that a proper empirical investigation has been ignored that would highlight the role of consumer resistance to innovation as an underlying mechanism between these relationships.

Finally, studies have underscored the important role played by consumption values (i.e., functional, social, emotional and epistemic values) in explaining consumer decision making of various smart products/services, such as home robots, smart toys, smart wearables, and smartphones (e.g., Hur et al., 2012; Kasilingam and Krishna, 2021; Park and Lee, 2014; Poushneh and Vasquez-Parraga, 2019; Wang et al., 2022; Wong et al., 2019; Zhang et al., 2020).

However, the literature has argued that, contrary to the effects of consumers' perceived barriers on a particular behaviour or attitude concerning a product/service, perceived values have also been found to have the opposite effects on those attitudes and behaviours shown by consumers. For instance, recent research by Talwar et al. (2020) found that risks, such as those related to privacy and security concerns, associated with online travel booking eroded the monetary value derived from the booking app. In the context of organic food, it was highlighted that perceived consumption values act as motivations towards positive consumer attitudes (e.g., use intention and purchase intention) in contrast with the functional and psychological barriers (which cause consumer resistance to innovation) that inhibit these positive attitudes (Kushwah et al., 2019). It was also found that inertial consumers who prefer to use only incumbent products/services perceived innovation to have a lower value and subsequently hesitated to use innovations (Gong et al., 2020). In addition, it was found that satisfaction derived from utilitarian and hedonic values encouraged consumers to recommend shopping places to other people, but these intentions to recommend could also be hindered by the barriers perceived (Han et al., 2018). In the context of a paid mobile media service, perceptions of value and technology barriers/risks acted in the form of positive and negative experiences, respectively, in their impact on consumer beliefs about technology benefits (Youn and Lee, 2019). Research also showed that barriers such as physical and mental discomfort and time and effort costs decreased the various consumption values involved in different behavioural activities of consumers, which resulted in the ceasing of the activities that were once preferred by the consumers (Zainuddin et al., 2017). In addition, online buyers who were motivated by the hedonic value associated with online purchases remained less concerned about the associated risks (security, privacy and order fulfilment), which further affected their online repurchase intentions (Chiu et al., 2014).

These studies highlight that consumers are likely to perceive both barriers (e.g., risks) and values (e.g., benefits) simultaneously that may influence their positive consumption decisions (e.g., adoption intention or purchase intention). However, *little is known about how perceived barriers and consumption values may interact to influence consumer resistance to innovation*. This leads to:

Research gap 4 – There is a void in the current research in respect of investigating the joint effects of perceived barriers and perceived values on consumer resistance to innovation, such that perceived values might act as strategies to mitigate the effects of perceived barriers.

2.4 Conclusion

This chapter reviewed the literature on consumer resistance to innovation and how such resistance could be mitigated. A detailed review of empirical works related to consumers' perceived barriers as factors responsible for consumer resistance to innovation was carried out. The empirical status of research on the consequences of resistance was also reviewed. Finally, a review was conducted of perceived consumption values that might act as useful strategies to mitigate the effect of perceived barriers on resistance.

Table 5 below provides a summary of the review of the literature on consumer resistance to innovation, highlighting the antecedents, moderators, mediators, and consequences of consumer resistance to innovation.

To test the various relationships addressed in the research gaps identified in this chapter, the next chapter discusses the hypotheses development and the conceptual framework of this study.

Table 5: Summary of the review of the literature on consumer resistance to innovation

Antecedents	Moderators	Mediators	Consequences
Functional barriers			
Usage barrier Bakhit 2016); Chaouali and Souiden (2019); Chen and Kuo (2017); Chouk and Mani (2019); Eriksson et al. (2021); H.-S. Chen et al. (2018); Kim et al. (2020); Kladkleeb and Vongura (2019); Kuisma et al. (2007); Laukkanen et al. (2007); Laukkanen et al. (2009); Leong et al. (2020); Luo et al. (2012); Ma and Lee (2018); Mani and Chouk (2018); Molesworth and Suortti (2002); Reinhardt et al. (2017); Santos and Ponchio (2021); Sivathanu (2019); Yu and Chantatub (2016); Yu et al. (2015) **Value barrier** Bakhit (2016); Chaouali and Souiden (2019); Chen and Kuo (2017); Eriksson et al. (2021); H.-S. Chen et al. (2018); Hazée et al. (2020); Kim et al. (2020); Kladkleeb and Vongura (2019); Kuisma et al. (2007); Laukkanen et al. (2007); Laukkanen et al. (2009); Leong et al. (2020); Luo et al. (2012); Ma and Lee (2018); Mani and Chouk (2018); Molesworth and Suortti (2002); Reinhardt et al. (2017); Santos and Ponchio (2021); Sivathanu (2019); Yu and Chantatub (2016); Yu et al. (2015) **Risk barrier** Abbas et al. (2017); Abbas et al. (2021); Bakhit (2016); Chaouali and Souiden (2019); Chen and Kuo (2017); Chi et al. (2015); Chouk and Mani (2019); Eriksson et al. (2021); H.-S. Chen et al. (2018); Hazée et al. (2020); Hong et al. (2020); Hosseini et al. (2016); Johnson and Venter (2016); Ju and Lee (2021); Kang and Kim (2009); Kim and Bae (2020a, 2020b); Kim and Park (2020); Kim et al. (2016, 2020); Kim et al. (2019); Kladkleeb and Vongura (2019); Kuisma et al. (2007); Laukkanen et al. (2007); Laukkanen et al. (2009); Lee (2012, 2013); Lee (2020); Leong et al. (2020); Y. Liu et al. (2021); Luo et al. (2012); Ma and Lee (2018); Maduku (2020); Mani and Chouk (2017, 2018, 2019); Matsuo et al. (2018); Molesworth and Suortti (2002); Nugroho et al. (2018); Oh et al. (2019); Pal et al. (2021); Park (2012); Rahman et al. (2021); Ram (1989); Reinhardt et al. (2017); Rodríguez Sánchez et al. (2020); Rodríguez Sánchez et al. (2020); Santos and Ponchio (2021); Sivathanu (2019); Wiedmann et al. (2011); Yu and Chantatub (2016); Yu et al. (2015)	**Age** H.-S. Chen et al. (2018); Laukkanen et al. (2007); Yoo et al. (2021) **Gender** H.-S. Chen et al. (2018) **Marital status** H.-S. Chen et al. (2018) **Education** H.-S. Chen et al. (2018)	**Usage barrier** Nel and Boshoff (2021) **Value barrier** Nel and Boshoff (2021) **Risk barrier** Nel and Boshoff (2021) **Cognitive -based initial dis-**	**Actual usage of innovation** Kladkleeb and Vongura (2019); Sivathanu (2019) **Intention to use** Kim et al. (2016); H.-J. Kim et al. (2017); Kim et al. (2020); Lee (2012, 2013); Park (2012); Rahman et al. (2021) **Participation intention** Kang and Kim (2009)

Psychological barriers

Tradition barrier
Bakhit (2016); Chaouali and Souiden (2019); Eriksson et al. (2021); H.-S. Chen et al. (2018); Kim et al. (2020); Kladkleeb and Vongura (2019); Kuisma et al. (2007); Laukkanen et al. (2007); Laukkanen et al. (2009); Leong et al. (2020); Ma and Lee (2018); Mani and Chouk (2018); Molesworth and Suortti (2002); Nel and Boshoff (2021); Reinhardt et al. (2017)Sivathanu (2019); Stackhouse et al. (2020); Yu and Chantatub (2016); Yu et al. (2015)

Image barrier
Bakhit (2016); Chaouali and Souiden (2019); Chen and Kuo (2017); Eriksson et al. (2021); H.-S. Chen et al. (2018); Hazée et al. (2020); Kim et al. (2020); Kladkleeb and Vongura (2019); Kuisma et al. (2007); Laukkanen et al. (2007); Laukkanen et al. (2009); Leong et al. (2020); Ma and Lee (2018); Mani and Chouk (2018); Molesworth and Suortti (2002); Nel and Boshoff (2021); Reinhardt et al. (2017); Santos and Ponchio (2021); Sivathanu (2019); Yu and Chantatub (2016); Yu et al. (2015)

Technology vulnerability barriers (technological dependence and technology anxiety)
Mani and Chouk (2017, 2018); Rahman et al. (2021)

Ideological barrier (scepticism)
Chouk and Mani (2019); Mani and Chouk (2018)

Other barriers

Individual barrier (inertia, status quo satisfaction, habit slips)
Ellen et al. (1991); H-J. Kim et al. (2017); Hsieh (2016); Labrecque et al. (2017); Mani and Chouk (2018); Nel and Boshoff (2019, 2020, 2021); Rahman et al. (2021); Stackhouse et al. (2020)

Complexity barrier – Hazée et al. (2020); Santos and Ponchio (2021)
Trialability barrier – Santos and Ponchio (2021)
Emotional barrier – Santos and Ponchio (2021)
Information barrier – Santos and Ponchio (2021)
Safety beliefs and Mutual benefit belief barriers – Chen and Kuo (2017)
Contamination and responsibility barriers – Hazée et al. (2020)
Price barrier – H.-S. Chen et al. (2018)

Income
H.-S. Chen et al. (2018)

E-lifestyle
Yu et al. (2015)

Environmental concern
H.-S. Chen et al. (2018)

Cognitive age
Chaouali and Souiden (2019)

Self-efficacy
Kim et al. (2020); Maduku (2020)

Car involvement
Wiedmann et al. (2011)

trusting beliefs
Nel and Boshoff (2021)

Cognitive effort
Nel and Boshoff (2020)

Alter-native attractive-ness
Nel and Boshoff (2020)

Existing usage patterns
Matsuo et al. (2018)

Discontinue intention
Chi et al. (2015)

Purchase intention
Nugroho et al. (2018)

App connectedness
Oh et al. (2019)

Continual intention to use
Kim and Park (2020)

Innovation acceptance
Kim and Bae (2020a, 2020b)

Innovation-related factors			
Usefulness – Hong (2020); Im et al. (2014); Kim et al. (2016); Lee (2012, 2013); Mani and Chouk (2017) **Ease-of-use** – Hong (2020); Im et al. (2014); Kim and Park (2020); Lee (2012, 2013); Nugroho et al. (2018) **Performance expectancy, effort expectancy** – Hosseini et al. (2016); Ju and Lee (2021); Kim and Bae (2020b) **Facilitating conditions** – Kim and Bae (2020b) **Price** – Abbas et al. (2017); Hosseini et al. (2016); Ju and Lee (2021); Mani and Chouk (2017) **Efficiency, convenience** – Y. Liu et al. (2021) **Complexity** – Abbas et al. (2017); Chouk and Mani (2019); H.-J. Kim et al. (2017); Hosseini et al. (2016); Johnson and Venter (2016); Ju and Lee (2021); Kim and Bae (2020a); Kim et al. (2016); Park (2012); Yoo et al. (2021) **Relative advantage** – Abbas et al. (2017, 2021); H.-J. Kim et al. (2017); Hosseini et al. (2016); Johnson and Venter (2016); Ju and Lee (2021); Kim and Bae (2020a); Kim et al. (2019); Nugroho et al. (2018); Park (2012); Yoo et al. (2021) **Compatibility** – Hosseini et al. (2016); Johnson and Venter (2016); Kim and Bae (2020a); Kim et al. (2019); Park (2012); Yoo et al. (2021) **Observability** – Johnson and Venter (2016); Park (2012) **Trialability** – Kim et al. (2019); Park (2012) **Novelty** – Leong et al. (2020); Mani and Chouk (2017) **Intrusiveness** – Maduku (2020); Mani and Chouk (2017) **Technological aspect** – Pal et al. (2021) **Quality, Content richness, Interactivity** – Park et al. (2016) **Convenience, Reliability** – Zhang et al. (2021)	**Ecological awareness** Wiedmann et al. (2011) **Consumer innovativeness** Abbas et al. (2017); Abbas et al. (2021) **Relative advantage** Nel and Boshoff (2020) **Experience** Matsuo et al. (2018); Nel and Boshoff (2019) **Fashion innovativeness** Ju and Lee (2021)	**Complex-ity barrier** Matsuo et al. (2018) **Inertia** Nel and Boshoff (2019) **Relative advantage** Nel and Boshoff (2019)	**Adoption intention** Hong (2020) **Intention to use** Im et al. (2014); H.-J. Kim et al. (2017); Yoo et al. (2021); Zhang et al. (2021)

Consumer-related factors	
<u>Age</u> – Mani and Chouk (2018); Leong et al. (2020) **<u>Gender</u>** – Mani and Chouk (2018); Leong et al. (2020) **<u>Income</u>** – Leong et al. (2020) **<u>Innovativeness</u>** – Chouk and Mani (2019); Ellen et al. (1991); Kim and Bae (2020a, 2020b); Lee (2012) **<u>Prior similar experience, Technographic</u>** – Kim et al. (2016) **<u>Novelty-seeking</u>** – Park (2012) **<u>Self-efficacy</u>** – Abbas et al. (2017); Ellen et al. (1991); Hosseini et al. (2016); Kim and Bae (2020a); Maduku (2020); Mani and Chouk (2017); Park (2012) **<u>Motivation</u>** – Abbas et al. (2017); Hosseini et al. (2016); Kim and Bae (2020b) **<u>Attitude towards existing products</u>** – Abbas et al. (2017); Hong (2020); Hosseini et al. (2016); Ma and Lee (2018) **<u>Individual mobiquity</u>** – Chouk and Mani (2019) **<u>Openness to innovation</u>** – Kim et al. (2019) **<u>Self-control</u>** – Ma and Lee (2018) **<u>User skill</u>** – Pal et al. (2021) **<u>Privacy control</u>** – Y. Liu et al. (2021b) **<u>Negative emotions</u>** – Abbas et al. (2017); Rieple and Snijders (2018)	**<u>Technological innovativeness</u>** Ju and Lee (2021) **<u>Communication strategies</u>** Laukkanen et al. (2009); Rodríguez Sánchez et al. (2020) **<u>Adoption triggers</u>** Reinhardt et al. (2017)
Market-related/External factors	
<u>Negative social impact</u> – Chi et al. (2015) **<u>subjective norms</u>** – Hong (2020); Kim et al. (2016); Park (2012) **<u>Social influence</u>** – Abbas et al. (2017); Ma and Lee (2018); Matsuo et al. (2018); Yoo et al. (2021) **<u>Provision of online and offline information</u>** – Kim et al. (2019) **<u>Legal and policy aspect</u>** – Pal et al. (2021) **<u>Government surveillance</u>** – Chouk and Mani (2019)	
Based on this review, four research gaps were identified from the literature and, as such, this study proposes the following variables to be explored in the form of hypothesized relationship testing	

Functional barriers – Perceived usage barrier, value barrier, and risk barrier *Psychological barriers* – Perceived tradition barrier, image barrier, technology vulnerability barriers and ideological barrier *Other barriers* – Individual barrier	*Perceived consumption values* – Perceived functional value (performance), functional value (convenience), social value, emotional value, and epistemic value	Negative word of mouth

Chapter 3 - Research Hypotheses and Conceptual Framework

This chapter focuses on the development of hypotheses relating to the relationships between the various variables of this study. Hypotheses were formulated based on empirical evidence from prior research and supported by appropriate theoretical underpinnings. In this chapter, first, hypotheses are proposed for three types of relationships between the variables: perceived barriers, consumer resistance to smart payment services, and NWOM. Second, hypotheses are developed for the moderating effects of perceived consumption values. Third, hypotheses for the moderated mediation relationships are proposed. Last, a conceptual framework is presented demonstrating all the proposed hypothesized relationships.

3.1 Conceptual model development

In the consumer market, companies launch their new products and services as 'innovations' from the perspective of offering something 'new' to consumers in order to benefit them. However, the definition of this 'newness' as perceived by the companies might be different from what is perceived by the consumers and, if the consumers fail to perceive such 'newness' in the offered innovation, they show resistance towards such innovations (Ram, 1987). Specifically, resistance is developed when consumers are threatened by the fact that the innovation is likely to bring changes in their established habits/routines and/or the innovation is likely to be associated with various risks or uncertainties (Ram and Sheth, 1989; Sheth, 1981). As a result, business corporations providing these innovations suffer a high rate of innovation failure due to consumer resistance and enormous amounts of scientific and marketing resources are wasted on developing and commercializing these failed innovations (Sheth, 1981).

In today's digital world, with the emergence of revolutionary smart financial services, such as smart payments and banking, firms are facing challenges in terms of the slow pace of adoption of these new technological innovations by consumers (Mani and Chouk, 2017). This can be accounted for by smart payment services being considered radical changes to the original service concept due to their novel characteristics, such as ubiquitous wireless connectivity, ability to perform functions autonomously, and intelligence (Porter and Heppelmann, 2014; Ram, 1987). Such radical changes might bring disruptions to consumers' daily habits, thereby triggering their resistance (Sheth, 1981). Therefore, to understand the phenomenon of consumer resistance to smart payment services, it is important to examine the key drivers of this phenomenon; that is, the barriers to adoption that are perceived by consumers.

Moreover, when innovation does not conform to the norms of a social system (Rogers, 2003), consumers may engage in boycotts, the spreading of negative information, online protests and other harmful activities that are detrimental to the companies offering the innovations, in order to express their resistance to the innovation (Kleijnen et al., 2009). Hence, spreading negative opinions (e.g., NWOM) about an innovation among social members can negatively influence potential adopters of the innovation, thus slowing their rate of innovation adoption (Jahanmir and Cavadas, 2018).

In light of these arguments, the following sections discuss the hypothesized relationships and the theoretical underpinning that govern the formation of relationships between perceived barriers, consumer resistance to smart payment services, and the further detrimental consequence of NWOM about smart payment services.

3.1.1 Direct effects

This section presents the theoretical underpinning that support the development of the hypotheses for the direct effects of perceived barriers on consumer resistance to smart payment services. This section also discusses the hypothesis development for the direct effect of consumer resistance to smart payment services on NWOM.

a) Theoretical underpinning

In the innovation literature, Ram and Sheth's (1989) theoretical framework (i.e., innovation resistance theory) identify various perceived barriers that lead to consumer resistance to innovation. This study utilizes this framework and its extension (Mani and Chouk, 2018) to guide the proposing of relationships between perceived barriers and consumer resistance to smart payment services. According to innovation resistance theory, the innovation-specific barriers perceived by consumers can be categorized as a) functional barriers and b) psychological barriers. The functional barriers are further classified as: a) usage barrier; b) value barrier and c) risk barrier. Psychological barriers are further classified as: a) tradition barrier and b) image barrier. Furthermore, Ram and Sheth's (1989) theoretical framework was extended in a recent study by Mani and Chouk (2018), in which two further psychological barriers were added: a) ideological barrier and b) technology vulnerability barriers (technology dependence and technological anxiety). The literature has also highlighted the formation of consumer resistance to innovation due to consumers' predisposition to prefer the status quo (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014). Hence, this factor refers to the individual barrier, which was included in the extended theoretical framework formulated by Mani and Chouk (2018). A detailed conceptualization of these barriers is provided in section 2.1.4 of Chapter 2. The next section discusses the development of hypotheses relating to the three key relationships.

b) Relationship between perceived barriers and consumer resistance to smart payment services

Perceived usage barrier

According to Ram and Sheth (1989), consumers perceive usage barriers due to compatibility issues with their existing work routines and previous usage experiences, which would require a long time for the changed routines to be consistent with the previous ones before the innovation is finally accepted. This barrier can also be related to the perception of complexity associated with the use of innovation (e.g., Kim et al., 2017; Laukkanen, 2016). In Rogers' (2003) diffusion of innovation theory, complexity refers to the "degree to which an innovation is perceived as difficult to understand and use" (p. 257). The usage barrier can be related to the two dimensions of complexity – the complexity of execution (is it easy to use?) and the complexity of the idea of innovation (is it easy to understand?) – and hence it has been postulated that higher innovation complexity leads to higher innovation resistance (Ram, 1987).

In the context of technological products/services, empirical research has shown that consumers have resisted and rejected innovations such as massive open online courses (MOOCs) (Ma and Lee, 2018), mobile health apps (Gurtner, 2014), and mobile banking (Elbadrawy and Abdel Aziz, 2011), as these innovations were complicated to understand, not consistent with usage patterns and consumers were unaware of how to use them. Pioneering research in the context of smart products and services highlights the role of a usage barrier in the form of the complexity of the innovation, leading to consumer resistance to innovation. For example, consumers have shown considerable resistance to smart banking services due to the presence of advanced, but complex, IoT devices that make it difficult for them to understand the operation of these devices (Chouk and Mani, 2019; Mani and Chouk, 2018). It has also been shown that one of the reasons for resistance to smart wearables by consumers was the complexity of these wearables and devices, as they were perceived to be difficult to operate or use (Hajiheydari et al., 2021; Sivathanu, 2018).

Hence, following Rogers' (2003) concept of complexity and research identifying complexity as a factor driving consumers' resistance (e.g., Laukkanen, 2016), it can be hypothesized that:

H1(a) – Perceived usage barrier (complexity) is positively related to consumer resistance to smart payment services.

Perceived value barrier

A value barrier is perceived when consumers evaluate the value of an innovation in terms of the price-to-performance tradeoff in comparison to its alternative and, due to the innovation having a lower value than its alternative, it is resisted by the consumers (Lian and Yen, 2013; Ram and Sheth, 1989). In the context of technological innovations such as smart products/services, this barrier can be related to the perception of the high price of the innovation (Mani and Chouk, 2018).

According to Zeithaml (1988), perceived price is what consumers give up or sacrifice in order to obtain a product or service. Empirical research has shown that consumers resisted mobile banking as the innovation did not provide any value for money over other banking methods or services (Laukkanen et al., 2007). In a similar context, consumers perceived value barrier towards electronic banking adoption as the service did not offer sufficient utility, leading to reluctance to use the channel (Borraz-Mora et al., 2017). For technological innovations for which providers charged premium prices, price-sensitive consumers perceived this as a barrier as they found a lack of performance in the innovation compared to other products (Antioco and Kleijnen, 2010). For instance, students perceived this barrier in respect of digital education in the form of less worth for the money (price) spent on MOOCs, since these courses yielded fewer credits (performance) for their studies (Ma and Lee, 2018). Furthermore, a review of smart home-related barriers highlighted that although home automation technology provides advantages of comfort and convenience, there exist various high costs such as the cost of installation, technology, maintenance, and repairs, which led to consumers being reluctant to install smart technology in their homes (Balta-Ozkan et al., 2013; Marikyan et al., 2019).

Hence, based on the above discussion and following Ram and Sheth's (1989) and Zeithaml's (1988) work, consumers resist technological innovations when they perceive that the innovation is associated with a high price with no or very little added value compared to its alternative. Thus, it can be hypothesized that:

H1(b) – Perceived value barrier (high price) is positively related to consumer resistance to smart payment services.

Perceived risk barrier

Risk perceptions associated with any innovation are considered one of the components that explain the psychology of innovation resistance (Sheth, 1981). Consumers perceive risks as uncertainties that may arise after an innovation is evaluated, and they perceive these uncertainties as potential threats to adoption (Lian and Yen, 2013). Previous studies in the innovation resistance literature have highlighted various types of risks as components of the risk barrier or overall perceived risk that explain consumer resistance to innovation (e.g., Hirunyawipada and Paswan, 2006; Hubert et al., 2019; Kang and Kim, 2009; Oh et al., 2019; Wiedmann et al., 2011).

In the context of smart products and services, it was, for the most part, security risks that were found to be the cause of innovation resistance. Instances show that security risk (e.g., security concerns related to the hacking of terminals in a smart home environment) is one of the most significant factors leading to consumer resistance to innovation (Y. Kim et al., 2017). Further, in the context of smart banking services, security risk was found to be one of the reasons for consumer resistance. This type of risk is of the utmost concern because consumers fear that due to the involvement of IoT devices in sharing sensitive data (e.g., credit/debit card numbers and personal information) over the internet, those data are highly vulnerable to hackers (Chouk and Mani, 2019; Mani and Chouk, 2018). Another study, in the context of smart lighting products, revealed privacy barriers as one of the reasons for innovation resistance, leading ultimately to the rejection of the innovation (Juric and Lindenmeier, 2018). Therefore, security concerns are considered threats to consumers' adoption of smart products and services (Marakhimov and Joo, 2017). Thus, based on Ram and Sheth's (1989) model, which considers risk as a barrier driving resistance, and following previous studies that have indicated that consumers resist innovations when they are more concerned about the security issues associated with that innovation, it can be hypothesized that:

H1(c) – Perceived risk barrier (security risk) is positively related to consumer resistance to smart payment services.

Perceived image barrier

As a cause of innovation resistance, consumers face an image barrier when the innovation produces image-based obstacles, such as unfavourable impressions of the brand, country or industry and negative stereotypes (Kleijnen et al., 2009; Lian and Yen, 2013; Ram and Sheth, 1989). In the context of internet-based applications, such as online banking and online shopping, this barrier has been perceived not only in terms of the negative image of the innovation, but also due to low credibility and low benevolence (Hong et al., 2015; Molesworth and Suortti, 2002).

The image barrier can also be viewed from the standpoint of self-image congruence, which can have an impact on consumer behaviour towards technological innovations (Antón et al., 2013), specifically smart products/services. According to self-congruity theory (Sirgy, 1985), self-image congruence is a key psychological variable that explains consumers' decision-making mechanisms. Hence, "the psychological comparison between this image of a product, the image of the typical user of that product, and the consumer's self-concept determines the congruence with self-image and, subsequently, consumer behavior" (Antón et al., 2013, p. 375). In line with this, previous research (e.g., Sung and Huddleston, 2018) suggests that congruence between the consumers' image and the product/service's image is likely to influence their attitude or behaviour towards a product, service or brand. Empirical studies in the context of smart banking services and smart homes have shown that consumers resisted innovation due to inconsistency between their image and that of the innovation, as they perceived the innovation as non-essential or too luxurious or too 'gadgetry' for their lifestyle (Balta-Ozkan et al., 2013; Mani and Chouk, 2018). In other words, self-image incongruence leads to consumer resistance towards smart innovations (Chouk and Mani, 2019).

Thus, in line with self-congruity theory and studies that have shown a negative impact of the incongruence between a consumer's self-image and the image of a product, service, or brand, it can be argued that the more consumers perceive the image of an innovation to be incompatible or in conflict with their self-image, the more resistance they are likely to show to that innovation. Therefore, it can be hypothesized that:

H1(d) – Perceived image barrier (self-image incongruence) is positively related to consumer resistance to smart payment services.

Perceived tradition barrier

A tradition barrier is perceived by consumers if an innovation is incompatible with their existing traditions, values, beliefs, norms, and culture (Joachim et al., 2018; Lian and Yen, 2013; Ram and Sheth, 1989). Pioneering research in the context of technological innovations shows that this barrier has been perceived in terms of a desire for personal contact or the need for human interaction. For example, due to the absence of facilities such as salespersons providing information on products and services in physical stores or bank personnel assisting in their financial transactions in banks, consumers were found to resist shopping or banking online, respectively (Chemingui and Ben lallouna, 2013; Laukkanen, 2016; Laukkanen et al., 2008; Lian and Yen, 2013). Another study also revealed that lack of human contact led to a resistance to buying cars online because consumers regarded buying a car as a social activity with friends and family rather than just sitting in front of a computer and buying a car online with no human contact (Molesworth and Suortti, 2002). It has been shown that students' resistance to MOOCs resulted from conflicts with traditional norms of the teaching-learning routine (e.g., an absence of instructors) (Ma and Lee, 2018).

In the case of smart products/services, consumers have resisted innovation because they found that the smartness attribute of autonomy (the ability of the product to operate independently without human or user interaction) conflicted with their traditional way of interacting with technology products (Rijsdijk et al., 2007). This finding is also in line with the results of Mani and Chouk (2018), in which consumers were found to show resistance to smart banking services due to the lack of human interaction with bank personnel. Hence, in line with Ram and Sheth's (1989) model and various empirical findings, it can be hypothesized that:

H1(e) – Perceived tradition barrier (need for human interaction) is positively related to consumer resistance to smart payment services.

Perceived technology vulnerability barriers

With respect to technologically advanced innovations, especially smart innovations, the technology vulnerability barrier can be explained in terms of technological dependence and technological anxiety (Mani and Chouk, 2018).

According to the technology adoption propensity (TAP) index, technological dependence refers to the sense or feeling of becoming overly dependent or being enslaved by technology, which has been found to be one of the factors hindering the adoption of technology by consumers (Ratchford and Barnhart, 2012). Technological dependence is also associated with a sense of isolation in the lives of individuals, since overuse of technology replaces interaction with other humans, thus keeping communication limited to machines (Mani and Chouk, 2017). Further, this factor relates to technostress, as it includes a feeling of loss of control over tasks due to the use of technology or an inability to cope with new computer technologies, which can have a negative impact on the attitudes, thoughts, and behaviour of consumers (Shu et al., 2011). This is in line with research that refers to technostress limiting the usefulness of technology, which can act as a potential barrier leading to consumer resistance towards the technology (Dunphy et al., 1995).

The second dimension, technology anxiety, has been studied in the context of using computers and the internet. Venkatesh (2000, p. 349) defined technological anxiety (for the particular case of the computer) as the degree of "an individual's apprehension, or even fear, when she/he is faced with the possibility of using computers". Computer (technology) anxiety involves a psychological response in the form of emotional fear resulting from negative outcomes when using a computer or technology (Barbeite and Weiss, 2004). When consumers feel anxious about using technology (e.g., computers or the internet), they may show apprehension towards that technology and, when this feeling reaches a certain threshold, they may start showing resistance to using it (Susskind, 2004). In the case of IoT-based innovations, such as self-service technologies (e.g., personal shopping assistants) (Evanschitzky et al., 2015; Meuter et al., 2003) and agricultural technologies (Pillai and Sivathanu, 2020), technology anxiety was found to reduce consumers' likelihood of innovation trials even before taking the final decision to reject or adopt an innovation. Furthermore, IoT-based devices enable users to connect to other similar devices that they own, as well as those owned by family members and friends. Continuous connectedness can, however, be harmful to heavy users of such devices, as they can also suffer from technology anxiety arising from the difficulty of multi-tasking with multiple devices (Touzani et al., 2018).

Hence, in line with the TAP index (Ratchford and Barnhart, 2012), in which dependence is identified as a factor inhibiting consumers' adoption of technology, works showing the influence of technology anxiety on consumers' behavioural intention to use a technology (e.g., Venkatesh, 2000), and research findings showing that consumers' overdependence and anxiety caused by technology can lead to reluctance to use smart services, it can be hypothesized that:

H1(f) – Perceived technological dependence is positively related to consumer resistance to smart payment services.
H1(g) – Perceived technology anxiety is positively related to consumer resistance to smart payment services.

Perceived ideological barrier

According to attribution theory, people attribute causes to events based on their cognitive perceptions and how this influences their attitudes and behaviour (Kelley and Michela, 1980). The theory explains that causal analysis is inherent to people's needs to understand events and classifies the way individuals attribute the causes to events into internal and external attributions. An internal attribution assigns the cause of a given event to that individual's characteristics and factors, whereas external attribution ascribes the cause of an event to being related to the surrounding environment (i.e., external to the individual). In marketing, attribution theory has been used to better understand consumer scepticism about firms' practices, messages, and new products (Skarmeas and Leonidou, 2013). Morel and Pruyn (2003) conceptualized consumer scepticism as a context- or situation-based approach that is triggered when an individual (even without having a trait-based sceptical predisposition) questions any aspect of a new product, such as the technical characteristics and functioning. Scepticism has been studied as a psychological tendency of doubt shown by consumers towards marketing discourses (e.g., advertisements) that seek to promote a new product, leading to consumers' propensity to resist (Banikema and Roux, 2014).

In line with studies in the context of smart innovations (e.g., Mani and Chouk, 2018), this study conceptualizes an ideological barrier in the form of general scepticism that refers to the consumer's doubt towards the marketing promises made by the companies offering the innovations. Research has highlighted that consumers are inhibited in their use of connected products/services due to scepticism in the form of doubts originating from the fear of personal data or sensitive private information being hacked and misused (Touzani et al., 2018). Recent research in the same context also reported that general scepticism towards IoT devices and services is one of the reasons for consumer resistance towards them (Chouk and Mani, 2019; Mani and Chouk, 2018). Further, it was argued that as IoT-based innovations consist of connected devices, consumers always suspect that they are under surveillance or are being watched by the companies offering such services and devices. This phenomenon is termed the Big Brother effect, which can increase scepticism, thereby leading to consumer resistance to IoT-based innovations (Mani and Chouk, 2017). Moreover, research has also suggested that a higher level of scepticism negatively influences consumers' attitudes towards innovations (Jahanmir and Cavadas, 2018). As such, these consumers are the least interested in adopting new innovations and hence are categorized as laggards and late adopters of innovation (Jahanmir and Lages, 2016; Rogers, 2003). Therefore, following attribution theory and research highlighting the impact of general scepticism on consumer attitudes towards smart innovations, it can be hypothesized that:

H1(h) – Perceived ideological barrier (general scepticism) is positively related to consumer resistance to smart payment services.

Perceived individual barrier

Individuals generally attempt to maintain their current situation or existing habits by using currently owned products and services. In this respect, status quo bias theory describes a behavioural bias that creates resistance to change and a mental attitude that perceives novelty as causing risks as opposed to benefits (Samuelson and Zeckhauser, 1988). Using numerous experiments, Samuelson and Zeckhauser (1988) showed that most decisions have a status quo option; that is, people prefer the situation to remain stable in order to minimize losses, rather than take risks to earn more. Such individuals prefer these situations because they feel safe and are familiar with the conventional or traditional forms of products and services, and hence resist any change that is related to the way they would use an innovative product or service (Heidenreich and Spieth, 2013). The preference for such nostalgic products and services, therefore, leads to an unwillingness to try new and innovative products and services, thereby forming a conservative outlook (Van Tonder, 2017). This conservative attitude of consumers develops from a tendency to prefer the existing situation (i.e., status quo satisfaction) (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014). In the context of technological innovations, research has found that habit-caused inertia negatively influences the use intention of new information systems (Polites et al., 2012). Moreover, in the context of smart products, the above-noted factor (i.e., status quo satisfaction) has been found to cause instant rejection of such products (Juric and Lindenmeier, 2018).

Hence, in line with status quo bias theory (Samuelson and Zeckhauser, 1988) and in line with recent empirical research (e.g., Mani and Chouk, 2018; Nel and Boshoff, 2020), this study assumes this barrier to be a personal predisposition to prefer the status quo due to a perception of the uncertainty of change (i.e., inertia), which may lead to consumer resistance to smart services (e.g., smart payment services).

Hence, it can be hypothesized that:

H1(i) – Perceived individual barrier (inertia) is positively related to consumer resistance to smart payment services.

c) Relationship between consumer resistance to smart payment services and NWOM

The innovation literature argues that when innovation does not conform to the norms of a social system, consumers may act as negative opinion leaders by spreading negative opinions among other social members, thereby reflecting their opposition to the change (Rogers, 2003), and turning would-be innovation adopters into resistors (Jahanmir and Cavadas, 2018). Negative opinion leaders and resistance leaders can exert a negative influence on their direct social ties, as well as those at the societal level (i.e., reaching beyond their direct social ties), respectively (Hietschold et al., 2020). Hence, it has been conceptually concluded that consumers who resist innovations tend to attack the innovation and actively engage in opposing activities that adversely affect the innovation’s success (Kleijnen et al., 2009), as they may not find the innovation to be suitable for them. As such, opponents exert a negative influence on the technology adoption decisions of other consumers (Cavusoglu et al., 2010). In addition, the literature has shown that consumers who perceive barriers not only speak negatively about the innovation, but also about the company offering the innovation, out of fear and insecurity and in order to influence others (M. Talwar et al., 2021). Such consumers associate innovation with uncertainties and risks and hence are likely to provide negative recommendations (Kaur, Dhir, Singh et al., 2020). It was also found that in addition to rejecting an innovation due to associated privacy concerns, consumers shared negative opinions about the innovation via a stronger and more proactive response, such as NWOM, thereby influencing other consumers to think negatively about the innovation (Li et al., 2021). The oppositional response associated with the feeling of anger towards a product/brand has also been found to lead to an increase in innovation criticism (Sjödin, 2008). Therefore, by extending innovation resistance theory, it can be hypothesized that:

H2 – Consumer resistance to smart payment services is positively related to NWOM.

3.1.2 Mediating role of consumer resistance to smart payment services

Thus far, arguments have been developed concerning the relationships between barrier perceptions and consumer resistance to smart payment services and those between consumer resistance to smart payment services and NWOM. This could suggest that consumer resistance to smart payment services is likely to mediate the relationship between barrier perceptions and NWOM.

As discussed above, consumers who perceive barriers can have a negative influence on their direct social ties with the help of their persuasive skills and expert knowledge by disseminating information disparaging an innovation (Kaur, Dhir, Singh et al., 2020). Studies have postulated that barrier perceptions (e.g., emotional barriers) can cause consumer resistance to innovation, which might further lead to NWOM-related behaviours (Bagozzi and Lee, 1999). As innovation is associated with uncertainty, the uncertainties or barriers perceived by consumers cause them to resist innovations (Ram and Sheth, 1989). Consequently, consumers are reluctant to adopt or recommend innovations (Kaur, Dhir, Ray et al., 2020, Kaur, Dhir, Singh et al., 2020). Research has also highlighted that barriers perceived by resistance leaders (initiators and aggregators) further turn into innovation criticism (Hietschold et al., 2020). Dissatisfaction resulting from difficulties involving inadequate performance relative to expectations can cause consumers to resist innovation (in the form of postponement); if the associated problems are not resolved, resistant consumers may further engage in negative communication about the innovation with others (Ju and Lee, 2020; Richins, 1983). Similarly, Van Tonder (2017) conceptualized that conservative consumers (who prefer their status quo) are likely to spread NWOM because they passively resist innovations that are likely to disrupt their status quo.

Liao et al. (2015) also demonstrated that functional and psychological barriers can lead to anti-consumption reactions, which can further transform into negative publicity regarding an innovation and hatred towards the brand. It was also found that associated privacy concerns (e.g., unauthorized use of personal information with external organizations) induced anger in consumers, leading them to refuse an innovation and encouraging them to spread negative information about that innovation to other consumers (Jung and Park, 2018). Therefore, in accordance with these scarce findings, it can be argued that a perception of barriers leads consumers to resist an innovation (e.g., smart payment services), which further influences these consumers to spread NWOM (about smart payment services). In other words, resistance seems to be the key underlying mechanism that may explain how and why barrier perceptions may lead consumers to spread NWOM. Accordingly, it can be hypothesized that:

H3(a) – Consumer resistance to smart payment services mediates the relationship between perceived usage barrier and NWOM.

H3(b) – Consumer resistance to smart payment services mediates the relationship between perceived value barrier and NWOM.

H3(c) – Consumer resistance to smart payment services mediates the relationship between perceived risk barrier and NWOM.

H3(d) – Consumer resistance to smart payment services mediates the relationship between perceived image barrier and NWOM.

H3(e) – Consumer resistance to smart payment services mediates the relationship between perceived tradition barrier and NWOM.

H3(f) – Consumer resistance to smart payment services mediates the relationship between perceived technological dependence and NWOM.

H3(g) – Consumer resistance to smart payment services mediates the relationship between perceived technology anxiety and NWOM.

H3(h) – Consumer resistance to smart payment services mediates the relationship between perceived ideological barrier and NWOM.

H3(i) – Consumer resistance to smart payment services mediates the relationship between perceived individual barrier and NWOM.

3.1.3 Moderating effects of perceived consumption values

This section presents the theoretical underpinnings that support the development of hypotheses for the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services. This section also discusses the importance of consumption values and their co-existence with barrier perceptions in the innovation literature.

a) Importance of consumption values

The theory of consumption values posits that consumption values (i.e., functional value, social value, emotional value, and epistemic value) are responsible for strengthening an individual's reason for buying or not buying a specific product/service or brand over the other (Sheth et al., 1991). A detailed conceptualization of these consumption values is given in section 2.2.2 of Chapter 2. Research has highlighted the significance of consumption values in a consumer's decision-making process. Specifically, functional value represents the cognitively perceived utility derived from a product/service's quality, performance, and reduction of perceived costs (Sweeney and Soutar, 2001). On the other hand, emotional, social and epistemic values represent the affectively perceived utility derived from a product/service's feelings or affective states (e.g., comfort, security, passion), ability to enhance one's social self-concept (e.g., social image and status seeking), and ability to provide novelty and enhance one's curiosity in using innovations (e.g., novel stimulation and satisfying the desire for knowledge), respectively (Alba and Williams, 2013; Sweeney and Soutar, 2001; Williams and Soutar, 2009). These consumption values have been studied to understand consumers' positive attitudes and behaviours, such as adoption intention (Park and Lee, 2011), purchase and repurchase intention (Lin et al., 2020; Talwar et al., 2020; Teng, 2018; Wang et al., 2020) and use intention (Yang and Lin, 2017) towards various technological products and services (e.g., online game items, organic food technology, online travel services, social networks, and location-based services).

b) Co-existence of perceived values and barriers

The literature has highlighted the integration of consumption values and barrier perceptions in understanding consumer decision making regarding a product or service. Kushwah et al. (2019), for example, highlighted that consumer purchase decisions were affected by motives such as consumption values and inhibitors such as functional and psychological barriers. Instances show that, in the context of shopping at airport stores, utilitarian and hedonic shopping values act as facilitators of product repurchase and recommendation intentions, whereas perceived disadvantages, such as time pressure and the risks associated with products, act as barriers to positive intentions (Han et al., 2018). In the context of social marketing, Zainuddin et al. (2017) reported that barriers (e.g., physical and mental discomfort and time and effort costs) to behaviour maintenance in social activities were likely to destroy the consumption values derived from such social activities. Another study found that perceived risks and technological barriers acted as inhibitors alongside consumption values acting as drivers to the continuous use intention of mobile media services (Youn and Lee, 2019). In conclusion, these two sets of factors (i.e., perceived consumption values and barriers) have been examined as gains and losses, benefits and costs, or enablers and inhibitors towards positive consumer attitudes and behaviours (e.g., Chiu et al., 2014; Cocosila and Trabelsi, 2016; Gupta and Kim, 2010; Jayashankar et al., 2018; de Kerviler et al., 2016; Krishen et al., 2016; Lee and Jung, 2019; Liébana-Cabanillas et al., 2014; Rahman et al., 2021; Xu et al., 2015; Zhu et al., 2017).

c) Theoretical underpinning

This study aims to investigate the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services. To provide theoretical support for these effects, this study adapted prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

Prospect theory outlines two stages in the consumer decision-making process. The initial phase is termed editing, during which preliminary analysis of the offered prospects or alternatives is carried out to generate a simpler representation of the prospects or alternatives. This phase consists of a number of operations, such as coding, combination, segregation, cancellation, simplification and the detection of dominance. The second phase is termed evaluation, in which the decision maker evaluates the edited prospects and chooses the one with the highest value (Kahneman and Tversky, 1979).

The concept of a coding operation is that individuals or consumers perceive the outcomes as either gains or losses, which are defined relative to a reference point. The reference point is related to the current asset position, which, according to this study, are the current and familiar traditional payment methods used by the consumers. As a result, people are likely to act differently; that is, to be either risk averse or risk seeking depending on the evaluated outcomes. In addition, a key tenet of this theory is that people tend to be psychologically loss averse; that is, they regret losses more significantly than they value gains of equal amount under uncertain conditions (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

Prospect theory also posits a ‘possibility effect’, which suggests that when the outcome of the risky option has a low probability, people overestimate small probabilities over moderate or high probabilities. Hence, people become risk seeking in the case of low probability gains, as they hope to achieve larger gains, and risk averse in the case of low probability losses, as they fear suffering larger losses (Kahneman and Tversky, 1979).

Therefore, the fundamental proposition of prospect theory in behavioural research highlights that one’s decision is an outcome of the comprehensive evaluation of the tradeoff between the ‘gains’ and ‘losses’ that could be brought by the target object (Schmidt and Zank, 2005). This theory has been applied in many previous studies and guided the explanation of consumer decision making by developing an integrative evaluation of gains and losses under situations associated with risks and uncertainties (e.g., Chiu et al., 2014; Chung and Koo, 2015; Wong et al., 2021). As such, in respect of explaining consumer decision making in the context of smart payment services, this theory was deemed suitable because decision making regarding any financial service is also associated with risk and uncertainties, specifically when the decision is in terms of resistance to innovation (e.g., Cruz et al., 2010; Laukkanen and Kiviniemi, 2010; Leong et al., 2020; Mohammadi, 2015; Swilley, 2010).

d) Buffering effects of consumption value perceptions

According to previous research findings, managers and innovators have frequently focused on reducing the impact of the perception of barriers, thus lowering or overcoming consumer resistance to innovation (e.g., Laukkanen et al., 2009; Reinhardt et al., 2017; Rodríguez Sánchez et al., 2020; Yeatts et al., 2017). Therefore, managers should devise strategies that might attract innovation-resistant consumers towards innovation, thus converting their resistance into acceptance. In line with this, innovators emphasize improving the utilitarian or functional attributes of an innovation, such as its usefulness, ease of use and relative advantage, together with inducing hedonic and social motivations to increase consumer attraction to the innovation (Claudy et al., 2015; Gupta and Arora, 2017; Hubert et al., 2019; Kim et al., 2017; Sivathanu, 2019). Moreover, these attributes and motivations should also emphasize providing certain types of 'value' to consumers, in order to encourage their usage and adoption of the innovation and reduce their resistance towards it (Kushwah et al., 2019; Roy et al., 2019; Youn and Lee, 2019).

Further, considering the context of this study (i.e., smart payment services) and in line with prospect theory, the innovation resistance literature demonstrates that as consumers are already familiar with traditional means of payment, they are emotionally attached to those methods, thereby forming a status quo bias with the traditional payment services they currently use. Consequently, these consumers are likely to perceive switching to an unfamiliar innovation (i.e., smart payment services) as a 'loss', thus making them risk averse and resistant to smart payment services (Heidenreich and Handrich, 2015; Talke and Heidenreich, 2014).

However, whereas the majority of the innovation literature focuses on barrier perceptions (i.e., losses) that lead to consumer resistance to innovation, prospect theory can be applied to understand the moderating role of consumption values as consumers' responses to smart payment services are also likely to be shaped by the potential 'gains' offered by these services (i.e., perceived consumption values provided by smart payment services). Hence, it can be argued that resistant consumers may become risk seeking when they perceive chances of acquiring consumption values (gains) from smart payment services, which may help to reduce their resistance to those services. This is further supported by research in the context of contactless mobile payments and related services, which found that consumers perceive more *gains* from these services in the form of *values* even if they perceive barriers such as various risk perceptions (Cocosila and Trabelsi, 2016). Findings from other studies also indicate that consumers' value perceptions regarding any product/service have successfully reduced the risk and other barrier perceptions associated with their use of that product/service (e.g., Anton et al., 2013; Jia et al., 2017; Khan et al., 2005).

Therefore, based on these arguments, the following sections present the development of hypotheses for the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services.

Moderating role of functional value

Previous research argues that when making decisions regarding innovations such as new financial products/services, consumers are likely to expect better *functional* convenience and efficiency, thereby reducing the likelihood of reliance on traditional payment methods (Leong et al., 2017; Park et al., 2019). Consumers also look for well-designed and efficient payment platforms, such as standardized user interfaces and aesthetic graphics in terms of the performance quality of the service (Chemingui and Ben lallouna, 2013; Zhang et al., 2019). Further, in the context of technology-based services, it was found that promoters of an innovation emphasize its utility in terms of its convenient usage, in order to mitigate consumers' concerns about privacy issues (Cocosila and Trabelsi, 2016). It was also reported that highly interested consumers can easily derive utilitarian benefits from technological innovations, resulting in their having low risk perceptions about such innovations (Anton et al., 2013). In addition, research indicates that in order to deal with consumer resistance to innovation and fierce competition among firms, innovation providers emphasize reinforcing those features of an innovation that maximize the consumers' perception of its utilitarian benefits (Cha, 2011). In the context of internet-based services, research suggests that functional convenience in service usage is important in lowering consumer concerns related to various associated risks (Lee and Jung, 2019).

Therefore, in line with the tenets of prospect theory, consumers are likely to act as risk seeking if they hope to gain functional value from smart payment services, making them less risk averse and thereby reducing the effect of barriers on consumer resistance to smart payment services. Hence, it can be hypothesized that:

H4 – Perceived functional value (performance) moderates the relationship between (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier, (i) perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (performance) is high rather than low.

H5 – Perceived functional value (convenience) moderates the relationship between (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier, (i) perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (convenience) is high rather than low.

Moderating role of social value

Social or symbolic benefits, such as enhancement of consumers' self-impression on others or the way the consumers are perceived by others, act as contributors towards encouraging the adoption of advanced payment services (de Kerviler et al., 2016). Research shows that consumers seek to gain a social image in terms of prestige, a superior profile, and a status symbol through the use of mobile payment systems (Liébana-Cabanillas et al., 2014, 2016). Provision of social approval and engagement with others as aspects of social value in technology-based services have been suggested as opportunities that can dismantle consumers' psychological incompatibilities, such as contradictions with traditions and norms, and functional incompatibilities, such as risks and uncertainties, which are associated with the use of such services (Groß, 2018). It has also been reported that innovation should be designed to reduce the negative impact of unfavourable product images with the help of communicable features that can enhance the users' social image and status (Antioco and Kleijnen, 2010). Research has also recommended that managers should strive to maintain the high standards of services in the form of creating social value that can decrease the risk factors, such as financial and social risk, associated with the services (Şen Küpeli and Özer, 2020).

Therefore, in line with the tenets of prospect theory, consumers are likely to act as risk seeking as they hope to gain social value from smart payment services, making them less risk averse and thereby reducing the effect of barriers on consumer resistance to smart payment services. Hence, it can be hypothesized that:

H6 – Perceived social value moderates the relationship between (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier, (i) perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived social value is high rather than low.

Moderating role of emotional value

Research has found that consumers' emotions and mental and psychological needs in terms of fun, enjoyment, and entertainment drive consumers to adopt mobile financial services (Chemingui and Ben lallouna, 2013; Park et al., 2019; Zhang et al., 2019). This finding can be further supported by another study in the context of proximity mobile payments (p-m payments), in which hedonic enhancement in the form of enjoyment was found to be a major factor in triggering the use intention of such services (de Kerviler et al., 2016). Furthermore, research has argued that a high emotional value derived from innovation is likely to attenuate concerns about the various associated risks perceived by consumers (Arruda Filho et al., 2020; Sharma et al., 2020). Hence, it is suggested that managers need to focus on positioning their innovations as being more emotionally oriented (e.g., feelings of well-being as an outcome of innovation adoption) in order to combat innovation resistance (Castro et al., 2019). Research further argues that inducing pleasure- and enjoyment-related elements in the activities of an internet-based service can increase its hedonic worth, which may help consumers to ignore any privacy concerns and other security-related risks associated with the use of the service (Chang et al., 2016; Gupta and Kim, 2010). It is also recommended that the hedonic benefits of a newly introduced product in the market should be communicated properly to consumers, which can help them to think about its compatibility with their current lifestyle and thereby reduce the likelihood of consumers' resistance towards the product (Anton et al., 2013). Research in the context of mobile-based shopping services also found that users should be provided with an emotional flow experience so that they can enjoy the service without any concerns about the incompatibility of the service with their shopping habits and needs (Groß, 2018).

Therefore, in line with the tenets of prospect theory, consumers are likely to act as risk seeking as they hope to gain emotional value from smart payment services, making them less risk averse and thereby reducing the effect of barriers on consumer resistance to smart payment services. Hence, it can be hypothesized that:

H7 – Perceived emotional value moderates the relationship between (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier, (i) perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived emotional value is high rather than low.

Moderating role of epistemic value

Research suggests that consumers' pre-adoption choice of mobile financial services is also driven by the ability of these services to induce *epistemic* curiosity, encouraging them to explore knowledge about using smartphones for the purpose of various financial transactions (Omigie et al., 2017). Novel mobile financial services also encourage consumers to explore other new technologies associated with these services (Prodanova et al., 2019). In addition, perceptions of novelty in an innovation are found to reduce consumers' level of discomfort about the innovation, resulting in less negative attitudes towards it (Albertsen et al., 2020). Innovations that increase consumers' curiosity in terms of acquiring knowledge about it can help reduce barriers and uncertainties, consequently increasing understanding of the innovation (Reinhardt et al., 2017). Consumers' perception of the inherent novelty of an innovation was also found to reduce their risk perceptions (Wells et al., 2010).

Therefore, in line with the tenets of prospect theory, consumers are likely to act as risk seeking as they hope to gain epistemic value from smart payment services, making them less risk averse and thereby reducing the effect of barriers on consumer resistance to smart payment services. Hence, it can be hypothesized that:

H8 – Perceived epistemic value moderates the relationship between (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier, (i) perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived epistemic value is high rather than low.

3.1.4 Moderated mediation

Thus far, the theoretical underpinnings for the mediating role of consumer resistance to smart payment services as well as the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services have been developed in this chapter. The theoretical rationale behind these proposed hypotheses also suggests that each type of perceived consumption value will conditionally influence the strength of the proposed indirect relationships between barriers and NWOM (through consumer resistance to smart payment services). Hence, this suggests a pattern of moderated mediation. Therefore, it can be hypothesized that:

H9 – Perceived functional value (performance) moderates the indirect effects of (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier and (i) perceived individual barrier on NWOM (through consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (performance).

H10 – Perceived functional value (convenience) moderates the indirect effects of (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier and (i) perceived individual barrier on NWOM (through consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (convenience).

H11 – Perceived social value moderates the indirect effects of (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier and (i) perceived individual barrier on NWOM (through consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived social value.

H12 – Perceived emotional value moderates the indirect effects of (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier and (i) perceived individual barrier on NWOM (through consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived emotional value.

H13 – Perceived epistemic value moderates the indirect effects of (a) perceived usage barrier, (b) perceived value barrier, (c) perceived risk barrier, (d) perceived image barrier, (e) perceived tradition barrier, (f) perceived technological dependence, (g) perceived technology anxiety, (h) perceived ideological barrier and (i) perceived individual barrier on NWOM (through consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived epistemic value.

3.2 Conceptual framework

Based on the hypotheses developed in this chapter and drawing on Ram and Sheth's (1989) theoretical framework, and its extension (Mani and Chouk, 2018), the theory of consumption values (Sheth et al., 1991) and prospect theory (Kahneman and Tversky, 1979) in guiding these hypothesized relationships, this study developed and tested the conceptual framework demonstrated in Figure 1.

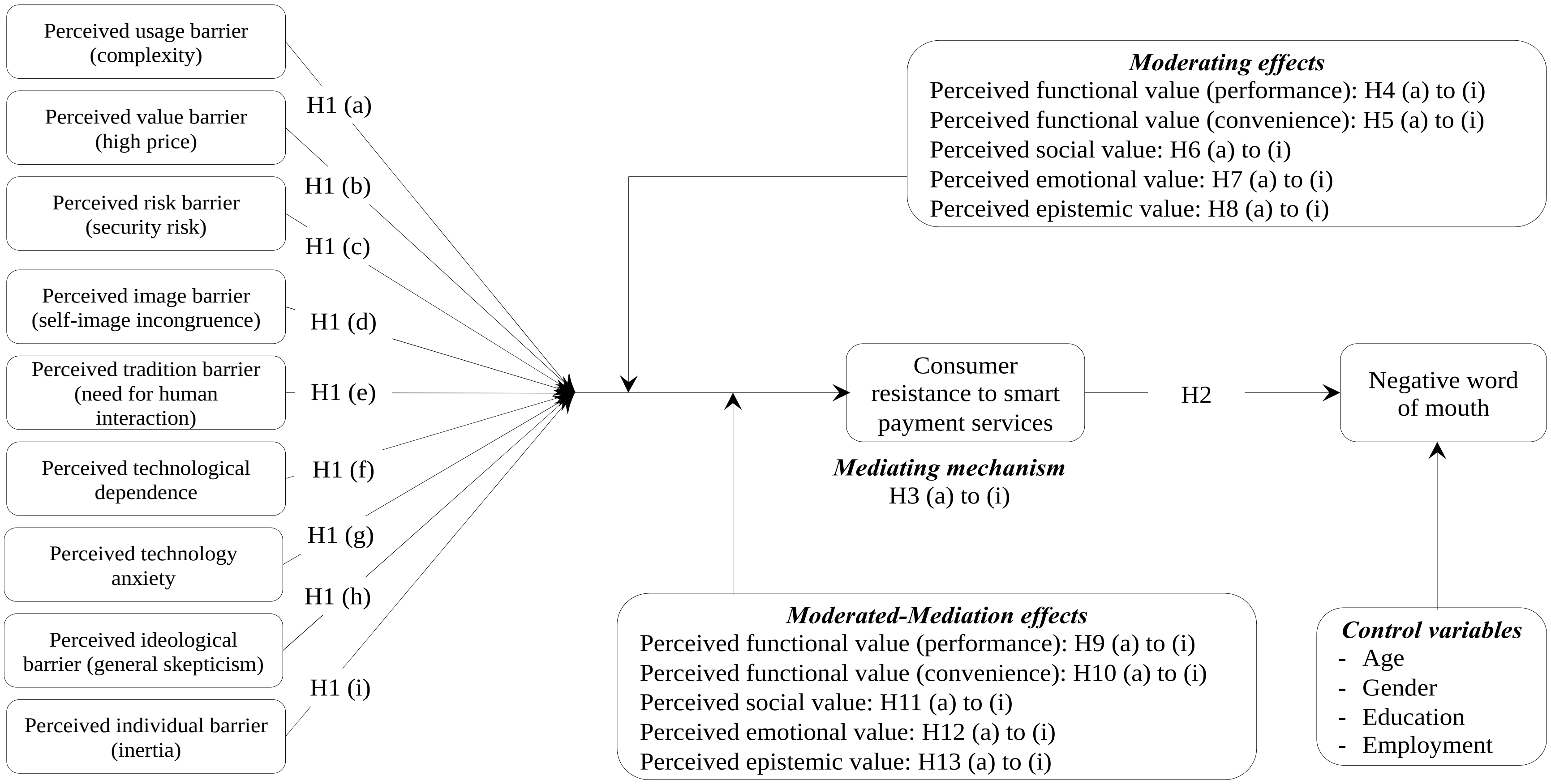


Figure 1: Conceptual framework

Chapter 4 – Research Methodology

This chapter discusses the philosophical paradigm and approach, together with the overall methodology, that was employed in this study to test the hypotheses developed in the previous chapter. The following sections provide an overview of various research philosophies and approaches that exist in social sciences research and explain the rationale for the research philosophy and approach adopted in the current study. Further, this chapter discusses and justifies the research design that was deemed the most suitable to adopt in this study for achieving the research objectives and answering the research questions. Finally, a full description is provided of the methodological choice of a quantitative study for this research, the study objectives, the sampling procedures and the complete data collection process.

4.1 Research philosophy

The term research philosophy refers to a "system of beliefs and assumptions about the development of knowledge" (Saunders et al., 2019, p. 130). At every stage of a research, the researcher makes several assumptions about the realities that he or she may encounter (i.e., the ontological assumptions), human knowledge (i.e., the epistemological assumptions) and the researcher's own values that may influence the research process (i.e., the axiological assumptions) (Burell and Morgan, 2017).

There also exist two opposing extremes across which the research philosophies of business and management are scattered on a continuum. The first extreme is known as objectivism, which argues that the social reality that is researched is external to the social actors. Ontologically, objectivism is also referred to as realism because it holds that social entities exist independently of the views of the social actors in terms of their thoughts and awareness about those social entities. Epistemologically, objectivists seek to uncover the truth of the social world with the help of observations and measurable facts. Axiologically, since objectivists believe that social entities and social actors are independent of each other, they try to keep their research free from personal values (Saunders et al., 2019).

The opposite extreme, known as subjectivism, ontologically assumes that there is no underlying reality, as every social actor perceives reality differently and hence multiple realities exist. Epistemologically, researchers, as social actors, influence the structures of social phenomena through their actions and perceptions. Axiologically, since the actions of social actors influence the reality of the social world, subjectivists conduct research by binding to personal values (Saunders et al., 2019).

In business and management research, the methodological approaches and techniques are determined based on five philosophies: *positivism, critical realism, interpretivism, postmodernism* and *pragmatism* (Saunders et al., 2019).

The first position, positivism, refers to the "philosophical stance of the natural scientist and entails working with an observable social reality to produce law-like generalizations" (Saunders et al., 2019, p. 144). Ontologically, positivists believe in universalism and view social entities as being as real as natural phenomena. Epistemologically, researchers following the positivist paradigm emphasize facts that can be measured as causal relationships, which will further generate credible and meaningful data (Crotty, 1998). Accordingly, this paradigm requires an existing theory for the development of hypotheses, which can then be tested and confirmed to generate further development of the theory. Axiologically, positivist researchers adopt a value-free perspective and try to remain detached from their research and data. Therefore, the focus is on collecting measurable and quantifiable data that can be statistically analysed (Saunders et al., 2019).

The second position, critical realism, focuses on explaining the structures of reality that are seen and observed by researchers. In other words, what is seen are sensations that are actual representations of the existing reality. This is different from the approach of direct realism underpinned by a positivist philosophy. Ontologically, critical realists view reality as external but believe that it cannot be accessed directly through observations and available knowledge (Saunders et al., 2019). Epistemologically, critical realists believe that knowledge is historical, the facts relating to which have been constructed by people over time (Bhaskar, 2013). Hence, the causal relationships developed under the notion of critical realism cannot be analysed statistically, as in the case of quantitative methods, although a range of methods can be applied (Reed, 2005). Axiologically, as social actors are involved in the social conditioning of the knowledge of reality, researchers following this notion strive to minimize any bias that may affect their collected data and to remain as objective as possible (Saunders et al., 2019).

The third position is interpretivism, which, in contrast to positivism, is based on the subjectivist approach. Ontologically, interpretivism is based on the notion that different people from different cultural backgrounds make different meanings of the different social realities. Therefore, from the perspective of business and management research, interpretivists like to analyse organizations as viewed differently by different groups of people (Saunders et al., 2019). Epistemologically, interpretivists focus on interpreting organizations and social worlds through narratives, language, culture and history, in order to develop new understandings and world views (Crotty, 1998). Axiologically, interpretivists believe that their values and interpretations of the collected data influence the research process. Under this notion, interpretivist researchers adopt an empathetic stance as they try to interpret and understand the social world from the perspective of each research participant (Saunders et al., 2019).

The next philosophical position is known as postmodernism, which interrogates positivism and objectivism more critically than does interpretivism. Ontologically, postmodernists emphasize the importance of language in explaining the social world, but it is argued that since language is partial and inadequate, there is no abstract way of describing the social world in a "right" or "true" manner (Foucault, 2012). Epistemologically, postmodernists seek to question the power relations that sustain dominant realities by taking apart or dismantling these realities and searching for instabilities within a widely accepted truth, thereby challenging the established ways of thinking and knowing (Calás and Smircich, 2019; Derrida, 2016; Kilduff and Mehra, 1997). Axiologically, unlike interpretivists, postmodernists adopt a value-constituted research process focusing on in-depth investigations of the social world, as they believe that power relations exist between the researcher and the research subjects that shape the research process (Calás and Smircich, 2019).

The last philosophical position to be considered here is pragmatism, which adopts the notion of both objectivism and subjectivism and strives to remain consistent between facts and values. Ontologically, pragmatists believe in reality as the practical consequence of ideas. Epistemologically, pragmatists value 'true' theories and knowledge for carrying out actions successfully. Hence, they focus on research problems, contributing practical solutions and guiding future practice. Axiologically, pragmatists believe in value-driven research that is initiated and sustained by researchers' doubts and beliefs. Furthermore, since the research problem and question are given priority, in order to address the research problem and question properly, multiple methods can be adapted to enable the collection of credible and relevant data (Kelemen and Rumens, 2008; Saunders et al., 2019).

The current research takes the positivism philosophical position as the study aims to investigate the various perceived barriers that lead consumers to resist smart payment services, explore NWOM as a further detrimental consequence of such resistance, and investigate the role of consumer resistance to smart payment services as an underlying mechanism that explains the translation of perceived barriers into NWOM. The research also aims to investigate the role of consumption value perceptions in buffering the effects of perceived barriers on consumer resistance to smart payment services, as well as the resulting NWOM. Hence, ontologically, the social actors in this context are the consumers who resist smart payment services and view the social entity in the form of their perceptions and opinions, rather than how the social entities exist. Therefore, this research adopts the notion of *realism* at an ontological level. Epistemologically, the research focuses on investigating the phenomenon of consumer resistance to innovation and the resulting NWOM with the help of measurable facts; that is, barriers, the effects of which are further proposed to be reduced by consumption values (another set of measurable facts). Axiologically, the current study is based on capturing the views of the respondents (consumers) as expressed in the form of their responses, rather than the researcher personally interacting with the respondents. Hence, the data to be collected were free from the personal values of the researcher.

4.2 Research approaches

In business and management research, whether the research is based on theory testing or theory building depends on the approach adopted by the researcher. The three approaches are *deductive*, *inductive* and *abductive* (Saunders et al., 2019).

The deductive approach is generally supported by the positivism philosophical position. This approach involves the falsification or verification of theory through a series of propositions or hypotheses based on the existing literature. To test the hypotheses formed, quantitative data are collected and analysed with the aid of a highly structured methodology. The results of the analysis are checked for consistency within the premises of a logical argument (that has been compared with existing theories) and inferences are made regarding acceptance or rejection of the hypotheses based on whether the theory is falsified or corroborated (Saunders et al., 2019).

In contrast, the inductive approach is most likely to be supported by the interpretivist philosophical position. This approach, in contrast to the deductive approach, is based on the notion of theory generation and building. Under this approach, the researcher collects qualitative data to explore a phenomenon and identify themes and patterns in order to formulate a theory. Researchers undertaking an inductive approach mostly focus on a concentrated context to explain the reasoning and hence study a small sample compared to those adopting the deductive approach (Saunders et al., 2019).

The third research approach is the abductive approach, which is mostly supported by the pragmatism, postmodernism and critical realism philosophical positions. This approach combines both deductive and inductive approaches, as it emphasizes theory generation or modification as well as the application of an appropriate existing theory to build a new theory or modify another existing theory. Under this approach, the researcher collects data to identify a phenomenon or themes, applies them in a conceptual framework and tests that conceptual framework through subsequent data collection (Saunders et al., 2019).

In following the positivism philosophical position in order to investigate the relationships between barriers, consumption values, consumer resistance to smart payment services and NWOM, rather than seeking to gain an in-depth understanding of the research area, *this study adopted a deductive research approach*. For this purpose, the current research developed hypotheses based on existing theories, the testing and analysis of which were carried out with the aid of quantitative data collected via an online survey from a large sample of consumers.

4.3 Research design

The research design refers to the plan that provides a path for answering the research question(s) formulated. This plan consists of clearly stated objectives that have been derived from the research question(s), the sources of the data to be collected and the method of analysing the collected data. It also includes the ethical concerns that are required to be addressed during the collection of the data. Research design is generally defined based on the purpose to be fulfilled by the study, which is divided into *exploratory, descriptive,* or *explanatory* (Saunders et al., 2019).

An exploratory research design generally seeks to ask open questions, which are likely to begin with 'What' or 'How'. The main purpose of this research design is to gain insights into a particular topic. This type of research is generally time consuming, as it includes a literature search and collecting data through interviews and focus group discussions with experts on the topic of interest. Exploratory research is advantageous as it is flexible and the research direction can be changed depending on the occurrence of new data and insights as the research progresses (Saunders et al., 2019).

A descriptive research design aims to gain an accurate description of events, persons, or situations for answering research questions beginning with or including 'Who', 'Where', 'When', 'How' or 'What'. This research design can sometimes be applied as a follow-up to or an extension of exploratory research or a piece of explanatory research (Saunders et al., 2019). This type of research design is constructed on existing theories by employing predefined variables from the literature to test the relationships between these variables. The data in this type of research design are generally collected by employing research instruments, such as questionnaires (Iacobucci and Churchill, 2018).

An explanatory research design is primarily concerned with explaining established cause-and-effect relationships between variables. The research questions that are asked during data collection generally begin with 'Why' or 'How' (Saunders et al., 2019). This type of research design is also known as a causal research design and mainly includes experimental methods to test the causal relationships (Ghauri and Grønhaug, 2010).

The current research does not attempt to gain an in-depth understanding of any specific event or phenomenon but to apply existing theories, which led to the development of the conceptual framework and hypotheses presented in Chapter 3. Therefore, *for this study, descriptive research was the most suitable*, the data for which were collected through the administration of questionnaires. An exploratory research design mainly focuses on collecting data through interviews and focus groups to gain deeper insights into a topic, hence this research design was unsuitable for the current study. Further, although descriptive and explanatory designs can both be applied to test hypotheses, an explanatory design pays particular attention to cause-and-effect relationships by using experiments. Since the present research study aims to examine direct, mediating, and moderating relationships among different variables of interest, rather than identifying cause-and-effect relationships, a descriptive research design was employed instead of an explanatory research design.

4.4 Quantitative study

In line with the deductive approach and descriptive research design examined above, this section outlines the quantitative study objectives and the data collection procedure used to fulfil the objectives stated below.

4.4.1 Quantitative study objectives

This study was designed to test the hypotheses formulated in the conceptual framework. The objectives were as follows:

1. To conduct an empirical investigation of the relationships between various latent constructs *vis-à-vis* perceived barriers, consumer resistance to smart payment services, and NWOM.
2. To test the mediating effect of consumer resistance to smart payment services between perceived barriers and NWOM.

3. To test the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services.
4. To test the indirect effects of perceived barriers on NWOM (via consumer resistance to smart payment services) conditioned on perceived consumption values.

The next section provides a detailed discussion of the sampling procedure and data collection methods used in this study.

4.4.2 Sampling procedure and sampling units

Sampling is a method of selecting a particular segment or subset of the population that is considered for an investigation. A sample that reflects the population accurately is known as a representative sample (Bryman, 2012).

A US sample was selected for this study because a number of smart payment services (e.g., Apple Pay and Google Pay) are available to use in the USA in the form of contactless payments at physical retail stores. However, despite the availability of these advanced smart payment services, the US population still prefers to use traditional payment methods (e.g., debit/credit cards and/or cash) rather than a fully digital contactless payment system (Euromonitor, 2019). Another report by de Best (2020) also highlighted that, as of 2019, the use of proximity mobile payment by the US people was only 29%, compared to those in the countries of the Asia-Pacific region, such as China (81%), indicating that US smartphone users were generally hesitant to adopt different forms of smart payment services. The author further added that, as of mid-2020, the use of credit or debit card payments was still the most popular means of payment in retail stores, restaurants, and other POS terminals in the USA (de Best, 2020). The global statistics (see Figure 2) further corroborate the Chinese as having the highest smart payment services penetration rate at POS in 2021 (almost 40%). South Korea and Vietnam both had rates of almost 30%. In Europe, Scandinavian countries, such as Denmark and Sweden, were among the leading countries with penetration rates of 24%. In comparison to these countries, the penetration rate in the USA is quite low (17.7%) (Statista, 2021).

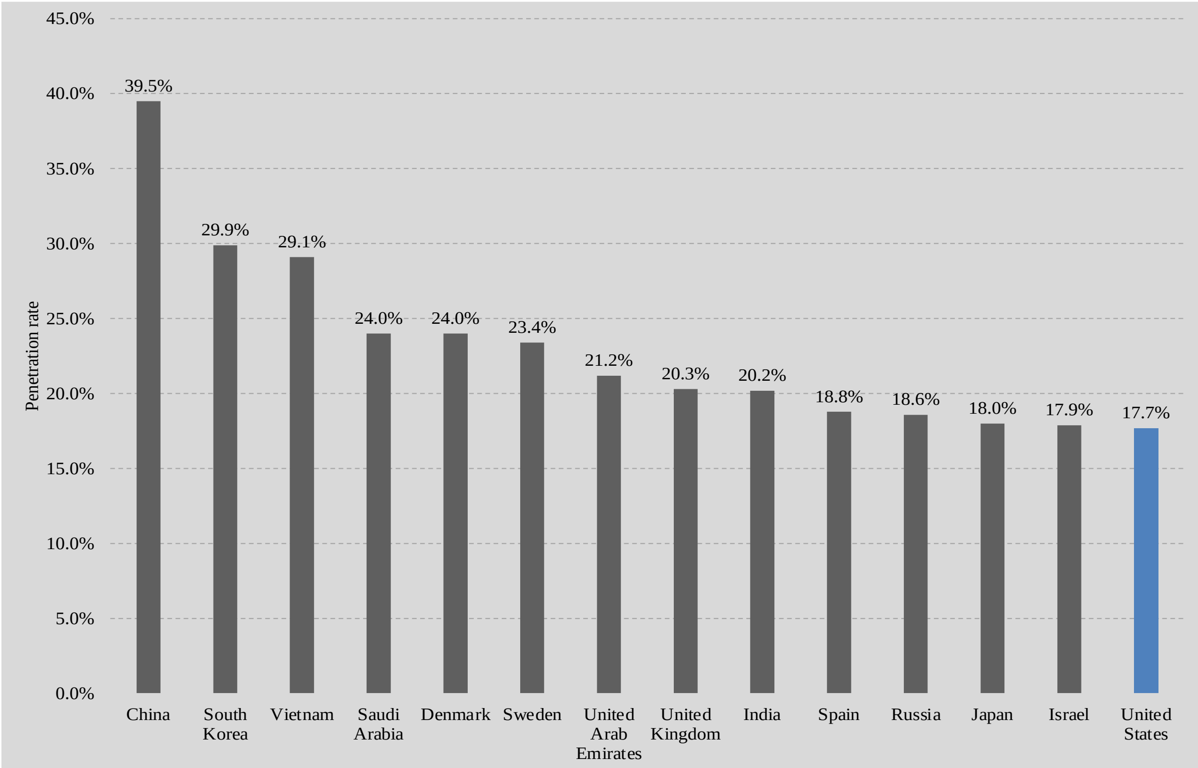


Figure 2: Penetration rate of smart payment services at POS in 2021

Further, according to Statista (2022b), a survey on different payment methods used by US consumers at POS platforms showed that smart payment services were used only by 18% of the respondents, indicating that consumers were still reluctant to use such payment services (see Figure 3). Further, a trend in the type of POS payment method from 2017 to 2021 shows that cards were still a popular POS payment method in the USA after the COVID-19 pandemic, as 40% of these payments were made by credit card and 30% by means of a debit card. However, the penetration of smart payment services (e-wallet, digital wallet and mobile wallet) was down as low as 11% in 2021 (Statista, 2022a) (see Table 6). These statistical data support the selection of US consumers as the survey participants for this present study.

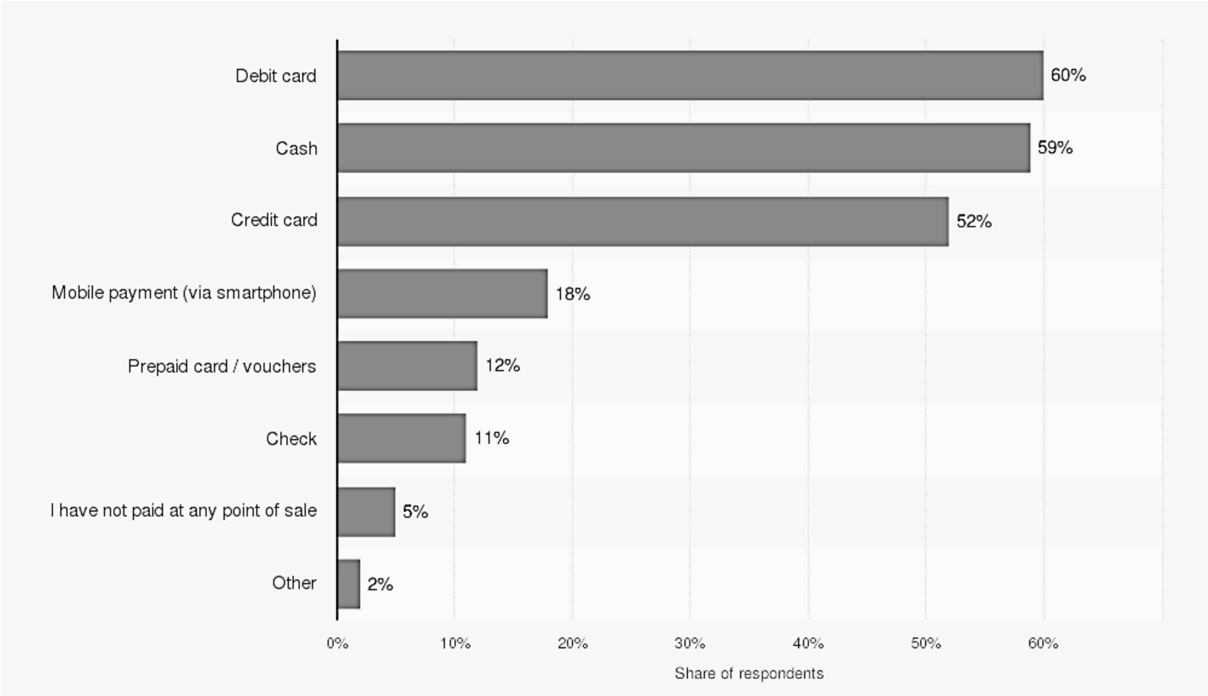


Figure 3: Payments at POS by type in the USA 2021

Table 6: Most popular in-store payment methods in the USA 2017-2021

Payment methods at point of sale	2017	2019	2020	2021
Credit card (%)	40	39	38	40
Debit card (%)	35	34	29	30
Cash (%)	16	15	12	11
E-wallet, digital/mobile wallet (%)	3	6	10	11

4.4.3 Data collection

This section provides a detailed description of the questionnaire that was employed to collect the data required for the study, the measurement scales of the different variables mentioned in the conceptual framework (Chapter 3), the pilot study conducted prior to the main study, and the data collection procedure.

a) Questionnaire design

This research employed a self-completion questionnaire, also known as a self-administered questionnaire, as it would allow the participants to complete it by themselves (Bryman, 2012). These types of questionnaires are generally distributed via the postal service or mail. Self-administered questionnaires have many advantages over structured interviews, such as being cheaper to administer, allowing the capture of responses from geographically widely spread samples, quicker to administer and a large number of questionnaires can be sent through the mail (offline and online). Interviewer effects, such as gender, social background and ethnicity, which might otherwise lead to biased answers by respondents, are absent (Bryman, 2012). This type of questionnaire is also free from interviewer variability, meaning they are free from the problem of the interviewer asking the questions in a different order. Another advantage is that the participants can attempt the questionnaire at any time at their convenience.

This study utilized an internet-based online social survey (Bryman, 2012) in which the questionnaire was designed using Qualtrics. When designing the questionnaire, the suggestions and remedies offered by Podsakoff et al. (2003) for reducing the effects of common method bias (CMB) were considered, such as assuring the survey participants that their responses would be anonymous, allowing them to answer honestly. The survey questionnaire was divided into four sections, which are discussed below.

In the *first section,* the questionnaire provided a brief introduction to the study. This was followed by two screening questions in which the participants were asked about their previous usage experience and subjective knowledge about any type of smart payment service (the questions are elaborated in section 4.3.3(f)). In the *second section,* a detailed description of the study was given, stating its objectives, and statements describing the maintenance of anonymity of participants' personal data; participation consent statements were also provided. The *third section* contained statements related to the variables of interest (i.e., perceived barriers, perceived consumption values, consumer resistance to innovation, and negative word of mouth). In addition, a few attention-checking questions (e.g., "Please click only on the answer Agree"; "In this statement, do not select any answer except Somewhat disagree") and other similar questions were randomly inserted in between the various statements on the study variables in order to ensure that only high-quality responses from attentive participants were recorded (Izogo et al., 2021; H. Liu et al., 2021; McLeay et al., 2022). In the *fourth and final section*, demographic information about the participants, such as their age, gender, education level and employment status, was recorded, which was further used as 'control variables' during the data analysis. The questionnaire ended with a note thanking the respondents for their participation.

b) Measurements

All the constructs were measured using established multi-item scales which were adopted from previous studies. However, the wording of the items for each construct was modified to fit the respective context of smart payment services. A seven-point Likert scale was used for all the scale items, in which the participants responded to the statements in the form of their agreement or disagreement level, which ranged from '*Strongly Disagree*' to '*Strongly Agree*'. The seven-point Likert scale was determined to be appropriate because most empirical studies in the innovation literature have used this scale for capturing the responses of their survey participants (e.g., Casidy et al., 2021; Mani and Chouk, 2018; Nel and Boshoff, 2020). The measurement scales of all the constructs included in the conceptual framework are discussed below.

Perceived barriers

Perceived usage barrier, which refers to perceived complexity, was measured using a three-item scale: *Learning to use smart payment service will not be easy for me; Smart payment service will not be easy to use;* and *It will not be easy to get results that I desire from smart payment service.* These items were adapted from Mani and Chouk (2018).

Perceived value barrier corresponds to perceived high price, which was measured using a three-item scale: *I think that the fees of the smart payment service will be high; I think that* *smart payment service will be costly*; and *I think that smart payment service will be expensive.* This scale was adapted from Mani and Chouk (2018).

Perceived risk barrier corresponds to perceived security risk, which was measured using a three-item scale: *The risk of an unauthorized third party overseeing the payment process through smart payment service will be high; The risk of abuse of usage information (credit/debit card details) will be high when using smart payment service*; and *The risk of abuse of billing information (e.g., credit/debit card number, transaction amount) will be high when using smart payment service*. This scale was adapted from Mani and Chouk (2018).

Perceived image barrier refers to self-image incongruence, which was measured using a three-item scale: *I identify with the typical image of a smart payment service user; I fit in with the typical image of a smart payment service user*; and *The image of the typical smart payment service user reflects the kind of person I am.* The scale items were retrieved from Mani and Chouk (2018) and were further reverse coded during the statistical analysis.

Perceived tradition barrier refers to need for human interaction, which was measured using a three-item scale: *Human contact in making payments makes the process enjoyable for the customer; I like interacting with the person who provides smart payment service*; and *Personal attention by the service employee is very important to me*. This scale was adapted from Mani and Chouk (2018).

Perceived technological vulnerability barriers refer to perceived technological dependence and perceived technology anxiety. Technological dependence was measured using a three-item scale: *I'm afraid of becoming dependent on the technology; The technology will reduce my autonomy*; and *I think my social life will suffer from my use of the technology.* Technology anxiety was also measured using a three-item scale: *I have avoided technology because it is unfamiliar to me; I hesitate to use most forms of technology for fear of making mistakes I cannot* *correct*; and *I feel apprehensive about using technology.* Both scales were retrieved from Mani and Chouk (2018).

Perceived ideological barrier corresponds to general scepticism. This scale was measured using a three-item scale: *I am sceptical toward smart payment services; I do not think smart payment service will be successful*; and *I doubt that smart payment services can actually do what their service providers promise*. This scale was adapted from Mani and Chouk (2018).

Perceived individual barrier corresponds to inertia, which was measured using a four-item scale: *I generally consider the change as a negative thing; I'd rather do the same old things than try new ones; In my opinion, traditional payment services are satisfactory so far*; and *Overall, I consider that my needs of making payments have been met by existing traditional payment services.* This scale was adapted from Mani and Chouk (2018).

Perceived consumption values

Perceived functional value corresponds to performance/quality and convenience. Performance/quality was measured using a four-item scale: *Smart payment services have consistent quality; Smart payment services are well designed; Smart payment services have an acceptable standard of quality*; and *Smart payment services will perform consistently.* Convenience was also measured using a four-item scale: *Using smart payment services is an efficient way to make payments at any time and any place; Using smart payment services is convenient at any time and any place; Using smart payment services will make my life easier*; and *Using smart payment services will fit in with the pace of my life.* The scale for performance/quality was retrieved from Turel et al. (2007) and Rezaei and Ghodsi (2014), originally validated by Sweeney and Soutar (2001). The scale for convenience was adapted from Yang and Lin (2017).

Perceived social value scale measurement, adapted from Sweeney and Soutar (2001), consisted of four items: *Using smart payment services would help me feel acceptable; Using smart payment services would improve the way I am perceived; Using Smart payment services would make a good impression on other people*; and *Using smart payment services would give me social approval.*

Perceived emotional value was measured using a five-item scale: *Smart payment service is one that I would enjoy; Smart payment service would make me want to use it; Smart payment service is one that I would feel relaxed about using; Smart payment service would make me feel good*; and *Smart payment service would give me pleasure.* This scale was adapted from Sweeney and Soutar (2001).

Perceived epistemic value was measured using a three-item scale: *When the things get boring, using smart payment service will give me new stimuli; Using smart payment service will continually give me new activities and changing contents*; and *Smart payment service will help me to experience novelty and change in my daily routine.* The scale items were adapted from Yang and Lin (2017).

Consumer resistance to smart payment services

The measurement scale for **consumer resistance to smart payment services** was retrieved from Mani and Chouk (2018) which included a six-item scale: *In sum, a possible use of smart payment services would cause problems that I don't need; I would be making a mistake by using smart payment services; The use of smart payment services would be connected with too many uncertainties; The smart payment services are not for me; I'm opposed to the use of smart payment services*; and *I'm opposed to the discourses extolling the benefits of smart payment services.*

<u>*Negative word of mouth*</u>

Negative word of mouth was measured using a seven-item scale: *I spread negative comments about the smart payment service; I share negative opinions about the smart payment service; I write negative remarks about the smart payment service on discussion forums; I take active part in negative discussions related to the smart payment service; I rave about the dark side of the smart payment service to others; I denigrate smart payment services to my friends*; and *I tell my friends not to use the smart payment service when they look for a similar service.* The scale items were adapted from Jahanmir and Cavadas (2018) and Grégoire et al. (2010).

c) Control variables

Control variables refer to those factors which are included in a research study to reduce the error terms and increase the statistical power (Schwab, 2013). The controls that were included in the current study were the demographic variables of the respondents: gender, age, education level and current employment status. Previous research in the innovation resistance literature has reported that these demographic variables may influence perceived barriers as well as consumers' resistance (e.g., Casidy et al., 2021; Joachim et al., 2018) and therefore, have been used as control variables.

Gender was captured in terms of *male* and *female*. Age was captured as an open-ended question in response to which the respondents entered the numeric value of their age. Restrictions were implemented such that only numeric values equal to or more than 18 could be entered for 'age'. Education level was measured in terms of five levels (*i.e., less than high school, high school graduate, graduate, postgraduate* and *doctorate*). Current employment status was recorded as *employed full-time, employed part-time, unemployed looking for work, unemployed not looking for work, retired* and *student*.

d) Ethical considerations

Business and management research involves human participants, which raises ethical concerns irrespective of whether the data are collected person-to-person or over the internet. Therefore, to conduct research studies in an ethically responsible manner, the researcher is required to adhere to certain ethical principles or codes of ethics, which are stated below (Saunders et al., 2019):

- *Integrity, fairness, and open-mindedness of the researcher* – The researcher is required to be truthful about the research (i.e., avoiding deception and misinterpretation of the data and findings).
- *Respect for others* – When the researcher is conducting the research, the rights of all the participants should be recognized and their dignity respected.
- *Avoiding harm* – Any harm to participants in terms of their emotional well-being and mental or physical health should be avoided. This may be caused by an intrusive research method creating mental or social pressure and ultimately leading to anxiety or stress.
- *Voluntary participation and right to withdraw* – Respondents have the right to determine the way in which they participate, which includes rights such as not having to answer all the questions, modifying the nature of their consent, and withdrawing from participation, as well as the data they provided.
- *Informed consent* – This involves providing sufficient information about the study to allow the participants to understand the implications of their participation. The researcher should abide by the consent given and not widen the scope of the research without seeking further consent from the participants.
- *Ensuring confidentiality of data and anonymity of participants* – The research should be designed to answer ‘Who’, ‘What’, ‘When’, ‘How’, and ‘Why’ questions and should

not focus on who is providing the data for these questions. Hence, unauthorized identification of the personal data of the participants should be avoided.

- *Responsibility of data analysis and reporting of findings* – Confidentiality must be maintained when analysing and reporting data. Findings should be reported accurately.

These principles were adhered to with agreement from the participants before commencing the data collection for both the pilot and the main study.

e) Pilot study

Before initiating the main study, a pilot study was conducted with a sample of PhD students at the Essex Business School at the University of Essex, UK. The pilot study was conducted online by sharing the survey link of the online questionnaire, designed on Qualtrics, with the students via email, which resulted in 20 completed questionnaires.

For the pilot survey, separate spaces for providing feedback were included after each section of the online questionnaire. The researcher also conducted some face-to-face feedback sessions with a few of the pilot study respondents based on their convenience and availability. The insights gained from this feedback, in both the online as well as the face-to-face interactions, helped the researcher to ensure that the various instructions for attempting the questions and the statements measuring the study variables/constructs were understandable and meaningful to the respondents. The online distribution of questionnaires also helped the researcher to review and resolve any shortcomings that may arise while distributing the questionnaire electronically for the main study. Minor changes were made to the questionnaire based on the feedback obtained from the pilot study, such as rewording a few of the statements measuring the constructs to make the questionnaire more understandable to the respondents.

f) Questionnaire administration

The data for the main study were collected using online self-administered or self-completion questionnaires, designed on Qualtrics. Age restrictions were included in the questionnaire to collect responses only from those participants who were above 18 years of age.

To increase the response rate, the online self-administered questionnaire was distributed among an online survey panel in Amazon Mechanical Turk (MTurk). MTurk, run by Amazon.com, is suitable for conducting academic behavioural research as it provides easy and inexpensive access to a large pool of online participants (Thomas and Clifford, 2017). This platform allows respondents, referred to as 'workers', to attempt surveys, called HITs (i.e., Human Intelligence Tasks), in return for an incentive (Goodman et al., 2013). Many previous empirical studies have used this crowdsourcing platform for data collection purposes, thus demonstrating the validity of this method and its superiority to other recruitment methods (e.g., recruitment via social media and face-to-face data collection) (e.g., Casidy et al., 2021; Casler et al., 2013; Höllig et al., 2020; Labrecque et al., 2017).

A project was created on MTurk. Additional quality assurance measures were used to ensure that only high-quality respondents ('workers') could participate in the survey. For instance, only those with a *more than 90% HIT approval rate* and more than *50 approved HITs* were permitted to participate in the survey. The location preferences were set to the United States (US) only. The workers were also paid a nominal compensation for completing the survey.

Further, the purpose of this study was to examine consumers' resistance to innovation (i.e., the innovation has not yet been 'adopted' by consumers) and NWOM. Therefore, all potential participants were asked to answer two screening questions that were included at the beginning of the questionnaire. The first was a "yes/no" question asking about participants' user experience regarding smart payment services: "*Have you ever used any of the Smart Payment*

Services such as Apple Pay, Google Pay, Samsung Pay, Fitbit Pay, LG Pay?" The second question asked about participants' subjective knowledge regarding smart payment services (*i.e., I have knowledge about Smart Payment Services*) and was based on a seven-point Likert scale, ranging from 'Strongly disagree' to 'Strongly agree'. Only non-users (i.e., those who had never used the innovation) who had reasonable knowledge about the innovation (i.e., responded 'Somewhat agree', 'Agree', and 'Strongly agree' to the subjective knowledge statement) were permitted to complete the survey.

Although MTurk helps to identify participants with a unique 'Worker ID', which allows each participant to submit a HIT only once, IP address restrictions were also implemented in Qualtrics to avoid multiple responses by the same worker. The questionnaire, designed on Qualtrics, was programmed with a Random ID which helped in generating random Survey Completion Codes for all the participants who completed the survey. At the end of the survey, the participants were also asked to submit their MTurk Worker ID in Qualtrics as well as their Survey Completion Code in MTurk before submitting the HIT. These steps helped the researcher to approve or reject the submitted HITs, ensuring that only valid submissions were paid for. The inclusion of attention-checking questions also ensured that the participants were attentive during the completion of the questionnaire. Failing to answer the attention-checking questions correctly resulted in the termination of the survey with a suitable message.

After the final submission of the survey responses, the HITs submitted by workers in MTurk were verified for valid responses by matching the Worker ID with a random ID (generated by Qualtrics) entered by the workers. Invalid HITs were rejected by the researcher and were republished to allow other workers to attempt the survey. Data were collected from 359 respondents, which generated a final sample of n = 356 completed and approved questionnaires. The demographic characteristics of this final sample of respondents are as follows:

Gender: 46.35% of the respondents were women and 53.65% were men.

Age: The respondents' age ranged from 19 to 72 years. The average age of the respondents was 36.47 years.

Employment status: The employment status of the respondents was recorded into six categories: (1) employed full-time; (2) employed part-time; (3) unemployed (looking for work); (4) unemployed (not looking for work); (5) retired; and (6) student. The majority of the respondents (76.12%) were employed full-time, followed by 11.52% employed part-time, and a few were students (0.56%). The other types of employment status consisted of those who were unemployed (looking for work: 2.81%; not looking for work: 6.46%) and retired (2.53%).

Highest education level: The respondents' education ranged from high school graduate to doctorate level. Among the respondents, the majority (56.46%) were graduates, followed by postgraduates (20.79%) and high school graduates (19.94%), while only a few (2.81%) held doctorates.

Chapter 5 – Quantitative Data Analysis

The data analysis was conducted in five steps. First, a thorough coding and preliminary examination of the collected data was carried out in IBM SPSS 27. Second, all the multi-item scale measurements were examined using exploratory factor analysis (EFA), followed by confirmatory factor analysis (CFA) to identify and remove poor-performing items. Third, the final descriptive statistics of the purified multi-item scales were discussed. Fourth, two methods – Harman's single factor test (Podsakoff et al., 2003) and the marker variable method (Lindell and Whitney, 2001) – were employed to rule out the impact of CMB. Finally, path analysis was carried out in Stata 16 using structural equation modelling (SEM) to test the hypotheses (i.e., direct effects, mediating effect, moderating effects, and moderated mediation effects) presented in the conceptual framework.

5.1 Data coding

The data collected via the online questionnaire were transferred to SPSS statistical software for preliminary analysis. The necessary coding of the study variables was carried out by providing names, labels, and scale types in SPSS.

5.2 Preliminary examination of the data

Before initiating the main data analysis, the collected data were examined in the following steps: *a) evaluation of missing data; b) identification of outliers;* and *c) testing the assumption for multivariate analysis* (Hair et al., 2014).

5.2.1 Missing data

Missing data are the values of one or more variables that are not available for further data analysis. It is the responsibility of the researcher to identify missing data and apply the necessary remedial actions so that the issues raised by the missing data do not affect the generalizability of the results (Hair et al., 2014). A four-step process for identifying missing data and applying appropriate remedies has been proposed by Hair et al. (2014). *However, the examination of the data collected for this study revealed no missing cases, indicating no need for the suggested four-step process*.

5.2.2 Outlier detection

The next step in the preliminary analysis of the data included identification of outliers in the collected data. Outliers are the observations that have unusually high or low values of the study variables that stand out from the other observations (Hair et al., 2014). To identify outliers in the data collected for this study, boxplots for each variable were plotted in SPSS. The boxplots revealed outliers in the total collected observations (n = 359). Further, multivariate outlier detection was carried out by calculating the Mahalanobis distance (D^2) for each observation (Hair et al., 2014). The value of D^2 is compared against the threshold value in the chi-squared distribution table at the .001 level of significance with 14 degrees of freedom *(df). The common outliers identified from both these tests (i.e., boxplots and D^2) were removed, which resulted in a final sample of n = 356 for further analysis.*

5.2.3 Assumption testing

As reported by Hair et al. (2014), multivariate techniques are mainly affected by four assumption tests: (a) normality; (b) homoscedasticity; (c) linearity; and (d) multicollinearity. All these tests were carried out for all the individual constructs in this study.

Normality

Normality refers to the shape of the data distribution of each variable involved in the study representing a normal distribution. The violation of non-normality can be judged based on two dimensions: the shape of the distribution and the sample size (Hair et al., 2014). The shape of a distribution can be measured by calculating *kurtosis* and *skewness* values. For a normal distribution, the *kurtosis* and *skewness* values should be zero. Any values other than zero imply non-normality, presenting a non-normal distribution (Hair et al., 2014). Furthermore, specific statistical tests, such as the Kolmogorov-Smirnov test (or KS test) (Hair et al., 2014) was conducted to test the hypothesis that the observed distribution deviates from the normal distribution. Hence, *a significant KS test indicates variation from normality* (Hair et al., 2014).

In this study, histograms were plotted for each variable in SPSS statistical software, which showed deviations from the expected zero values for kurtosis and skewness. However, the detrimental effects of non-normality can be reduced if a large sample size is present, such that for a sample size greater than 200, the effects of non-normality may be negligible (Hair et al., 2014). *As the sample size in this study is n = 356, this represents negligible effects of non-normality. The Kolmogorov-Smirnov test returned significant results, suggesting further examination. The descriptive statistics revealed positive and negative combinations of skewness and kurtosis values for different variables, although the values were below the suggested threshold levels* (Byrne, 2016; Hair et al., 2014). A detailed discussion of the descriptive statistics for each variable after factor analyses is presented in section 5.4.

Homoscedasticity

The assumption that a dependent variable represents equal levels of variance across a range of independent variables is referred to as homoscedasticity. If this dispersion (i.e., variance of the dependent variable value) is unequal across the values of the independent variable, then the assumption of homoscedasticity is violated and the relationship is said to be heteroscedastic (Hair et al., 2014). *To test this assumption, graphical tests of equal variance dispersion (i.e., a standardized residual scatter plot of the dependent variable) were carried out, which revealed uniform dispersion of the dependent variable across independent variables, thereby satisfying the assumption of homoscedasticity*.

Linearity

All multivariate techniques based on correlational measures of association require the assumption of linearity to be satisfied because correlations present only a linear relationship between the independent and dependent variables (Hair et al., 2014). Scatter plots among the dependent and independent variables in this study were plotted. *The scatter plots revealed that most of the observation points fell along a straight line, thereby representing a linear relationship with minor deviations from the straight line. Hence, the assumption of linearity was satisfied*.

Multicollinearity

Multicollinearity is the association between three or more independent variables present in a regression equation which predict the dependent variable. The simplest method of identifying collinearity is to examine a correlation matrix of the independent variables, in which high correlations (i.e., .90 or more) represent sufficient collinearity (Hair et al., 2014). However, to assess multicollinearity statistically, two common measures, known as *Tolerance* and the *variance inflation factor (VIF),* can be calculated, which are basically the inverse of each other (Hair et al., 2014). Tolerance is the amount of variability of an independent variable *not explained by the other independent variables*, implying that high tolerance values lead to a low degree of multicollinearity. VIF is simply calculated as the inverse of Tolerance. The suggested cutoff value for Tolerance is .10 and the threshold value for VIF is 10 (Hair et al., 2014). *By carrying out linear regression, the collinearity statistics for each independent variable showed acceptable values of Tolerance above .10 and VIF below 10*.

5.3 Factor analysis

The purpose of factor analysis is to define the underlying structure of the scale items present in an analysis. In multivariate analysis, there are a large number of items that may overlap (i.e., correlate with other items) and it is the responsibility of the researcher to manage these items by grouping the highly correlated items together (Hair et al., 2014). Factor analysis is a tool for defining sets of items that are highly intercorrelated and these sets are known as *factors*. Factor analytic techniques can be either *exploratory* or *confirmatory*, depending on the purpose. In exploratory factor analysis (EFA), the purpose is to search for a defined set of variables, whereas confirmatory factor analysis (CFA) serves a purpose in cases in which researchers have a predefined data structure based on the theoretical understanding (Hair et al., 2014). *In this study, EFA was conducted to identify poorly performing items, followed by CFA to remove redundant or non-reflective items.*

5.3.1 Exploratory factor analysis

The purpose of EFA is to purify measures by omitting the 'garbage items' and to keep only those items in the measure that are highly intercorrelated. The following steps were carried out before conducting the EFA.

Sample-to-item ratio

To conduct EFA, an ideal sample size of 100 or larger is necessary. As a rule of thumb, a desired ratio of five observations (sample) per item is recommended; however, a more acceptable ratio would be 10:1 (Hair et al., 2014). In this study, the sample-to-item ratio was below 10:1. *Therefore, this indicated the need for group-based EFA, whereby Group 1 consisted of items measuring perceived barriers and consumer resistance to innovation and Group 2 contained items measuring perceived consumption values and negative word of mouth.*

Data appropriateness of factor analysis

A statistical test known as *Bartlett's test of sphericity* provides a means for the statistical analysis of correlations among the items in a correlation matrix. As a rule of thumb, a statistically significant Bartlett's test of sphericity (i.e., sig. < .05) indicates the items are intercorrelated and hence the data are appropriate for factor analysis (Hair et al., 2014). Furthermore, another measure, known as the *Kaiser-Meyer-Olkin (KMO)* measure, indicates the extent to which items in a construct are interrelated to each other or, in other words, it is a measure of the homogeneity of the items. It has been recommended that a KMO measure of value of ≥ .90 is excellent but < .50 is unacceptable (Sharma, 1996). Hence, *in SPSS, both statistical measures (i.e., Bartlett's test of sphericity and KMO) were calculated for both groups 1 and 2.*

Selecting the factor extraction method

The selection of a factor extraction method depends on the objective of the factor analysis and prior knowledge of some characteristics of the relationships between the items. The factor extraction method can be chosen from between two methods: *component analysis* and *common factor analysis*. Both methods are widely used by researchers. However, differences exist between them (Hair et al., 2014).

<u>Component analysis</u>, also known as principal component analysis, is used for data reduction purposes and considers total variance to derive the factors containing small proportions of unique variance. In contrast, the objective of <u>common factor analysis</u> is only to consider the shared variance to identify latent dimensions or constructs and there is little knowledge of the amount of specific and error variance of the items (Hair et al., 2014).

In this study, since the latent constructs were already known and the objective was data reduction by identifying and eliminating problematic items, principal component analysis was used as a factor extraction method, the results of which are reported in the later sections.

Selecting a factor rotation method

In order to interpret factors, a rotation method needs to be selected to achieve a simpler and theoretically meaningful factor solution. There are two methods of rotation: *oblique factor rotation* and *orthogonal factor rotation*. Oblique factor rotation assumes the theoretically underlying dimensions to be correlated to each other and this assumption is the inverse in the case of orthogonal rotation. There are three main orthogonal approaches: Quartimax, Varimax and Eqimax. The oblique approaches include Oblimin, Promax, Orthoblique, Dquart and Doblimin. However, orthogonal rotation methods are most widely used and are the most suitable when the objective is data reduction (Hair et al., 2014). *Therefore, in this study, an orthogonal rotation type (i.e., Varimax) was used*.

Factor loadings

After the application of a suitable factor extraction method and rotation technique, and in order to interpret the factors, a decision is made to differentiate between the factors based on the factor loadings, which are the correlation of the item and the factor. Factor loadings in the range of ± .30 to ± .40 are considered sufficient for the interpretation of factor structure, but loadings of ± .50 or greater are considered practically significant. Furthermore, the value of factor loadings based on a differing sample size can be considered significant (Hair et al., 2014). According to Hair et al. (2014), loadings of .30 are considered significant for a minimum sample size of 350*, which corresponds to the sample size of this study (i.e., n = 356). However, this study considers a loading value of .40 as significant in the EFA analysis.*

Reliability

Reliability is conceptualized as the internal consistency among the items of a scale such that the individual items of that scale should all be measuring the same construct and are thus highly intercorrelated. To assess the internal consistency of a scale, a diagnostic measure known as <u>Cronbach's alpha</u> is used, the minimum threshold value for which is .70. However, in exploratory research, a value with a lower limit of .60 may also be acceptable. The values of Cronbach's alpha can be calculated using statistical software packages such as SPSS.

Based on the steps discussed to perform EFA, the following sections present the EFA and reliability results of individual constructs and the two measurement groups (1 and 2). As mentioned above, *EFA was conducted using the principal component factor extraction method along with Varimax rotation in SPSS statistical software*.

a) EFA and reliability results for individual constructs

Perceived usage barrier (complexity)

The analysis consisted of three scale items, which resulted in a KMO value of .751 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 85.368%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .937. The reliability statistics revealed a Cronbach's alpha value of .914, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 7 shows the results of the EFA and reliability statistics.

Table 7: EFA and reliability results for perceived usage barrier (complexity)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.751	ub1	.926	85.368%	.914
Bartlett's test of sphericity	Approx. χ^2	752.196	ub2	.937		
	df	3	ub3	.909		
	sig.	.000				

Perceived value barrier (high price)

The analysis consisted of three scale items, which resulted in a KMO value of .772 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 89.440%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .947. The reliability statistics revealed a Cronbach's alpha value of .941, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 8 shows the results of the EFA and reliability statistics.

Table 8: EFA and reliability results for perceived value barrier (high price)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.772	vb1	.944	89.440%	.941
Bartlett's test of sphericity	Approx. χ^2	953.348	vb2	.947		
	df	3	vb3	.946		
	sig.	.000				

Perceived risk barrier (security risk)

The analysis consisted of three scale items, which resulted in a KMO value of .751 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 84.421%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .933. The reliability statistics revealed a Cronbach's alpha value of .908, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 9 shows the results of the EFA and reliability statistics.

Table 9: EFA and reliability results for perceived risk barrier (security risk)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.751	rb1	.904	84.421%	.908
Bartlett's test of sphericity	Approx. χ^2	707.303	rb2	.920		
	df	3	rb3	.933		
	sig.	.000				

Perceived image barrier (self-image congruence)

The analysis consisted of three scale items, which resulted in a KMO value of .742 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 87.104%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .952. The reliability statistics revealed a Cronbach's alpha value of .926, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 10 shows the results of the EFA and reliability statistics.

Table 10: EFA and reliability results for perceived image barrier (self-image congruence)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.742	ib1	.930	87.104%	.926
Bartlett's test of sphericity	Approx. χ^2	857.355	ib2	.952		
	df	3	ib3	.917		
	sig.	.000				

Perceived tradition barrier (need for human interaction)

The analysis consisted of three scale items, which resulted in a KMO value of .698 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 73.313%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .891. The reliability statistics revealed a Cronbach's alpha value of .817, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 11 shows the results of the EFA and reliability statistics.

Table 11: EFA and reliability results for perceived tradition barrier (need for human interaction)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.698	tb1	.891	73.313%	.817
Bartlett's test of sphericity	Approx. χ^2	384.244	tb2	.836		
	df	3	tb3	.841		
	sig.	.000				

Perceived technological dependence

The analysis consisted of three scale items, which resulted in a KMO value of .735 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 79.825%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .909. The reliability statistics revealed a Cronbach's alpha value of .873, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 12 shows the results of the EFA and reliability statistics.

Table 12: EFA and reliability results for perceived technological dependence

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.735	td1	.876	79.825%	.873
Bartlett's test of sphericity	Approx. χ^2	542.975	td2	.909		
	df	3	td3	.894		
	sig.	.000				

Perceived technology anxiety

The analysis consisted of three scale items, which resulted in a KMO value of .745 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 84.415%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .939. The reliability statistics revealed a Cronbach's alpha value of .908, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 13 shows the results of the EFA and reliability statistics.

Table 13: EFA and reliability results for perceived technology anxiety

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.745	ta1	.907	84.415%	.908
Bartlett's test of sphericity	Approx. χ^2	713.167	ta2	.939		
	df	3	ta3	.911		
	sig.	.000				

Perceived ideological barrier (general scepticism)

The analysis consisted of three scale items, which resulted in a KMO value of .662 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 73.171%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .907. The reliability statistics revealed a Cronbach's alpha value of .815, which is above the minimum value of .70, indicating internal consistency. However, the item total statistics revealed that Cronbach's alpha could be increased to .858 if idb1 (i.e., the first item) is deleted. Table 14 shows the results of the EFA and reliability statistics.

Table 14: EFA and reliability results for perceived ideological barrier (general scepticism)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.662	idb1	.757	73.171%	.815
Bartlett's test of sphericity	Approx. χ^2	425.863	idb2	.907		
	df	3	idb3	.894		
	sig.	.000				

Perceived individual barrier (inertia)

The analysis consisted of four scale items, which resulted in a KMO value of .513 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 48.969%. The factor loadings of all the items, except for inb3 and inb4, were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .922. The reliability statistics revealed a Cronbach's alpha value of .701, which is above the minimum value of .70, indicating internal consistency. However, the item total statistics revealed that Cronbach's alpha could be increased to .715 if item inb4 is deleted. Table 15 shows the results of the EFA and reliability statistics.

Table 15: EFA and reliability results for perceived individual barrier (inertia)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.513	inb1	.911	48.969%	.701
Bartlett's test of sphericity	Approx. χ^2	428.647	inb2	.922		
	df	6	inb3	.394		
	sig.	.000	inb4	.351		

Perceived functional value (performance)

The analysis consisted of four scale items, which resulted in a KMO value of .815 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 70.841%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .859. The reliability statistics revealed a Cronbach's alpha value of .862, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 16 shows the results of the EFA and reliability statistics.

Table 16: EFA and reliability results for perceived functional value (performance)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.815	pv1	.839	70.841%	.862
Bartlett's test of sphericity	Approx. χ^2	650.148	pv2	.837		
	df	6	pv3	.859		
	sig.	.000	pv4	.832		

Perceived functional value (convenience)

The analysis consisted of four scale items, which resulted in a KMO value of .793 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 69.971%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .891. The reliability statistics revealed a Cronbach's alpha value of .858, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 17 shows the results of the EFA and reliability statistics.

Table 17: EFA and reliability results for perceived functional value (convenience)

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.793	cv1	.800	69.971%	.858
Bartlett's test of sphericity	Approx. χ^2	654.224	cv2	.774		
	df	6	cv3	.875		
	sig.	.000	cv4	.891		

Perceived social value

The analysis consisted of four scale items, which resulted in a KMO value of .848 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 84.824%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .933. The reliability statistics revealed a Cronbach's alpha value of .940, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 18 shows the results of the EFA and reliability statistics.

Table 18: EFA and reliability results for perceived social value

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.848	sv1	.911	84.824%	.940
Bartlett's test of sphericity	Approx. χ^2	1289.286	sv2	.933		
	df	6	sv3	.914		
	sig.	.000	sv4	.925		

Perceived emotional value

The analysis consisted of five scale items, which resulted in a KMO value of .890 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 79.599%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .909. The reliability statistics revealed a Cronbach's alpha value of .936, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 19 shows the results of the EFA and reliability statistics.

Table 19: EFA and reliability results for perceived emotional value

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.890	ev1	.886	79.599%	.936
Bartlett's test of sphericity	Approx. χ^2	1489.339	ev2	.877		
	df	10	ev3	.874		
	sig.	.000	ev4	.909		
			ev5	.915		

Perceived epistemic value

The analysis consisted of three scale items, which resulted in a KMO value of .755 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 84.999%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .935. The reliability statistics revealed a Cronbach's alpha value of .912, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 20 shows the results of the EFA and reliability statistics.

Table 20: EFA and reliability results for perceived epistemic value

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.755	epv1	.935	84.999%	.912
Bartlett's test of sphericity	Approx. χ^2	728.589	epv2	.915		
	df	3	epv3	.916		
	sig.	.000				

Negative word of mouth

The analysis consisted of seven scale items, which resulted in a KMO value of .953 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 88.963%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .953. The reliability statistics revealed a Cronbach's alpha value of .979, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 21 shows the results of the EFA and reliability statistics.

Table 21: EFA and reliability results for negative word of mouth

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			**Factor loadings (>.40)**		**Total variance**	**Cronbach's alpha (>.70)**
KMO measure		.953	Nwom1	.941	88.963%	.979
Bartlett's test of sphericity	Approx. χ^2	3769.460	Nwom2	.931		
	df	21	Nwom3	.942		
	sig.	.000	Nwom4	.947		
			Nwom5	.941		
			Nwom6	.949		
			Nwom7	.953		

Consumer resistance to smart payment services

The analysis consisted of six scale items, which resulted in a KMO value of .916 (i.e., > .50) with a significant Bartlett's test of sphericity, indicating data appropriateness. The total variance explained by the item combination is 74.433%. The factor loadings of all the items were above the minimum level of .40, indicating intercorrelation of the items, with the highest value of .912. The reliability statistics revealed a Cronbach's alpha value of .931, which is above the minimum value of .70, indicating internal consistency. The item total statistics also did not reveal any further improvement in the Cronbach's alpha value. Table 22 shows the results of the EFA and reliability statistics.

Table 22: EFA and reliability results for consumer resistance to smart payment services

KMO and Bartlett's test (KMO >.50, BTS sig. <.05)			Factor loadings (>.40)		Total variance	Cronbach's alpha (>.70)
KMO measure		.916	r1	.796	74.433%	.931
Bartlett's test of sphericity	Approx. χ^2	1639.183	r2	.869		
	df	15	r3	.859		
	sig.	.000	r4	.888		
			r5	.912		
			r6	.849		

b) EFA – Group 1

For Group 1, EFA was conducted for 34 items using the principal component factor extraction method along with Varimax rotation. The initial analysis showed a KMO measure of .948, which is more than .50, indicating data appropriateness for conducting the analysis. The Bartlett's test of sphericity was also significant, with a value of less than .50. The selection of factor extraction based on Eigen values > 1 resulted in a five-factor structure with all the loadings above the cutoff point of .04. However, conceptually, the items should load on 10 different factors, since the items measured 10 different constructs. Hence, the analysis revealed that there were heavy cross-loadings of items in the resulting factor structure. According to Hair et al. (2014), a remedy for this would be to specify a fixed number of factors to be extracted based on theoretical grounds, allowing the detection of problematic items. Therefore, after fixing the number of factors to be extracted to 10, the results revealed that the majority of the constructs loaded on separate factors. However, after the removal of problematic items, the final 10-factor structure revealed loadings of items belonging to a particular construct on separate factors. Furthermore, the unidimensionality of the factors was tested in the CFA that followed. Table 23 demonstrates the final 10-factor solution after removing the problematic items.

Table 23: EFA – final results – Group 1

	Perceived usage barrier (complexity)	Perceived value barrier (high price)	Perceived risk barrier (security risk)	Perceived image barrier (self-image incongruence)	Perceived tradition barrier (need for human interaction)	Perceived technological dependence	Perceived technology anxiety	Perceived ideological barrier (general scepticism)	Perceived individual barrier (inertia)	Consumer resistance to smart payment services
ub1	.594									
ub2	.681									
ub3	.646									
vb1		.797								
vb2		.801								
vb2		.801								
rb1			.840							
rb2			.829							
rb3			.832							
ib1				.909						
ib2				.929						
ib3				.854						
tb1					.772					
tb2					.653					
tb3					.837					
td1						.690				
td2						.603				
ta1							.828			
ta2							.735			
ta3							.682			

idb2	.630		
idb3	.556		
inb3		.832	
inb4		.747	
r1			.729
r2			.782
r3			.678
r4			.752
r5			.795
r6			.724

Note: Extraction method: principal component analysis; Rotation method: Varimax with Kaiser normalization
Kaiser-Meyer-Olkin measure of sampling adequacy = .937; Bartlett's test of sphericity approx. χ^2 = 9303.209; df = 435; sig. = .000

c) EFA – Group 2

For Group 2, EFA was conducted for 27 items using the principal component factor extraction method along with Varimax rotation. The initial analysis showed a KMO measure of .963, which is more than .50, indicating data appropriateness for conducting the analysis. The Bartlett's test of sphericity was also significant, with a value of less than .50. The selection of factor extraction based on Eigen values > 1 resulted in a three-factor structure with all the loadings above the cutoff point of .04. However, conceptually, the items should load on six different factors since the items measured six different constructs. Hence, the analysis revealed that there were heavy cross-loadings of items in the resulting factor structure. According to Hair et al. (2014), a remedy for this would be to specify a fixed number of factors to be extracted based on theoretical grounds, allowing the detection of problematic items. Therefore, fixing the number of factors to be extracted to six and after removal of problematic items, all the constructs loaded on separate factors. Furthermore, the unidimensionality of the factors was tested in the CFA that followed. Table 2 shows the final six-factor solution after removing the problematic items.

Table 24: EFA – final results – Group 2

	Perceived functional value (performance)	Perceived functional value (convenience)	Perceived social value	Perceived emotional value	Perceived epistemic value	Negative word of mouth
pv2	.740					
pv3	.765					
cv3		.757				
cv4		.779				
sv1			.714			
sv2			.765			
sv3			.790			
sv4			.766			
ev1				.385		
ev4				.586		
ev5				.572		
epv1					.622	
epv2					.633	
epv3					.759	
Nwom1						.914
Nwom2						.914
Nwom3						.894
Nwom4						.893
Nwom5						.889
Nwom6						.912
Nwom7						.913

Note: Extraction method: principal component analysis; Rotation method: Varimax with Kaiser normalization
Kaiser-Meyer-Olkin measure of sampling adequacy = .957; Bartlett's test of sphericity approx. χ^2 = 8729.425; df = 210; sig. = .000

5.3.2 Confirmatory factor analysis

EFA provides the researcher with information about how many factors are appropriate to represent the collected data depending on the factor loading results. CFA is different from EFA in that the researcher specifies the number of factors as well as the items that will load onto a particular factor based on theory (Hair et al., 2014). Moreover, CFA helps the researcher to confirm or reject a theory by identifying how the theoretically specified factors match the actual data (Hair et al., 2014). Hence, CFA is based on measurement theory, whereby predefined factors or conceptual constructs are specified in the measurement model (Hair et al., 2014).

According to Hair et al. (2014), CFA is a stepwise process which includes the following: *a) development of a measurement model; b) measurement model specification and identification; c) assessment of measurement model fit*; and *d) assessment of measurement model validity.*

Development of a measurement model

In developing an overall measurement model for CFA, *unidimensionality* is important when more than two constructs are involved in the analysis. This term refers to the concept that a set of measured items should relate to only one construct (Hair et al., 2014).

Furthermore, the constructs should be defined as either *reflective* or *formative*. *Reflective measurement theory* is based on the assumption that latent constructs cause the measured items. In contrast, *formative measurement theory* assumes that formative constructs are not latent and hence an error in the formative measurement model is an inability of the measured items to define the constructs (Hair et al., 2014). *Therefore, in this study, the constructs used in the CFA are latent or reflective constructs and hence in CFA the arrows are drawn from the latent construct towards the measured items*.

Measurement model specification and identification

As CFA tests the measurement theory, the researcher specifies the indicators or items that measure the particular constructs based on the theoretical ground. Furthermore, for *model identification*, the measurement models are defined by the degree of identification or degrees of freedom, which further helps to determine whether the measurement model is under-identified, just identified or over-identified. The degrees of freedom can be calculated by the equation, $df=\frac{1}{2}\left(p(p+1)\right)-k$; where p is the total number of measured items and k is the number of paths to estimate. For conducting CFA, it is recommended to have an *overidentified model* which consists of positive degrees of freedom (Hair et al., 2014).

Assessment of measurement model fit

Once the measurement model is specified, its *goodness of fit (GOF)* is interpreted. GOF is an indicator which compares the estimated covariance matrix to the observed covariance matrix; in other words, it compares theory to reality. The closer the values of the two matrices, the better the model is said to fit. Furthermore, GOF is measured in terms of the number of fit indices, which include <u>absolute fit indices</u> and <u>incremental fit indices</u> (Hair et al., 2014).

The first fit statistic under the category of absolute fit indices is the χ^2 *statistic*, which is a mathematical function of sample size (N) and the difference between the observed and estimated covariances. Moreover, the value of χ^2 increases with an increase in the value of N. For a good model fit, low values of χ^2 are recommended. Furthermore, *normed chi-square* is the measure of the ratio of χ^2 to degrees of freedom (χ^2:df), the recommended value of which should be less than 3:1 to imply better fit (Hair et al., 2014). Another measure, known as *root mean square error of approximation (RMSEA),* represents the model fit to the population and not just the sample, thereby correcting the χ^2 statistic to reject models with a large sample size. RMSEA values less than .07 are considered for a better fitting model (Hair et al., 2014).

The second category of fit indices (i.e., incremental fit indices) is used to compare the model fit in relation to some alternative baseline model (null model) (Hair et al., 2014). Under this category, the first is the *comparative fit index (CFI)*, which is insensitive to model complexity. Better fitting models should have a CFI value greater than .90 (Hair et al., 2014). Second, the *Tucker Lewis index (TLI)* compares the normed chi-square of the null and specified models, the values of which can also be below 0 or above 1. However, for a better model fit, TLI values approaching 1 are considered good (Hair et al., 2014).

Assessment of measurement model validity

Construct validity deals with the accuracy of measurement, such that the measured items only reflect those latent constructs that they are designed to measure. Construct validity is measured by *convergent validity* and *discriminant validity*. Convergent validity is measured in terms of *factor loadings*, *average variance extracted* and *construct reliability* (Hair et al., 2014).

High factor loadings refer to high convergent validity, which means that the high loadings shown by the measured items converge on a common latent construct. As a rule of thumb, the factor loadings should be greater than .50, although .70 or higher is ideal. In SEM programs such as Stata, the standardized regression coefficients represent the factor loadings shown by the measured items (Hair et al., 2014).

Another measure for indicating convergent validity is *average variance extracted (AVE)*, which refers to the measure of mean variance extracted for the item loadings on the construct. For sufficient convergence, an AVE value of more than .50 is recommended. AVE is represented by the following equation (Hair et al., 2014):

Equation (1): $$\mathrm{AVE}=\frac{\sum_{i=1}^{n} L_i^2}{n}$$

where, L_i = standardized factor loadings
n = number of items

The last measure for indicating convergent validity is *construct reliability (CR)*, which is measured by the following equation (Hair et al., 2014):

Equation (2): $CR=\frac{(\sum_{i=1}^{n} L_i)^2}{(\sum_{i=1}^{n} L_i)^2+(\sum_{i=1}^{n} e_i)}$

where, L_i = standardized factor loadings
n = number of items
e = error variance terms for a construct $=1-L_i^2$

As a rule of thumb, to indicate adequate convergent validity, CR with a value more than .70 suggests good reliability. However, CR values between .60 and .70 may be acceptable if the values of other measures indicating convergent validity are good (Hair et al., 2014).

The second measure of construct validity is *discriminant validity*, which indicates that a single construct is unique and distinct from other constructs. In other words, it also means that individual measured items should represent only one construct. To test this validity, the AVE value of each latent construct should be greater than the squared correlation estimates with all other constructs (Hair et al., 2014).

The following section presents the CFA results of two measurement models conducted in Stata 16.

a) CFA – Measurement model 1

Specification and identification

Measurement model 1 is specified with 10 reflective latent constructs. The 10 latent constructs are perceived usage barrier (complexity), reflected by three items (ub1 to ub3); perceived value barrier (high price), reflected by three items (vb1 to vb3); perceived risk barrier (security risk), reflected by three items (rb1 to rb3); perceived image barrier (self-image incongruence), reflected by three items (ib1 to ib3); perceived tradition barrier (need for human interaction), reflected by three items (tb1 to tb3); perceived technological dependence, reflected by three items (td1 to td3); perceived technology anxiety, reflected by three items (ta1 to ta3); perceived ideological barrier (general scepticism), reflected by three items (idb1 to idb3); perceived individual barrier (inertia), reflected by four items (inb1 to inb4); and consumer resistance to smart payment services, reflected by six items (r1 to r6). Further error terms were associated with each measured item in the measurement model.

For identification of measurement model 1, the degrees of freedom were calculated. The total number of items was 34 (p), and the number of distinct parameters to be estimated was 113 (k). Thus, putting these values into the equation: $df=\frac{1}{2}\left(p(p+1)\right)-k$, the degrees of freedom were calculated as $df=\frac{1}{2}\left(34(34+1)\right)-113=482$. *The positive degrees of freedom indicated that measurement model 1 was overidentified and hence recommended for CFA.* Figure 4 demonstrates the initial measurement model 1 consisting of all 34 measured items.

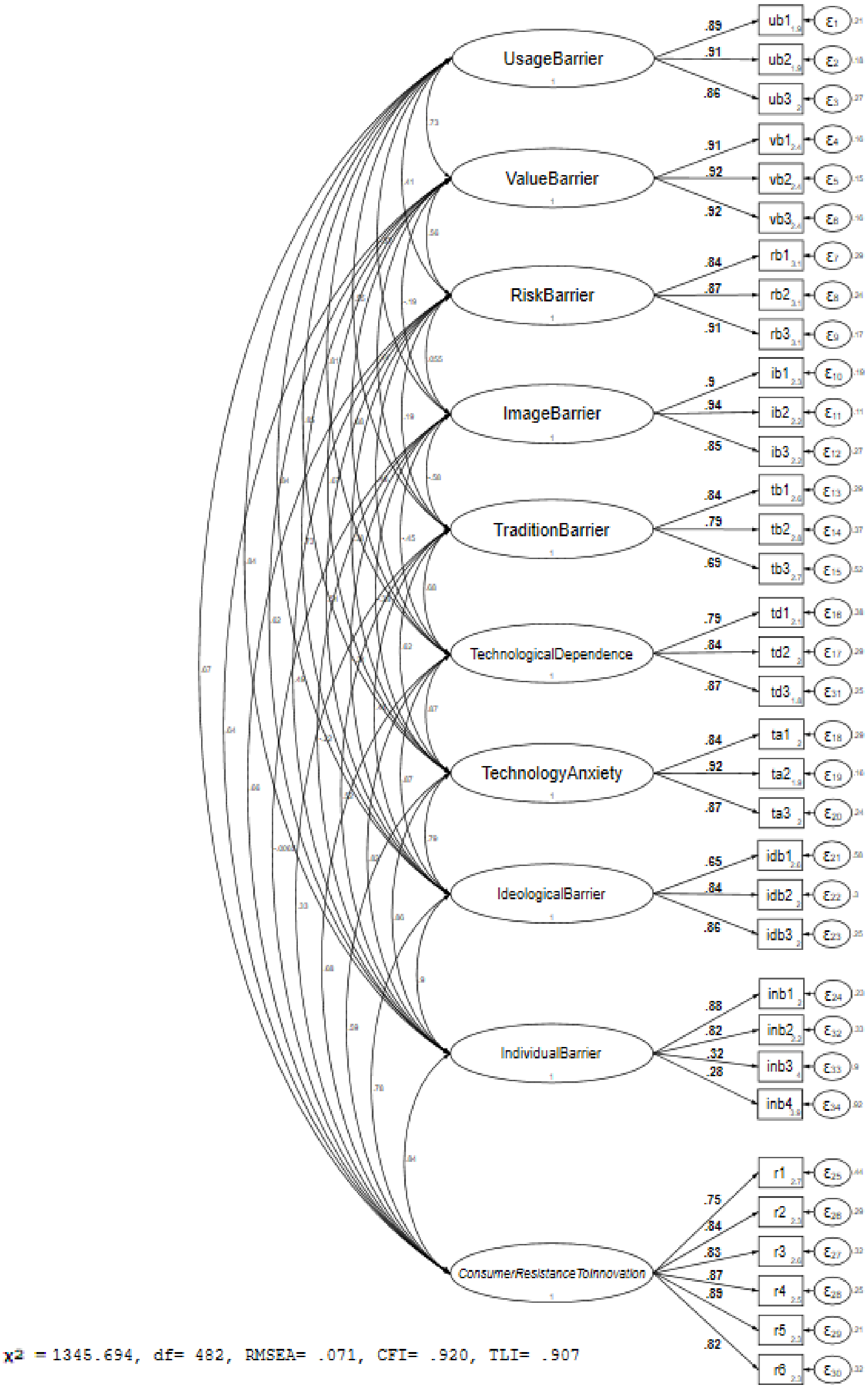


Figure 4: Initial measurement model 1

Assessment of model fit and construct validity

CFA was conducted with 10 latent constructs and 34 measured items. The initial measurement model was analysed for model fit and construct validity. Further, based on the EFA, initial model fit and initial construct validity values, the problematic items were removed to achieve the best possible model fit and proper construct validity.

The results of initial model fit were analysed in terms of absolute fit indices (χ^2/df, RMSEA) and incremental fit indices (CFI, TLI). Table 25 demonstrates the fit statistics from the initial CFA output. The results show that the model fit indices can be improved.

Table 25: Initial fit statistics – measurement model 1

Model fit indices	**χ^2 (df)**	**χ^2/df <3**	**RMSEA <.07 with CFI >.92**	**CFI >.90**	**TLI >.90**
All items	1345.694 (482)	2.792	.071	.920	.907

The values of the construct validity measures were also analysed. Factor loadings were interpreted which were represented as standardized weights in the Stata output. The initial results revealed that most of the factor loadings of the items exceeded the ideal threshold value of .70. However, inb3 and inb4 of the latent construct *perceived individual barrier (inertia)* showed factor loadings less than the minimum threshold value of .50.

Further, the AVE of all 10 latent constructs was calculated using Equation (1). For example, the AVE of *perceived usage barrier (complexity)* was calculated as $\frac{.890^2+.907^2+.856^2}{3}$=.783. The AVEs of the other latent constructs were similarly calculated. The initial results revealed that the AVEs of all the latent constructs were above .50, except for the construct *perceived individual barrier* (AVE=.405).

Next, CR was calculated using Equation (2). For example, the CR of *perceived usage barrier (complexity)* was calculated as $\frac{(.890+.907+.856)^2}{(.890+.907+.856)^2+(.207+.177+.267)} = .915$. The CR values of the other latent constructs were similarly calculated. The initial results revealed that the CR values for all the constructs were above the minimum value of .70.

Table 26 demonstrates the CR and AVE values of all the latent constructs in the measurement model.

Table 26: Initial convergent validity results – measurement model 1

	UB	**VB**	**RB**	**IB**	**TB**	**TD**	**TA**	**IdB**	**InB**	**R**
CR	.915	.941	.909	.928	.820	.873	.909	.832	.819	.933
AVE	.783	.842	.767	.812	.606	.695	.769	.622	.405	.696

Note: AVE = average variance extracted; CR = construct reliability
UB = usage barrier; VB = value barrier; RB = risk barrier; TB = tradition barrier; IB = image barrier; TD = technological dependence; TA = technology anxiety; IdB = ideological barrier; InB = individual barrier; R = consumer resistance to smart payment services

Last, the discriminant validity of all the latent constructs was analysed. For this, the AVE of each latent construct was compared against its squared correlation value with the other latent constructs. The initial results revealed that the AVE values were less than the corresponding inter-construct squared correlations for three constructs: *perceived technological dependence, perceived ideological barrier (general scepticism)* and *perceived individual barrier (inertia)*, indicating discriminant validity problems. The initial results for the other latent constructs satisfied discriminant validity.

Since the model fit indices could be improved and problems were found in respect of construct validity, measurement model 1 was improved by applying the modification indices generated by the Stata output and the removal of problematic items revealed in the results of EFA and initial CFA on a step-by-step basis.

Improving model fit and construct validity

First, item td3, measuring the construct *perceived technological dependence*, was removed from the model, as it was identified as a problematic item in EFA. The removal of this item improved all the model fit indices and the AVE of the construct from .695 to .713. Moreover, the discriminant validity problem for this construct was resolved. Therefore, the other two items (td1 and td2) remained in measurement model 1, reflecting the construct.

Second, item idb1, measuring the construct *perceived ideological barrier (general scepticism)*, was removed as it was a problematic item in EFA, showing the lowest factor loading among the other items measuring the same construct. The removal of this item improved all the model fit indices: CR from .832 to .861 and AVE from .622 to .754. Moreover, the discriminant validity problem for this construct was resolved. Therefore, the other two items (idb2 and idb3) remained in measurement model 1, reflecting the construct.

Third, item inb2, measuring the construct *perceived individual barrier (inertia)*, was removed as it was a problematic item in EFA. The removal of this item also revealed some improvements in model fit indices but no improvements in construct validity measures. Hence, in the next step, another problematic item measuring the same construct was removed.

In the last step, item inb1, measuring the construct *perceived individual barrier (inertia)*, was removed as it was a problematic item in EFA. The removal of this item improved all the model fit indices, increased the AVE of the construct to .530 and solved the discriminant validity problems. Finally, this construct is reflected by two measured items (inb3 and inb4) in the final measurement model 1. Table 27 demonstrates the model fit results on the basis of the step-by-step removal of problematic items.

Table 27: Modifications and final fit statistics – measurement model 1

Model fit indices	**χ^2 (df)**	**χ^2/df <3**	**RMSEA<.07 with CFI >.92**	**CFI >.90**	**TLI >.90**
All items	1345.694 (482)	2.792	.071	.920	.907
Removing td3	1123.434 (447)	2.513	.065	.935	.923
Removing idb1	970.215 (417)	2.326	.061	.945	.934
Removing inb2	907.982 (388)	2.340	.061	.946	.935
Removing inb1	785.592 (360)	2.182	.058	.954	.944

Hence, the final model fit statistics of measurement model 1 (χ^2 = 785.592; df = 360; RMSEA = .058; CFI = .954; and TLI = .944) were within an acceptable range, indicating a good fit.

Furthermore, the factor loadings (standardized coefficients generated by the Stata output) of the measured items, reflecting their corresponding latent constructs, were above the minimum value of .50, with a majority of them exceeding the ideal value of .70, with the highest value of .945 for the item ib2 reflecting the latent construct *perceived image barrier (self-image congruence)*. The CR values of all the latent constructs were above the minimum value of .70 with the highest value of .941 shown by the construct *perceived value barrier (high price)*. Further, the AVE values of all the latent constructs were more than the minimum value of .50, with the highest value of .842 determined by *perceived value barrier (high price)*.

Table 28 shows the factor loadings of all the items, and the CR and AVE of all the latent constructs in the final measurement model 1.

Table 28: Final factor loadings, CR and AVE – measurement model 1

Items		**Latent construct**	**Factor loadings**	**CR**	**AVE**
ub1	<---	Perceived usage barrier (complexity)	.890	.915	.783
ub2	<---		.907		
ub3	<---		.857		
vb1	<---	Perceived value barrier (high price)	.914	.941	.842
vb2	<---		.922		
vb3	<---		.916		
rb1	<---	Perceived risk barrier (security risk)	.839	.908	.767
rb2	<---		.873		
rb3	<---		.913		
ib1	<---	Perceived image barrier (self-image incongruence)	.902	.927	.812
ib2	<---		.945		
ib3	<---		.852		
tb1	<---	Perceived tradition barrier (need for human interaction)	.841	.819	.606
tb2	<---		.795		
tb3	<---		.691		
td1	<---	Perceived technological dependence	.813	.833	.713
td2	<---		.875		
ta1	<---	Perceived technology anxiety	.835	.909	.768
ta2	<---		.919		
ta3	<---		.873		
idb2	<---	Perceived ideological barrier (general scepticism)	.835	.861	.754
idb3	<---		.900		
inb3	<---	Perceived individual barrier (inertia)	.640	.700	.530
inb4	<---		.807		
r1	<---	Consumer resistance to smart payment services	.751	.933	.696
r2	<---		.835		
r3	<---		.834		
r4	<---		.869		
r5	<---		.890		
r6	<---		.816		

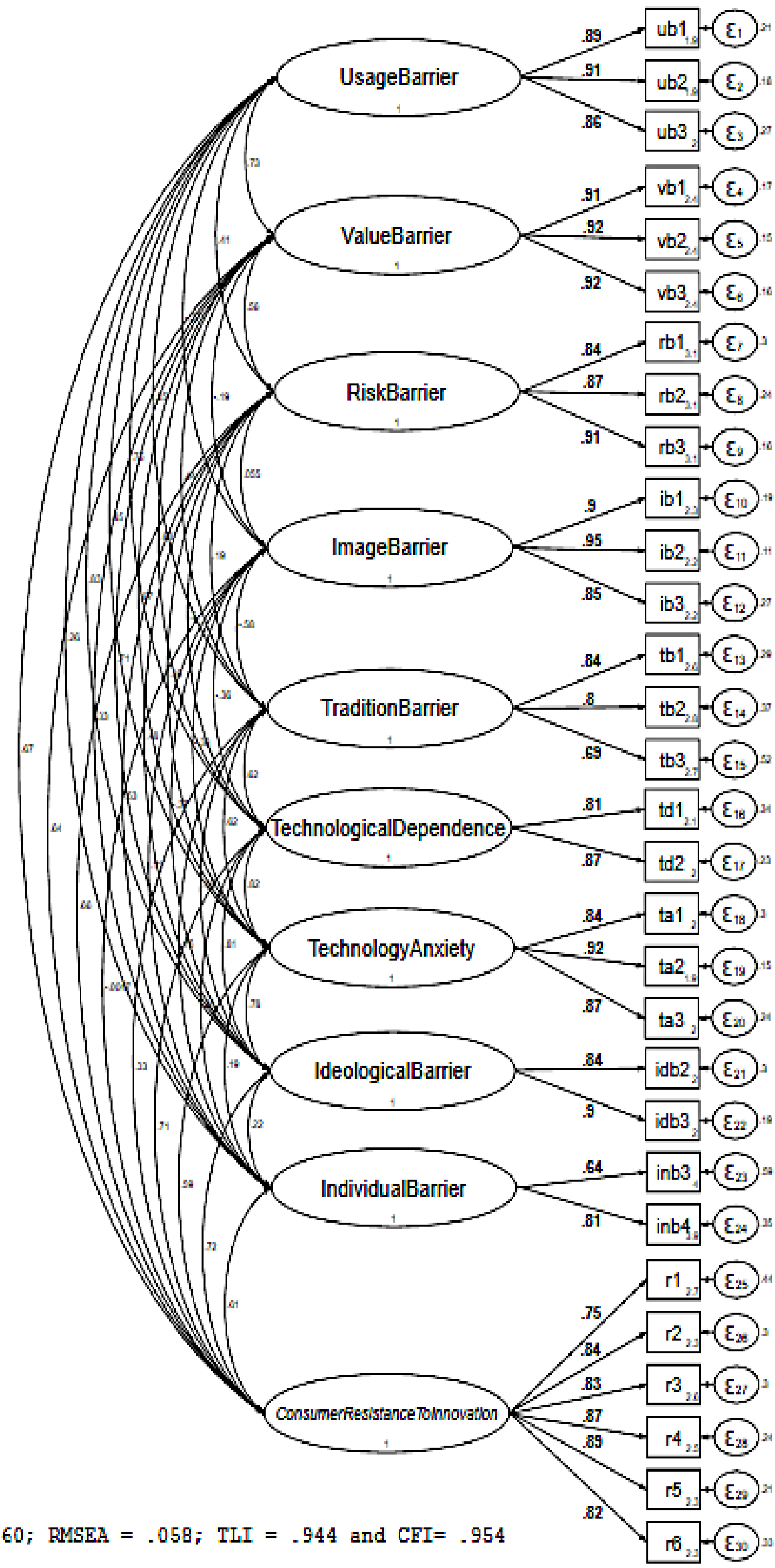
In accordance with Fornell and Larcker's (1981) criterion, the AVE value of each latent construct (as highlighted in Table 29) exceeds its corresponding inter-construct squared correlations, thereby indicating discriminant validity among the latent constructs. Table 29 demonstrates the discriminant validity results of the final measurement model 1.

Table 29: Final discriminant validity results – measurement model 1

Latent constructs	**UB**	**VB**	**RB**	**IB**	**TB**	**TD**	**TA**	**IdB**	**InB**	**R**
UB	***0.783***	0.530	0.169	0.133	0.303	0.564	0.728	0.695	0.065	0.445
VB	0.530	***0.842***	0.317	0.037	0.193	0.469	0.444	0.509	0.112	0.411
RB	0.169	0.317	***0.767***	0.003	0.035	0.248	0.146	0.228	0.279	0.437
IB	0.133	0.037	0.003	***0.812***	0.338	0.132	0.146	0.228	0.279	0.437
TB	0.303	0.193	0.035	0.338	***0.606***	0.386	0.380	0.232	0.024	0.109
TD	0.564	0.469	0.248	0.132	0.386	***0.713***	0.673	0.661	0.059	0.598
TA	0.728	0.444	0.146	0.146	0.380	0.673	***0.768***	0.610	0.035	0.351
IdB	0.695	0.509	0.228	0.228	0.232	0.661	0.610	***0.754***	0.048	0.518
InB	0.065	0.112	0.279	0.279	0.024	0.059	0.035	0.048	***0.530***	0.377
R	0.445	0.411	0.437	0.437	0.109	0.598	0.351	0.518	0.377	***0.696***

Note: UB = usage barrier; VB = value barrier; RB = risk barrier; IB = image barrier; TB = tradition barrier; TD = technological dependence; TA = technology anxiety; IdB = ideological barrier; InB = individual barrier; R = consumer resistance to smart payment services
Diagonal elements in bold represent the AVE values.

Figure 5 demonstrates the final measurement model 1 with adequate model fit and construct validity.



χ2 = 785.592; df = 360; RMSEA = .058; TLI = .944 and CFI= .954

Figure 5: Final measurement model 1

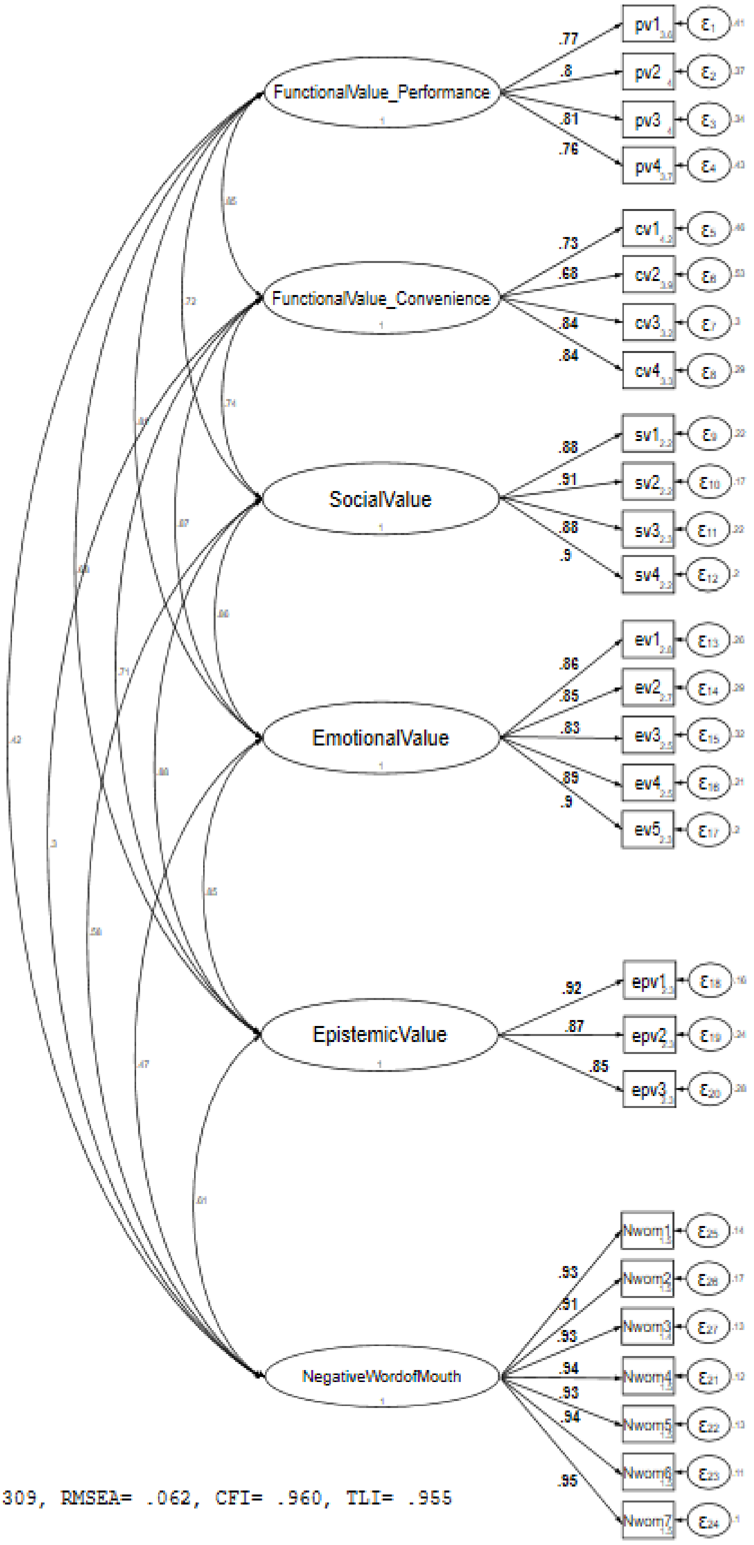
b) CFA – Measurement model 2

Specification and identification

Measurement model 2 was specified with six reflective latent constructs: perceived functional value (performance), reflected by four items (pv1 to pv4); perceived functional value (convenience), reflected by four items (cv1 to cv4); perceived social value, reflected by four items (sv1 to sv4); perceived emotional value, reflected by five items (ev1 to ev5); perceived epistemic value, reflected by three items (epv1 to epv3); and negative word of mouth, reflected by seven items (Nwom1 to Nwom7). Further error terms were associated with each observed variable in measurement model 2.

The degrees of freedom were calculated for identification of measurement model 2. The total number of items was 27 (p) and the number of distinct parameters to be estimated was 69 (k). Thus, putting these values into the equation: $df=\frac{1}{2}\left(p(p+1)\right)-k$, the degrees of freedom were calculated as $df=\frac{1}{2}\left(27(27+1)\right)-69=309$. *The positive value of the degrees of freedom indicated that measurement model 2 was overidentified and hence recommended for CFA.*

Figure 6 shows the initial measurement model 2 consisting of all 27 measured items.



χ2= 728.563, df= 309, RMSEA= .062, CFI= .960, TLI= .955

Figure 6: Initial measurement model 2

Assessment of model fit and construct validity

CFA was conducted with six latent constructs and 27 measured items. The initial measurement model 2 was analysed for model fit and construct validity. Based on the EFA, initial model fit and initial construct validity values, problematic items were removed to achieve the best possible model fit and appropriate construct validity.

The results of initial model fit were analysed in terms of absolute fit indices (χ^2/df, RMSEA) and incremental fit indices (CFI, TLI). Table 30 demonstrates the fit statistics from the initial CFA output. Although the initial values of the model fit indices were acceptable, these could be further improved.

Table 30: Initial fit statistics – measurement model 2

Model fit indices	**χ^2 (df)**	**χ^2/df <3**	**RMSEA<.07 with CFI >.92**	**CFI >.90**	**TLI >.90**
All items	728.563 (309)	2.357	.062	.960	.955

The values of the construct validity measures were then analysed. The standardized coefficients generated from the Stata output were represented as factor loadings. The initial results revealed that the majority of the factor loadings of the items were above the ideal threshold level of .70. Only one item of the latent construct *perceived functional value (convenience)* (i.e., cv2) showed a factor loading of less than .70 but above the minimum level of .50.

The AVEs of all six latent constructs were calculated using Equation (1). For example, the AVE of *perceived functional value (performance)* is calculated as $\frac{.766^2+.795^2+.813^2+.756^2}{4}$=.614. The AVE values of the other latent constructs were similarly calculated. The initial results revealed that the AVE values of all the latent constructs were above .50.

Construct reliability was calculated using Equation (2). For example, the CR of *perceived functional value (performance)* is calculated as $\frac{(.766+.795+.813+.756)^2}{(.766+.795+.813+.756)^2+(.413+.367+.339+.428)}$ = .863. The

CR values of the other latent constructs were similarly calculated. The initial results revealed that the CR for all the constructs was above the minimum value of .70. Table 31 shows the CR and AVE values of all the latent constructs in the initial measurement model 2.

Table 31: Initial convergent validity results – measurement model 2

	PV	**CV**	**SV**	**EV**	**EpV**	**NWOM**
CR	.863	.863	.941	.936	.912	.979
AVE	.614	.604	.798	.745	.775	.871

Note: PV = functional value (performance); CV = functional value (convenience); SV = social value; EV = emotional value; EpV = epistemic value; NWOM = negative word of mouth

Last, the discriminant validity of all the latent constructs was analysed. For this, the AVE value of each latent construct was compared against its squared correlation values with all the other latent constructs. The initial results revealed that the AVE values were less than the inter-construct squared correlations for three latent constructs: *perceived functional value (performance), perceived functional value (convenience),* and *perceived emotional value*, thereby indicating discriminant validity problems.

Since the model fit indices could be improved and there were problems in terms of construct validity, measurement model 2 was improved by applying the modification indices generated by the Stata output and the removal of problematic items revealed in the EFA results and the initial CFA on a step-by-step basis.

Improving model fit and construct validity

First, item cv2, measuring the construct *perceived functional value (convenience)*, was removed from the model as it was identified as a problematic item in EFA, showing the lowest factor loading among the items reflecting the construct. The removal of this item improved all the model fit indices and the AVE of the construct from .604 to .646.

Second, the item cv1, measuring the construct *perceived functional value (convenience)*, was removed as it was a problematic item in EFA, showing the next lowest factor loading among the items reflecting the construct. The removal of this item improved some of the model fit indices and the AVE of the construct from .646 to .722. However, the other two items (cv3 and cv4) remained in the measurement model reflecting the construct. Moreover, the discriminant validity problem of the construct was resolved at this stage.

Third, the item pv4, measuring the construct *perceived functional value (performance)*, was removed as it was a problematic item in EFA, showing the lowest factor loading among the items measuring the same construct. The removal of this item improved some of the model fit indices and the AVE from .614 to .632.

Fourth, the item pv1, measuring the construct *perceived functional value (performance)*, was removed as it was a problematic item in the EFA, showing the next lowest factor loading among the items measuring the same construct. The removal of this item revealed a minor improvement in the model fit indices and increased the AVE from .632 to .661. Moreover, the discriminant validity problem of the construct was also resolved. The other two items (pv2 and pv3) remained in the measurement model reflecting the latent construct.

Fifth, the item ev3, measuring the construct *perceived emotional value*, was removed as it was a problematic item in EFA, showing the lowest factor loading among the items measuring the same construct. The removal of this item revealed minor improvements in the model fit indices and increased the AVE of the construct from .745 to .759. However, this did not resolve the discriminant validity problem and hence the removal of further problematic items was continued.

In the final step, item ev2, measuring the construct *perceived emotional value*, was removed as it was a problematic item in EFA, showing the next lowest factor loading among the items measuring the same construct. The removal of this item improved the majority of the model fit indices and increased the AVE of the construct from .759 to .774. Finally, the removal of this item resolved the discriminant validity problem and hence the construct is reflected by three measured items (ev1, ev4 and ev5). Table 32 demonstrates the model fit results of the removal on a step-by-step basis of problematic items.

Table 32: Modifications and final fit statistics – measurement model 2

Model fit indices	**χ^2 (df)**	**χ^2/df <3**	**RMSEA<.07 with CFI >.92**	**CFI >.90**	**TLI >.90**
All items	728.563 (309)	2.357	.062	.960	.955
Removing cv2	630.604 (283)	2.228	.059	.966	.961
Removing cv1	574.829 (259)	2.219	.059	.969	.964
Removing pv4	525.314 (236)	2.225	.059	.971	.966
Removing pv1	492.254 (214)	2.300	.061	.971	.966
Removing ev3	442.520 (193)	2.298	.060	.973	.967
Removing ev2	392.041 (173)	2.266	.060	.975	.970

The final model fit statistics of measurement model 2 (χ^2 = 392.041; df = 173; RMSEA = .060; CFI= .975 and TLI = .970) were within an acceptable range, indicating a good fit.

Furthermore, all the factor loadings (standardized coefficients generated by the Stata output) of the measured items reflecting their corresponding latent constructs were above the ideal value of .70 and as high as .949 as shown by the item Nwom7, reflecting the latent construct *negative word of mouth*. The CR values of all the latent constructs were above the minimum value of .70, with the highest value of .976 shown by the construct *negative word of mouth*. Further, the AVE values of all the latent constructs were above the minimum value of .50, with the highest value of .868 shown by the construct *negative word of mouth*.

Table 33 shows the factor loadings of all the items and the CR and AVE values of all the constructs in the final measurement model 2.

Table 33: Final factor loadings and convergent validity – measurement model 2

Items		Latent construct	Factor loadings	CR	AVE
pv2	<---	Functional value (performance)	.824	.796	.661
pv3	<---		.801		
cv3	<---	Functional value (convenience)	.863	.839	.722
cv4	<---		.835		
sv1	<---	Social value	.883	.941	.798
sv2	<---		.912		
sv3	<---		.881		
sv4	<---		.897		
ev1	<---	Emotional value	.837	.913	.774
ev4	<---		.890		
ev5	<---		.909		
epv1	<---	Epistemic value	.916	.912	.775
epv2	<---		.874		
epv3	<---		.847		
Nwom1	<---	Negative word of mouth	.921	.976	.868
Nwom2	<---		.903		
Nwom3	<---		.934		
Nwom4	<---		.942		
Nwom5	<---		.931		
Nwom6	<---		.941		
Nwom7	<---		.949		

Moreover, in accordance with Fornell and Larcker’s (1981) criterion, the AVE value of each construct (highlighted in Table 34) exceeds its corresponding inter-construct squared correlations, thereby indicating the discriminant validity among the latent constructs. Table 34 demonstrates the discriminant validity results of the final measurement model 2.

Table 34: Final discriminant validity results – measurement model 2

Latent constructs	PV	CV	SV	EV	EpV	NWOM
PV	***0.661***	0.649	0.471	0.601	0.419	0.169
CV	0.649	***0.722***	0.573	0.659	0.531	0.110
SV	0.471	0.573	***0.798***	0.758	0.770	0.340
EV	0.601	0.659	0.758	***0.774***	0.746	0.248
EpV	0.419	0.531	0.770	0.746	***0.775***	0.370
NWOM	0.169	0.110	0.340	0.248	0.370	***0.868***

Note: PV = functional value (performance); CV = functional value (convenience); SV = social value; EV = emotional value; EpV = epistemic value; NWOM = Negative word of mouth.
Diagonal elements in bold represent AVE values.

Figure 7 shows the final measurement model 2 with adequate model fit and construct validity.

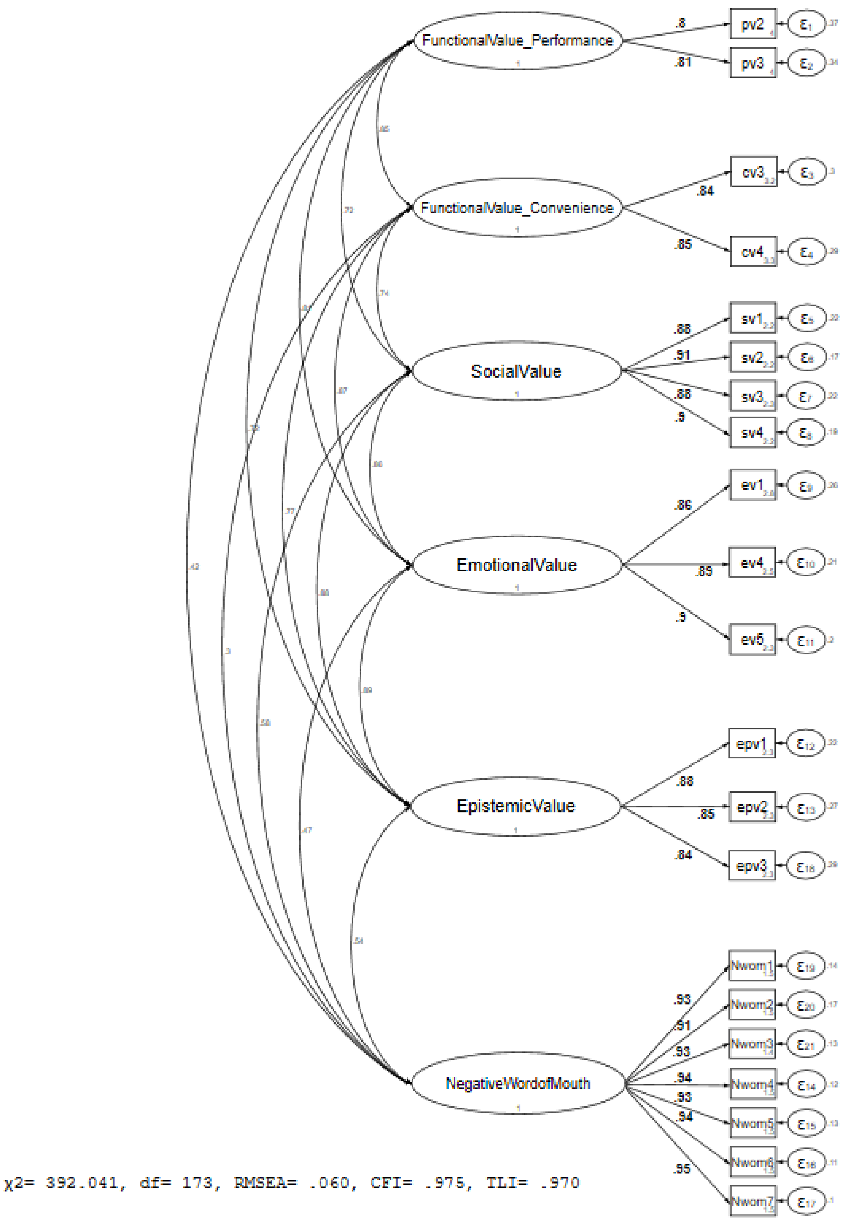


Figure 7: Final measurement model 2

5.4 Descriptive analyses of the final latent constructs

a) Consumer resistance to smart payment services

The final latent construct is reflected by six items: r1, r2, r3, r4, r5 and r6. The final scale has a maximum value of 6.13, a minimum value of .91 and a mean value of 3.88. A histogram was plotted to show the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. A specific test for statistical normality, the Kolmogorov-Smirnov test, was also performed and analysed for statistical significance. The results revealed that the KS test was significant with a value of .078, indicating non-normality. However, the skewness value of -.330 and the kurtosis value of -.749 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, demonstrating minor departures from the normal distribution. Figure 8 shows the distribution of the construct *consumer resistance to smart payment services*.

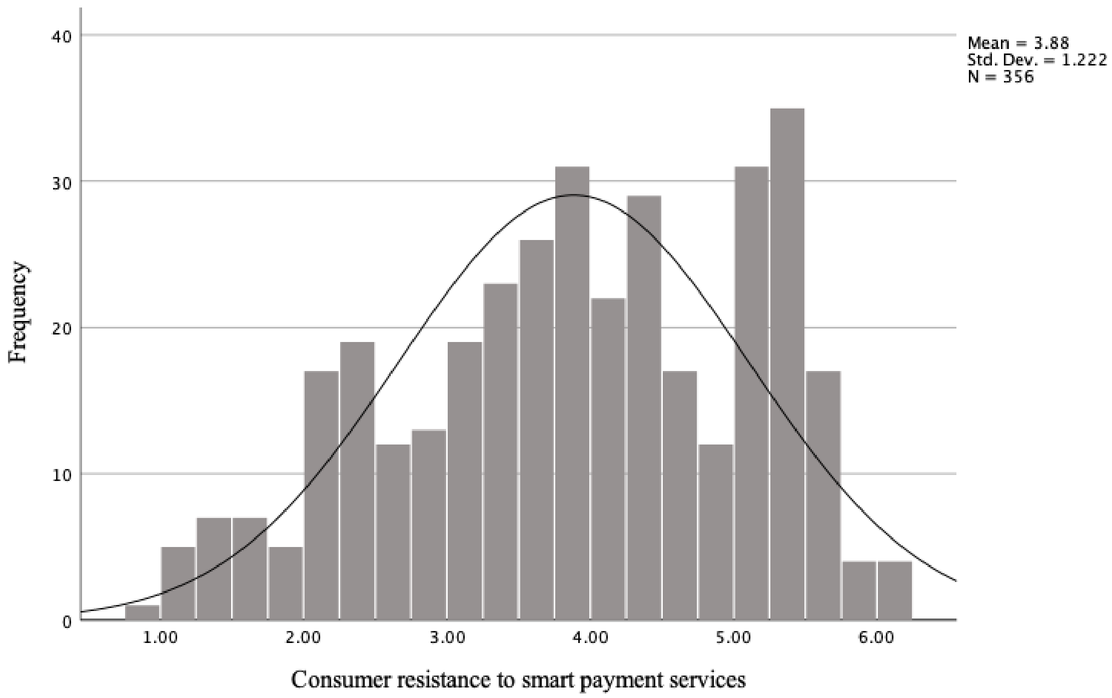


Figure 8: Histogram plot for consumer resistance to smart payment services

b) Perceived usage barrier (complexity)

The final latent construct is reflected by three items: ub1, ub2 and ub3. The final scale has a maximum value of 6.52, a minimum value of .80 and a mean value of 3.46. A histogram was plotted to show the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .092, indicating non-normality. However, the skewness value of .270 and kurtosis value of -1.141 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, showing only minor departures from a normal distribution. Figure 9 demonstrates the distribution of the construct *perceived usage barrier*.

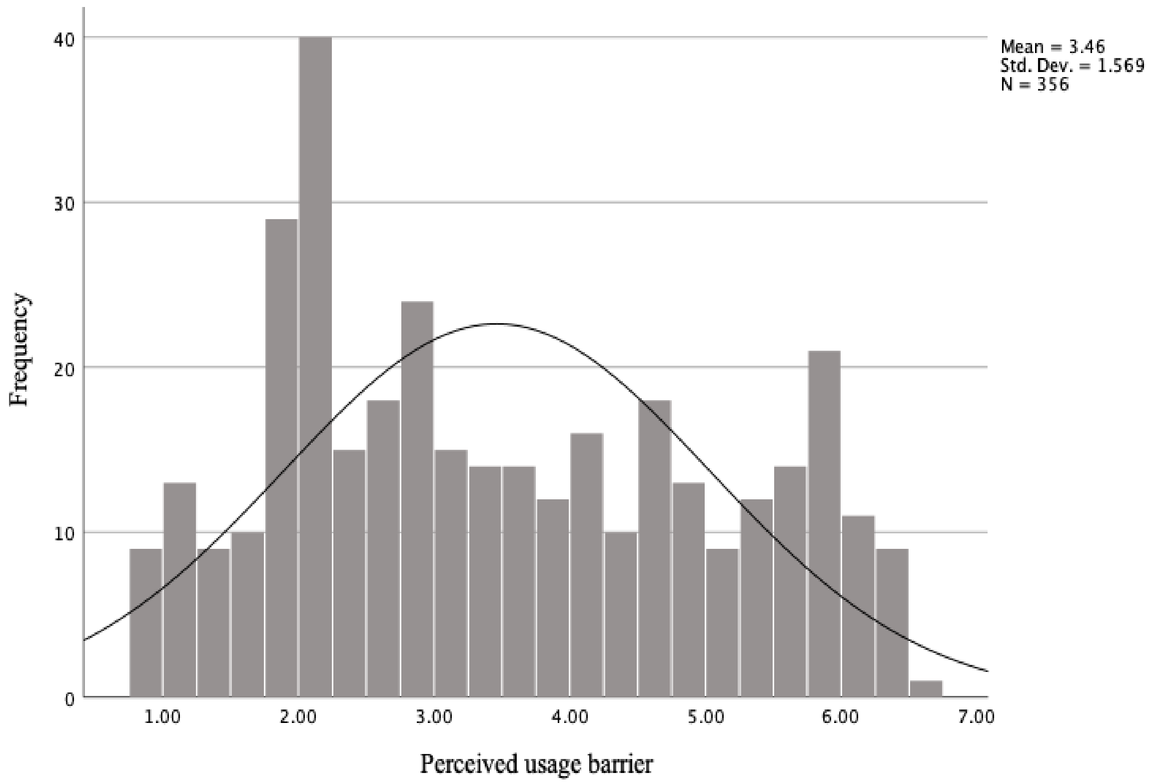


Figure 9: Histogram plot for perceived usage barrier (complexity)

c) Perceived value barrier (high price)

The final latent construct is reflected by three items: vb1, vb2 and vb3. The final scale has a maximum value of 6.79, a minimum value of 1 and a mean value of 4.14. A histogram was plotted to show the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and analysed for statistical significance. The results revealed that the KS test was significant with a value of .080, indicating non-normality. However, the skewness value of -.275 and the kurtosis value of -.967 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 10 shows the distribution of the construct *perceived value barrier*.

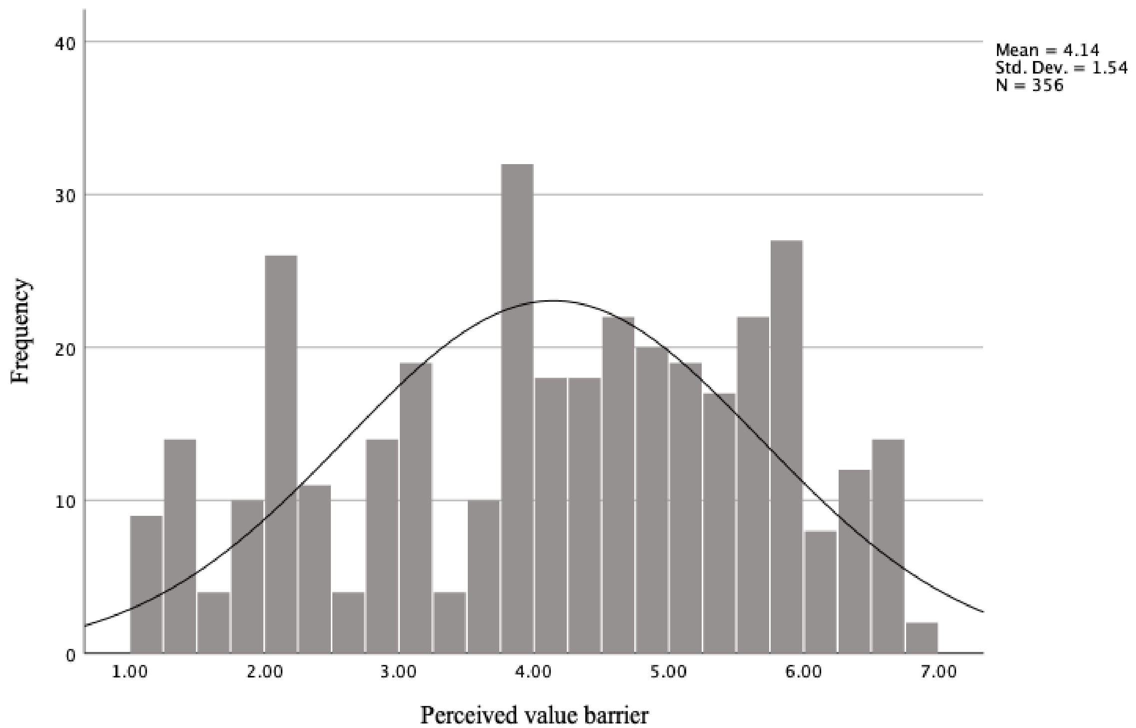


Figure 10: Histogram plot for perceived value barrier (high price)

d) Perceived risk barrier (security risk)

The final latent construct is reflected by three items: rb1, rb2 and rb3. The final scale has a maximum value of 6.40, a minimum value of .91 and a mean value of 4.32. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and analysed for statistical significance. The results reveal that the KS test was significant with a value of .076, indicating non-normality. However, the skewness value of -.542 and the kurtosis value of -.380 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 11 shows the distribution of the construct *perceived risk barrier*.

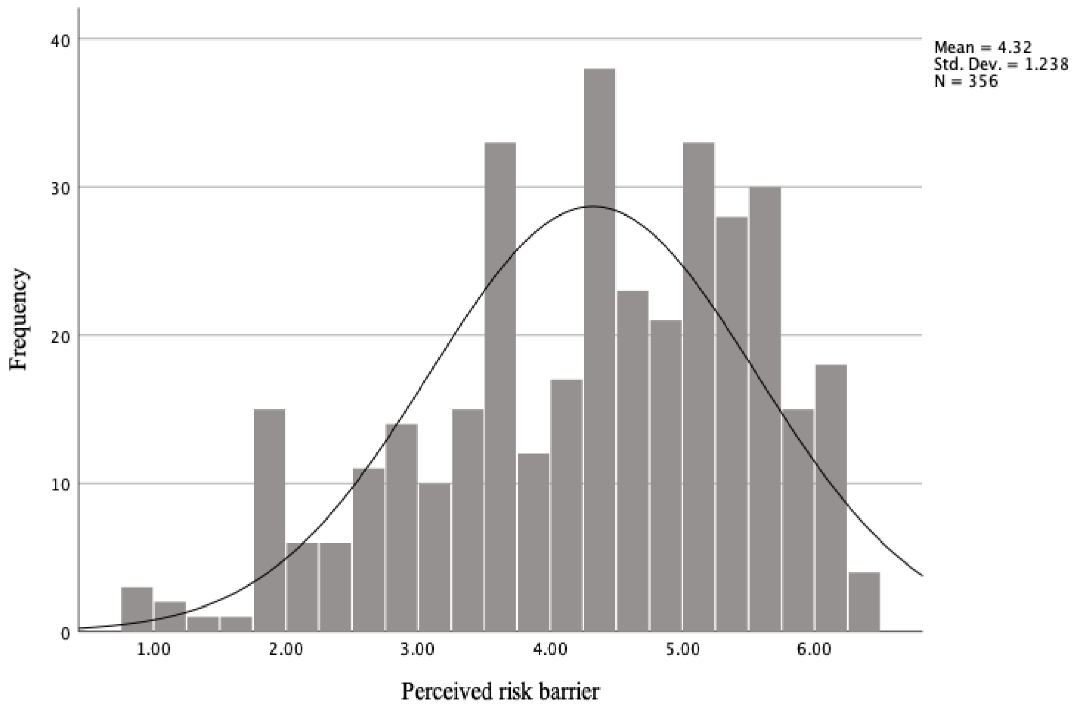


Figure 11: Histogram plot for perceived risk barrier (security risk)

e) Perceived image barrier (self-image incongruence)

The final latent construct is reflected by three items: ib1, ib2 and ib3. The final scale has a maximum value of 6.22, a minimum value of .47 and a mean value of 3.15. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results analysed for statistical significance. The results revealed that the KS test was significant with a value of .077, indicating non-normality. However, the skewness value of .340 and the kurtosis value of -.784 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 12 shows the distribution of the construct *perceived image barrier*.

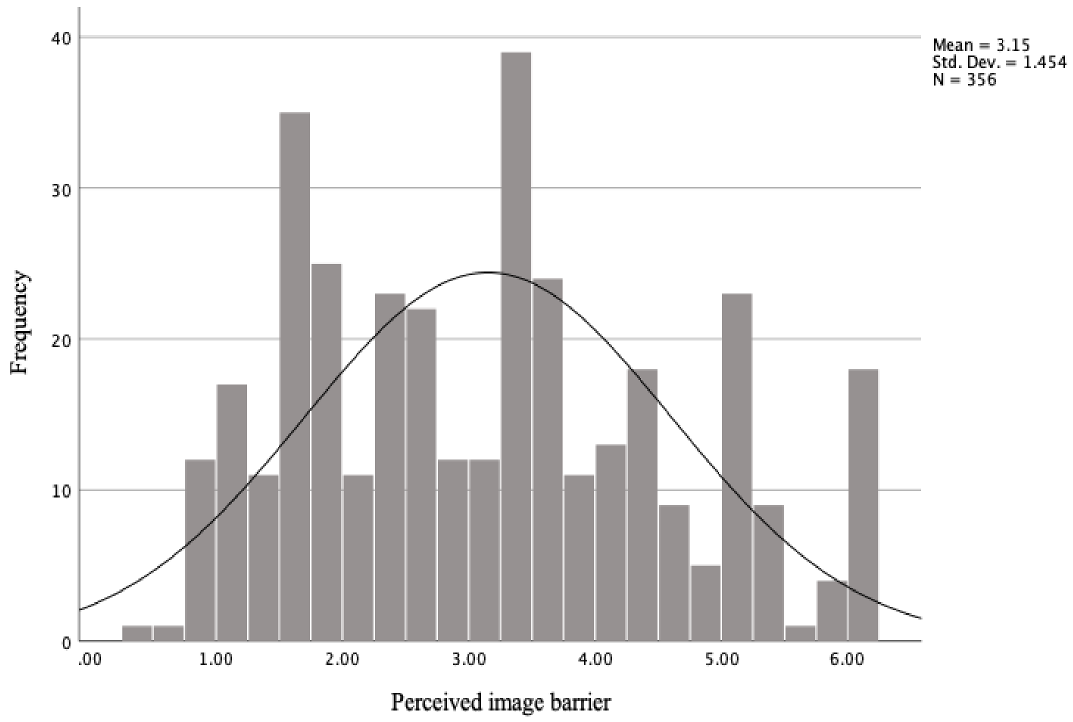


Figure 12: Histogram plot for perceived image barrier (self-image incongruence)

f) Perceived tradition barrier (need for human interaction)

The final latent construct is reflected by three items: tb1, tb2 and tb3. The final scale has a maximum value of 5.77, a minimum value of .003 and a mean value of 3.43. A histogram was plotted to depict the normal distribution of the variable, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results reveal that the KS test was significant with a value of .048, indicating non-normality. However, the skewness value of -.228 and the kurtosis value of -.514 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 13 shows the distribution of the construct *perceived tradition barrier*.

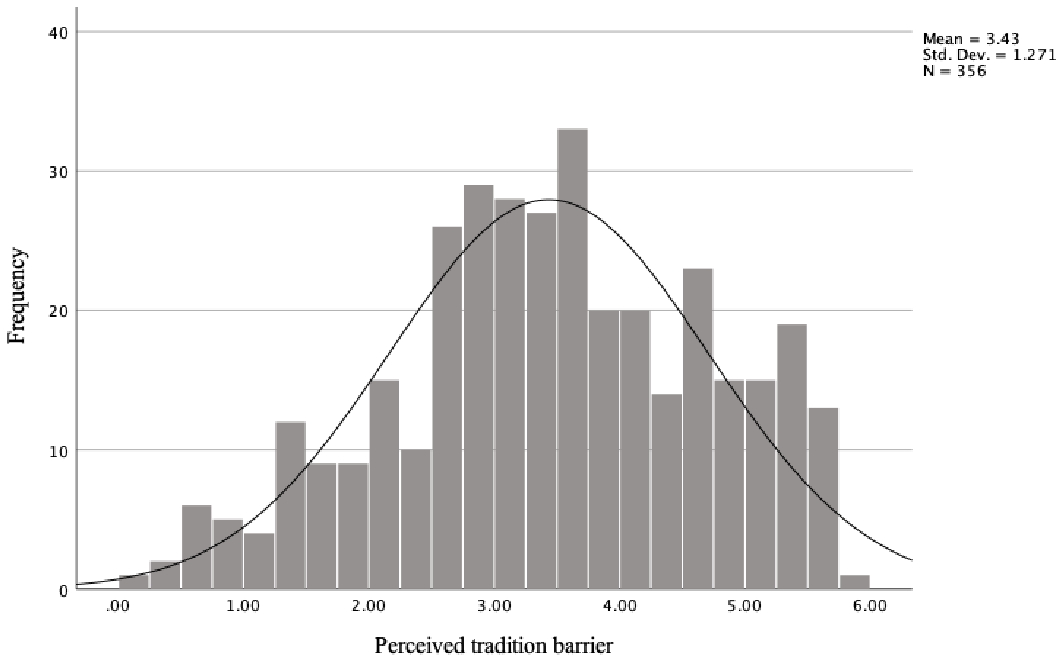


Figure 13: Histogram plot for perceived tradition barrier (need for human interaction)

g) Perceived technological dependence

The final latent construct is reflected by two items: td1 and td2. The final scale has a maximum value of 6.16, a minimum value of .92 and a mean value of 3.56. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .063, indicating non-normality. However, the skewness value of .121 and the kurtosis value of -1.070 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 14 shows the distribution of the construct *perceived technological dependence*.

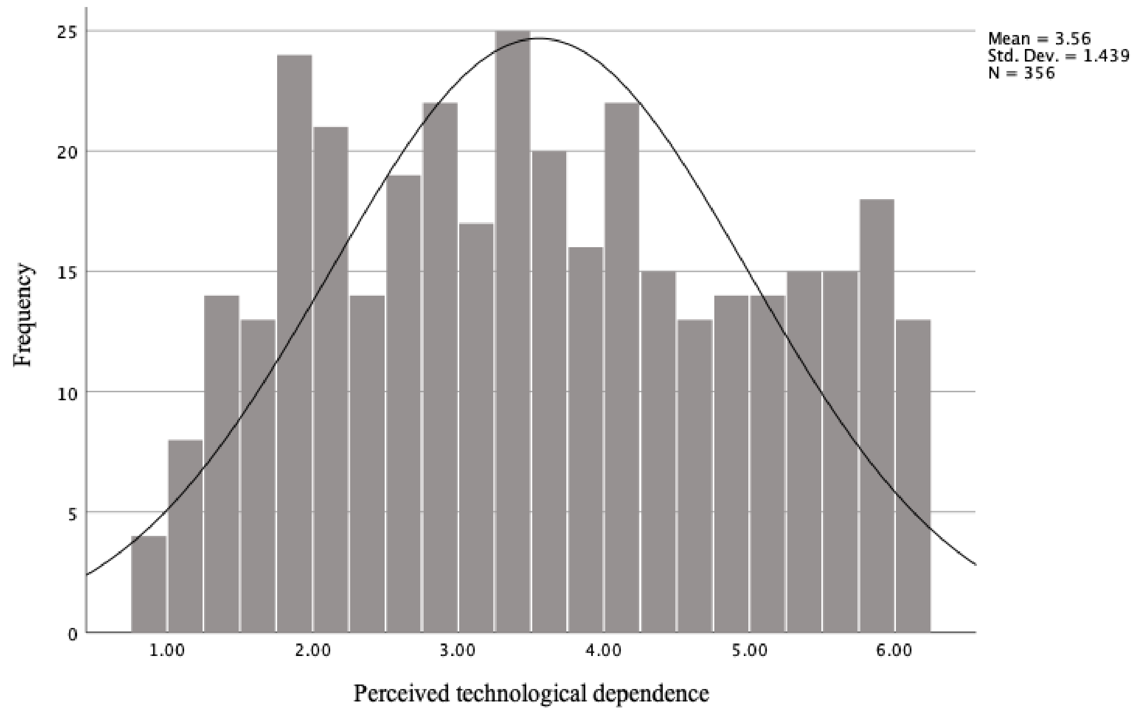


Figure 14: Histogram plot for perceived technological dependence

h) Perceived technology anxiety

The final latent construct is reflected by three items: ta1, ta2 and ta3. The final scale has a maximum value of 6.19, a minimum value of .92 and a mean value of 3.35. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .087, indicating non-normality. However, the skewness value of .201 and the kurtosis value of -1.136 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 15 shows the distribution of the construct *perceived technology anxiety*.

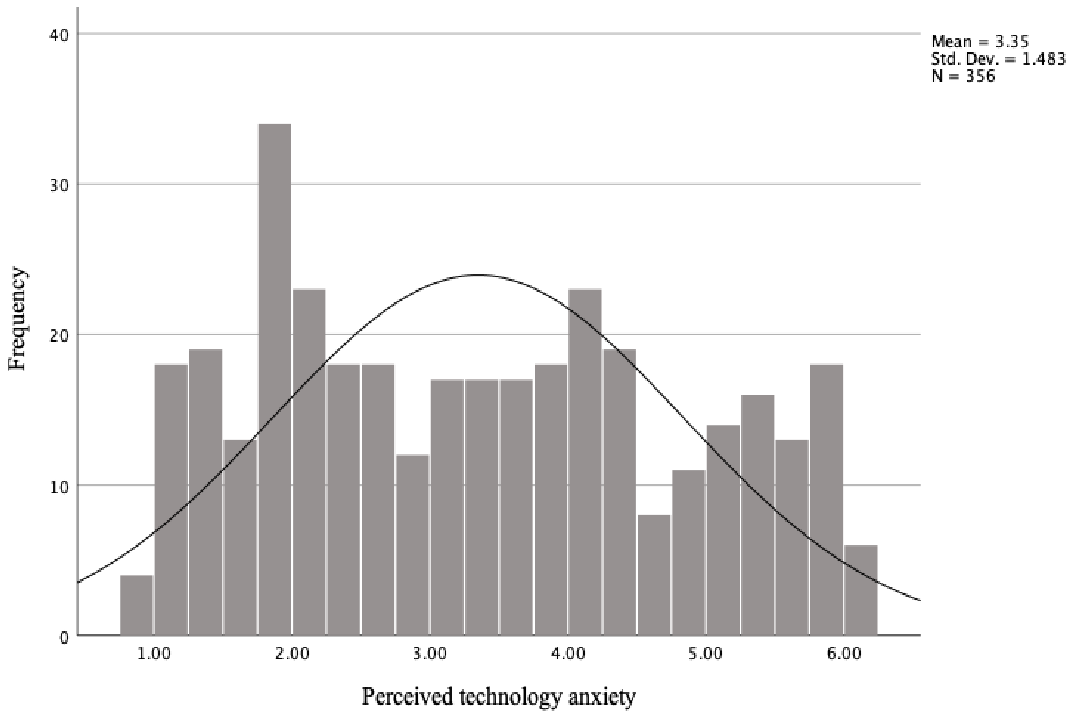


Figure 15: Histogram plot for perceived technology anxiety

i) Perceived ideological barrier (general scepticism)

The final latent construct is reflected by two items: idb2 and idb3. The final scale has a maximum value of 5.57, a minimum value of .004 and a mean value of 2.81. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results analysed for statistical significance. The results revealed that the KS test was significant with a value of .077, indicating non-normality. However, the skewness value of .216 and the kurtosis value of -1.003 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 16 shows the distribution of the construct *perceived ideological barrier*.

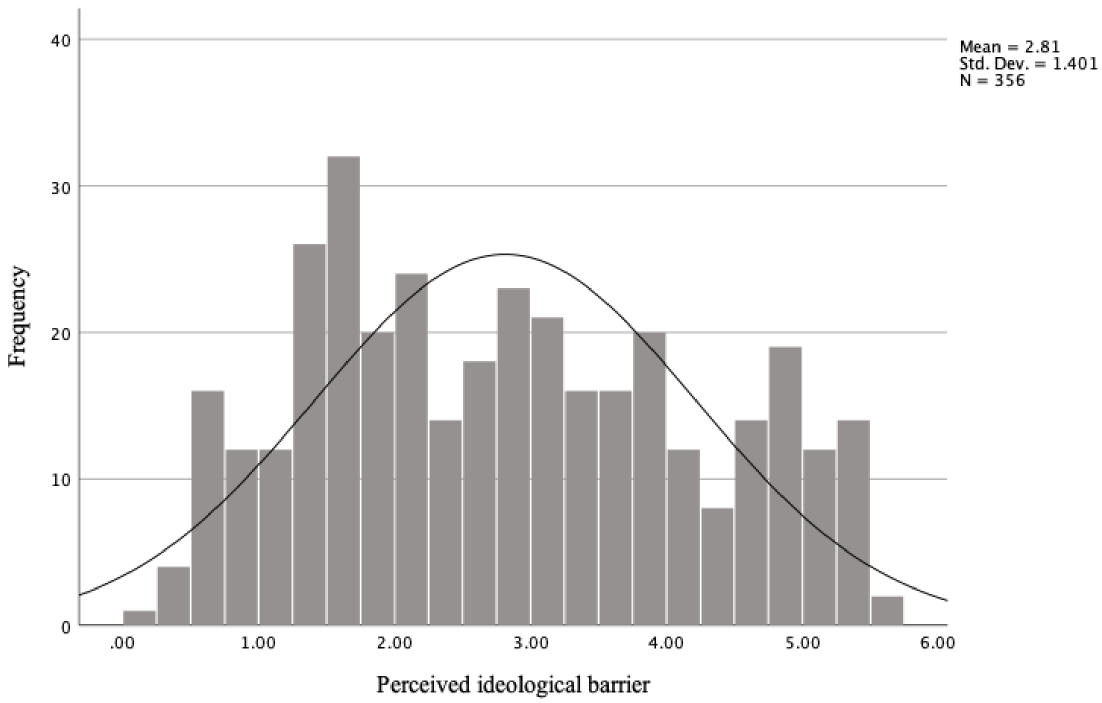


Figure 16: Histogram plot for perceived ideological barrier (general scepticism)

j) Perceived individual barrier (inertia)

The final latent construct is reflected by two items: inb3 and inb4. The final scale has a maximum value of 4.88, a minimum value of .63 and a mean value of 3.28. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .091, indicating non-normality. However, the skewness value of -.660 and the kurtosis value of .441 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 17 demonstrates the distribution of the construct *perceived individual barrier*.

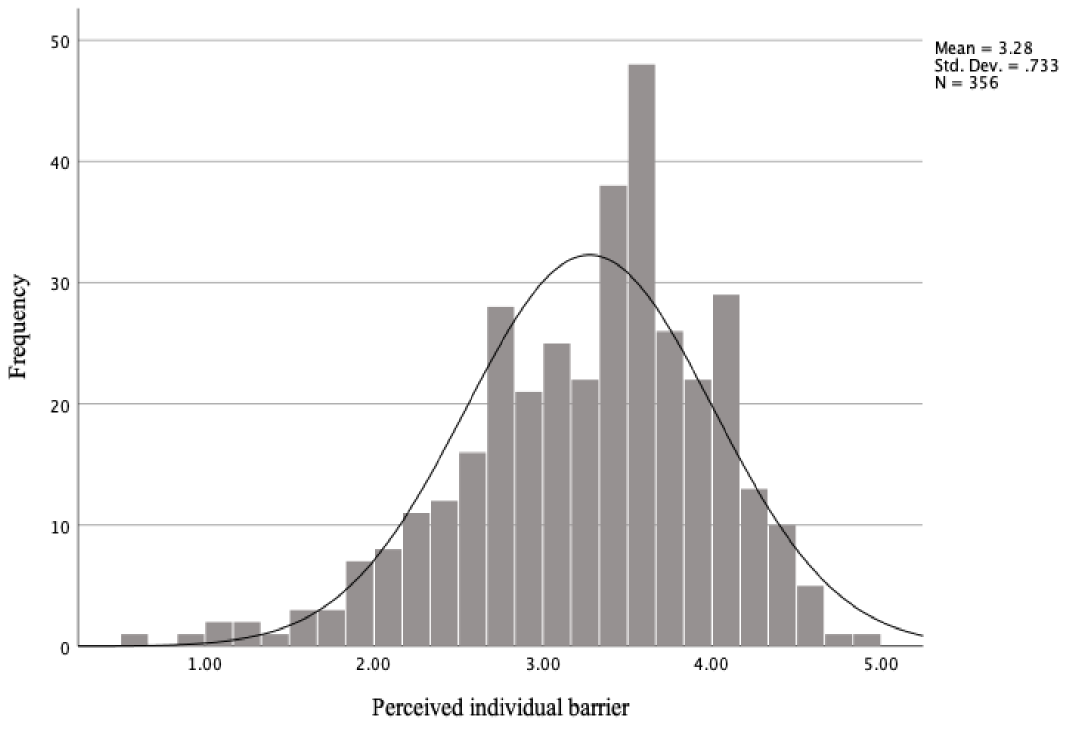


Figure 17: Histogram plot for perceived individual barrier (inertia)

k) Perceived functional value (performance)

The final latent construct is reflected by two items: pv2 and pv3. The final scale has a maximum value of 5.85, a minimum value of .85 and a mean value of 4.04. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .064, indicating non-normality. However, the skewness value of -.211 and the kurtosis value of .011 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 18 shows the distribution of the construct *perceived functional value (performance)*.

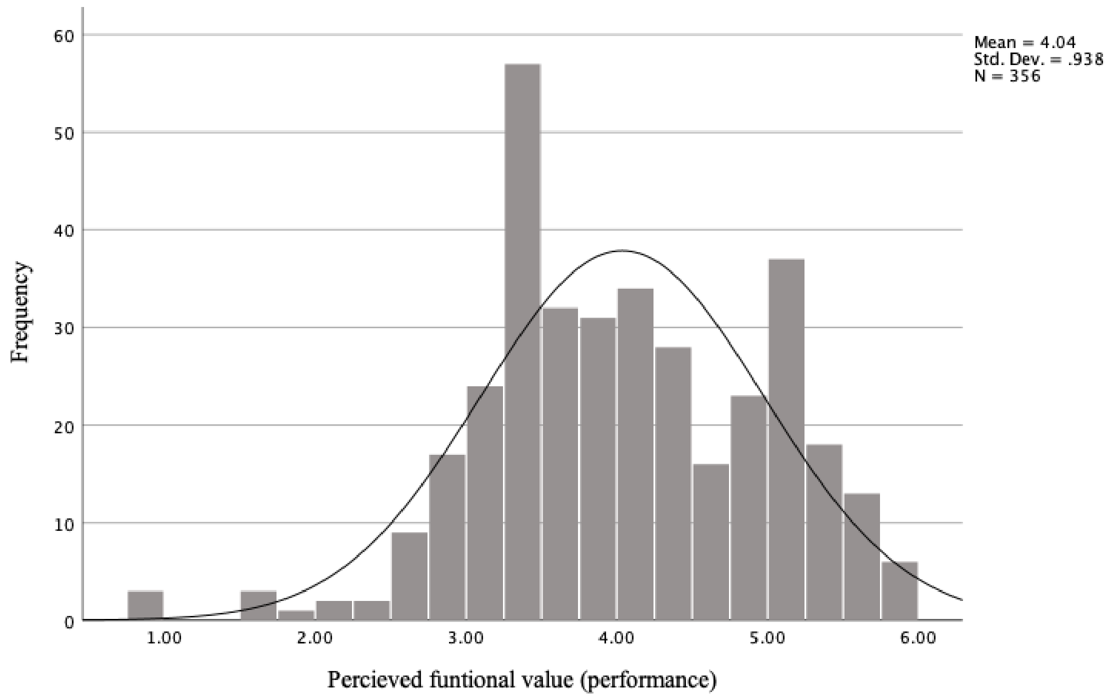


Figure 18: Histogram plot for perceived functional value (performance)

l) Perceived functional value (convenience)

The final latent construct is reflected by two items: cv3 and cv4. The final scale has a maximum value of 6.79, a minimum value of .77 and a mean value of 4.36. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .068, indicating non-normality. However, the skewness value of -.407 and the kurtosis value of -.220 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 19 shows the distribution of the construct *perceived functional value (convenience)*.

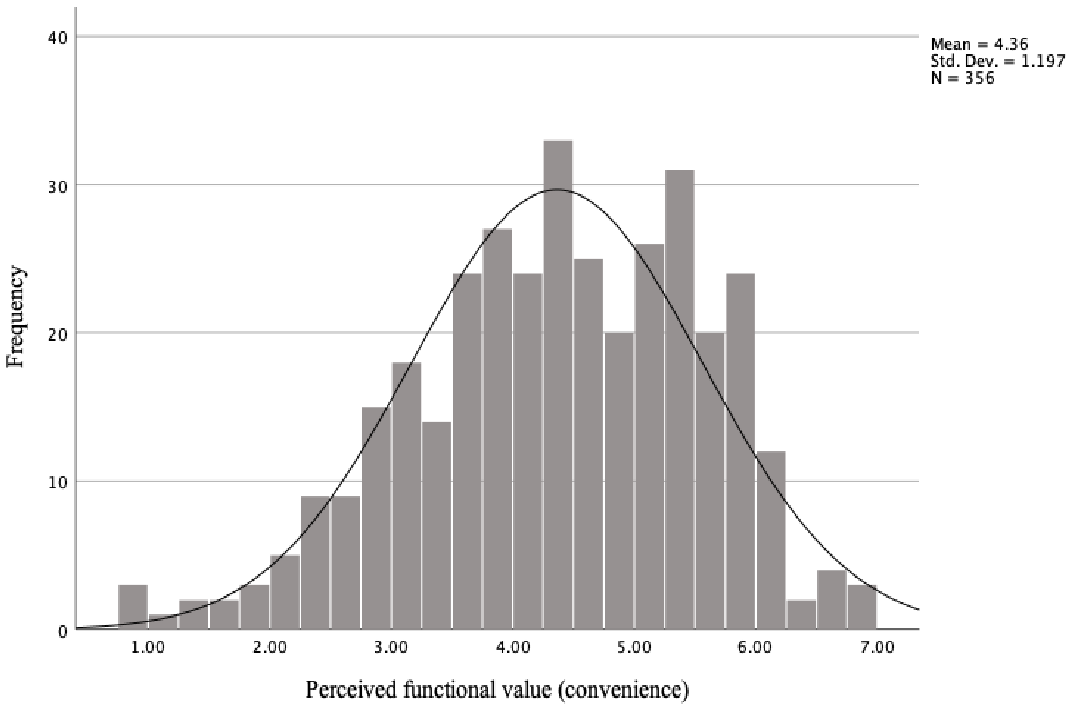


Figure 19: Histogram plot for perceived functional value (convenience)

m) Perceived social value

The final latent construct is reflected by four items: sv1, sv2, sv3 and sv4. The final scale has a maximum value of 6.89, a minimum value of 1.01 and a mean value of 4.09. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .076, indicating non-normality. However, the skewness value of -.158 and the kurtosis value of -.988 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 20 shows the distribution of the construct *perceived social value*.

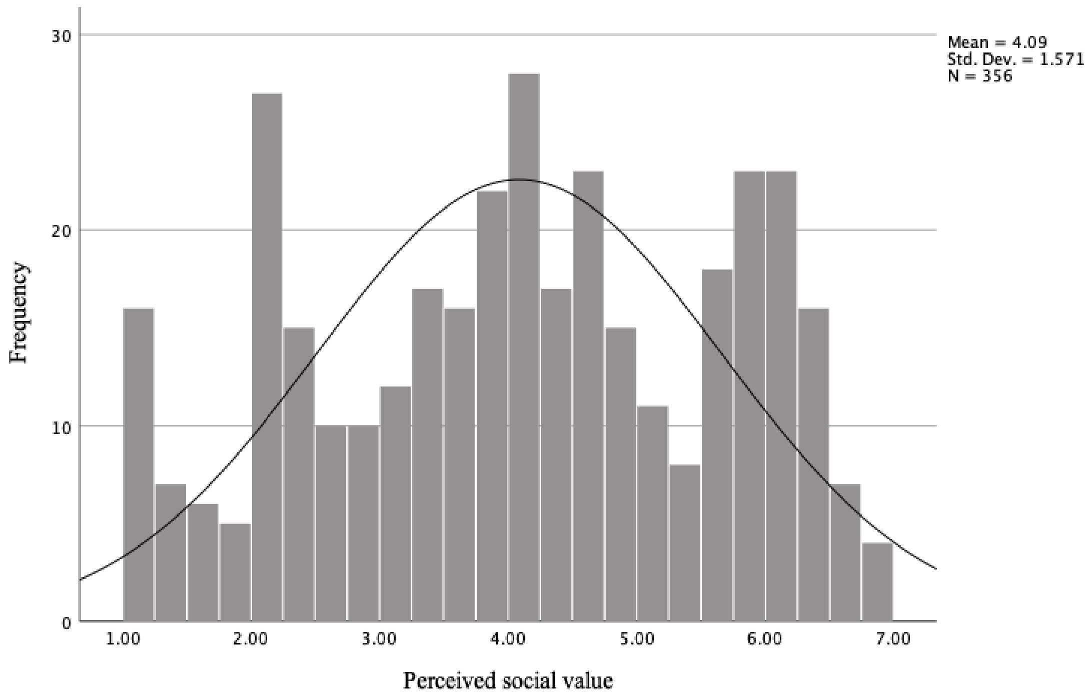


Figure 20: Histogram plot for perceived social value

n) Perceived emotional value

The final latent construct is reflected by three items: ev1, ev4 and ev5. The final scale has a maximum value of 7.29, a minimum value of 1.04 and a mean value of 4.51. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .057, indicating non-normality. However, the skewness value of -.225 and the kurtosis value of -.714 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 21 shows the distribution of the construct *perceived emotional value*.

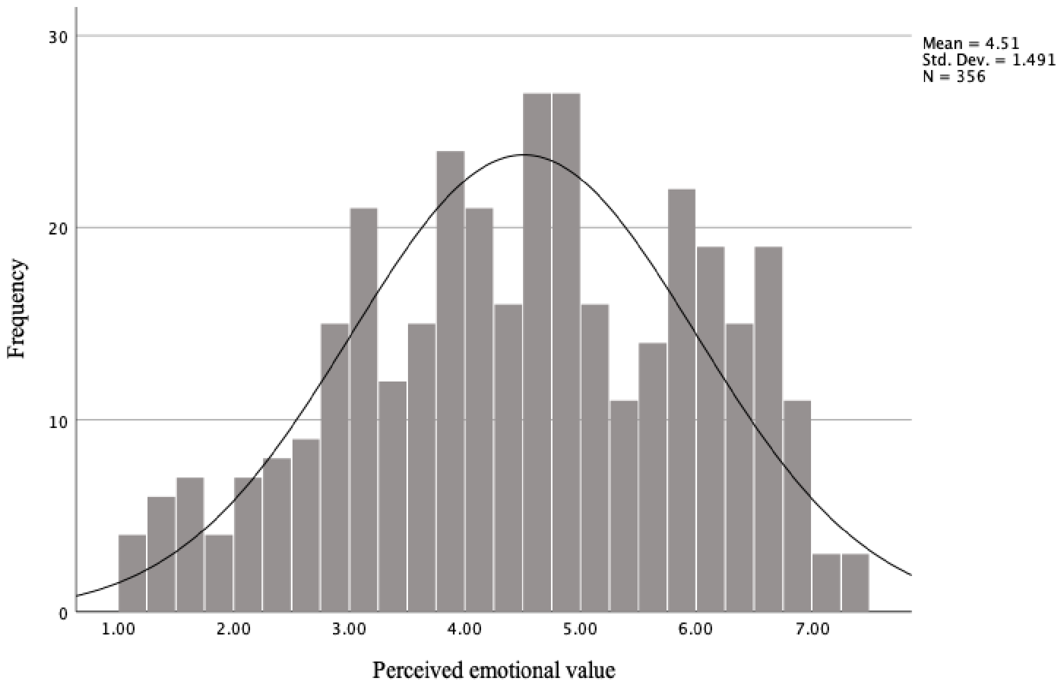


Figure 21: Histogram plot for perceived emotional value

o) Perceived epistemic value

The final latent construct is reflected by three items: epv1, epv2 and epv3. The final scale has a maximum value of 6.25, a minimum value of .91 and a mean value of 3.71. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .052, indicating non-normality. However, the skewness value of -.183 and the kurtosis value of -.894 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 22 shows the distribution of the construct *perceived epistemic value*.

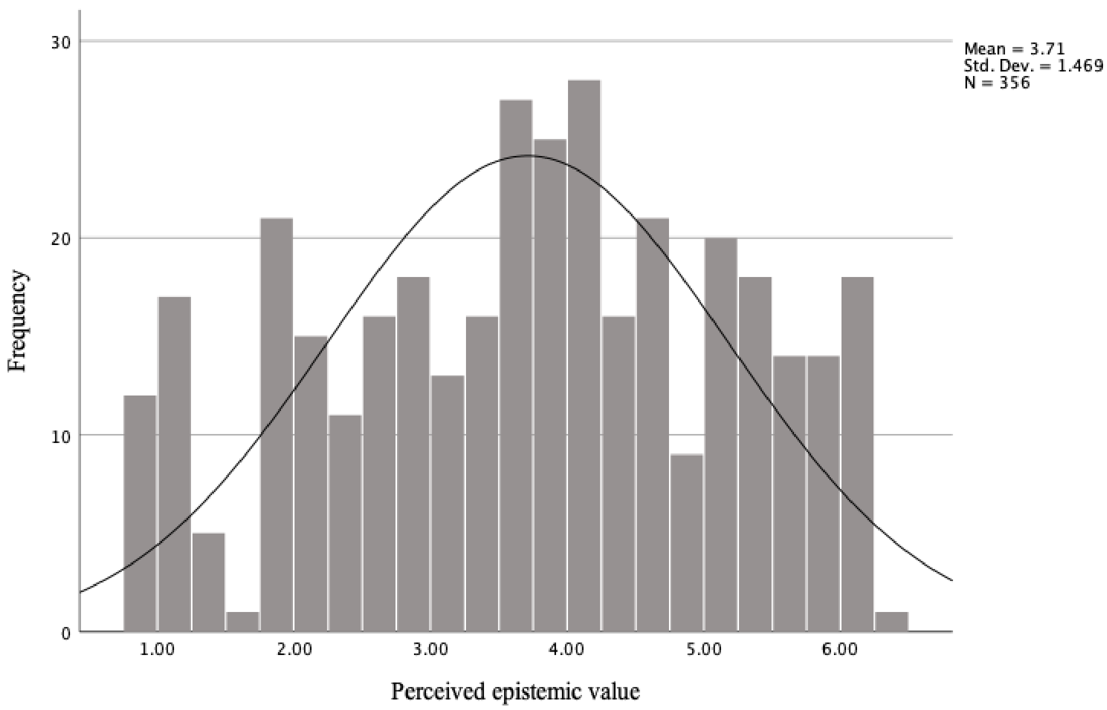


Figure 22: Histogram plot for perceived epistemic value

p) Negative word of mouth

The final latent construct is reflected by seven items: Nwom1, Nwom2, Nwom3, Nwom4, Nwom5, Nwom6 and Nwom7. The final scale has a maximum value of 6.03, a minimum value of .91 and a mean value of 2.82. A histogram was plotted to depict the normal distribution of the construct, together with the skewness and kurtosis values depicting the shape of the distribution. The KS test was also performed and the results were analysed for statistical significance. The results revealed that the KS test was significant with a value of .194, indicating non-normality. However, the skewness value of .514 and the kurtosis value of -1.243 were within the threshold value ranges of -1 to +1 (Hair et al., 2014) and -7 to +7 (Byrne, 2016) respectively, indicating minor departures from a normal distribution. Figure 23 shows the distribution of the construct *negative word of mouth*.

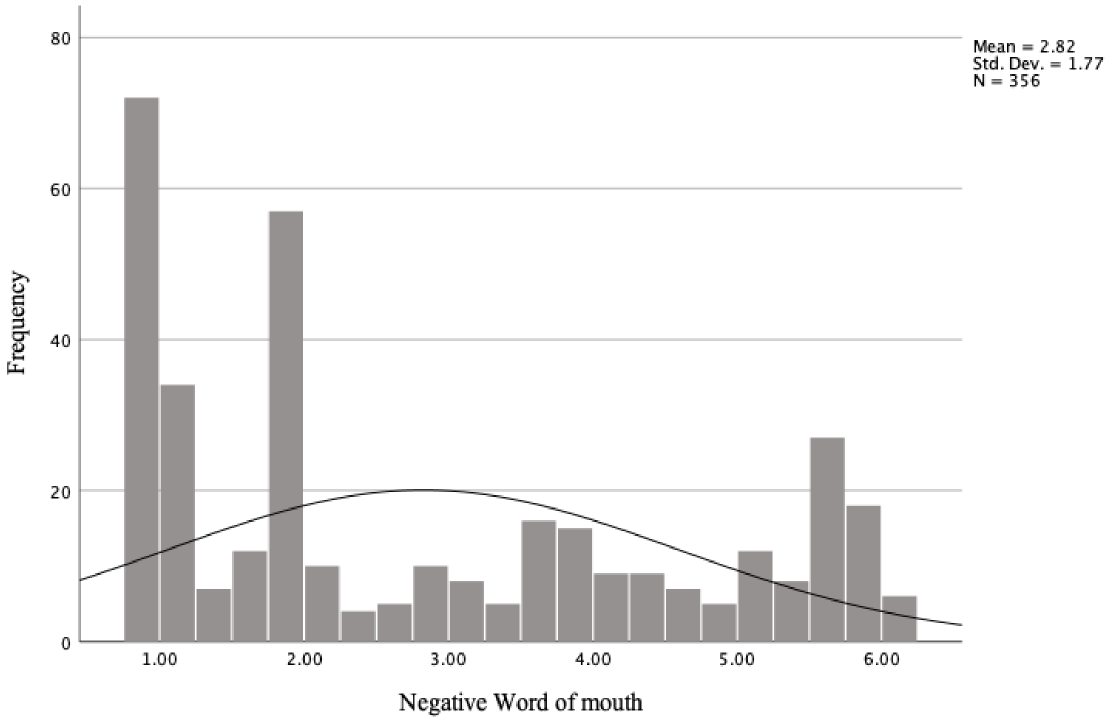


Figure 23: Histogram plot for negative word of mouth

The above descriptive analyses reveal that all the variables represent minimal variation from a normal distribution. Moreover, the large sample size (n = 356) reduced the effect of non-normality (Hair et al., 2014). Therefore, all the constructs were shown to be suitable for conducting SEM without the need for transformation.

5.5 Common method bias

Two methods were employed to test for the impact of CMB: Harman's single factor test (Podsakoff et al., 2003) and the marker variable method (Lindell and Whitney, 2001). According to Harman's single factor test, CMB is present when a single factor emerges from the factor analysis or when one factor accounts for the majority of the variance. A CFA approach to Harman's single-factor test was conducted with all items loading on a single factor. CFA yielded $\chi^2 = 11000.435$; df = 1223; RMSEA = .150; TLI = .471 and CFI = .493, indicating extremely poor fit compared to those of the two measurement models (1 and 2). Therefore, as a diagnostic technique, this indicated that CMB is not a problem.

Moreover, for the marker variable method, respondents' perception of *social desirability*, based on Reynolds (1982), was used as the marker variable. Social desirability was measured using four items (7-point Likert scale ranging from Strongly disagree to Strongly agree). A marker variable is one that is unrelated to all the variables of interest in a research study. This marker variable was included in the measurement models and inter-construct correlations were calculated. The mean correlation was 0.101. Further, the difference in bivariate correlations and partial correlations (controlling the effect of the marker variable) among the constructs of the study was calculated. This resulted in an average difference of 0.070. Hence, there is not much difference between the adjusted and unadjusted correlation matrices and all the unadjusted significant correlations remained significant after the adjustment, thereby revealing that CMB is not a major concern in this study.

5.6 Path analysis

SEM is conducted to account for the relationships among the various latent constructs (represented by the variables) by converting a measurement model into a structural model. A structural model is developed based on some underlying theory that defines the hypothesized relationships among the latent constructs (Hair et al., 2014).

SEM is a multivariate technique applied in both measurement and structural models. Hence, it is based on a number of steps. The earlier steps include defining the individual constructs, the development of a measurement model, and assessing the validity of the measurement model (Hair et al., 2014). These steps are discussed in the previous section (section 5.3.2). The next steps consist of *specifying the structural model* and *assessing the validity of the structural model.*

5.6.1 Structural model - specification

In this step, two types of constructs are defined in a structural model where latent constructs predict other latent constructs. The first type are *exogenous constructs*, which are multi-item equivalents of the independent variables. The second type of constructs are *endogenous constructs*, which are multi-item equivalents of the dependent variables. Since they are dependent on other constructs, dependence is represented in a visual path diagram by a path (a single-headed arrow) from the exogenous constructs (Hair et al., 2014).

In this study, a structural model was developed, based on theory, that consisted of the perceived barriers (exogenous constructs) that are connected to consumer resistance to smart payment 188ervices (endogenous construct) with a single-headed arrow, and consumer resistance to innovation is connected to negative word of mouth (endogenous construct). Furthermore, the endogenous constructs are not fully explained and hence an error term is associated with them

(Hair et al., 2014). Figures 24 and 25 demonstrate the structural models, without and with the control variables, respectively, developed in Stata 16.

Moreover, the degrees of freedom (df) of the two structural models were computed using the following equation: df=$\frac{1}{2}\big(p(p+1)\big)$-k. For the structural model without control variables, df=$\frac{1}{2}\big(37(37+1)\big)$-121=582 and with control variables, df=$\frac{1}{2}\big(41(41+1)\big)$-171=690.

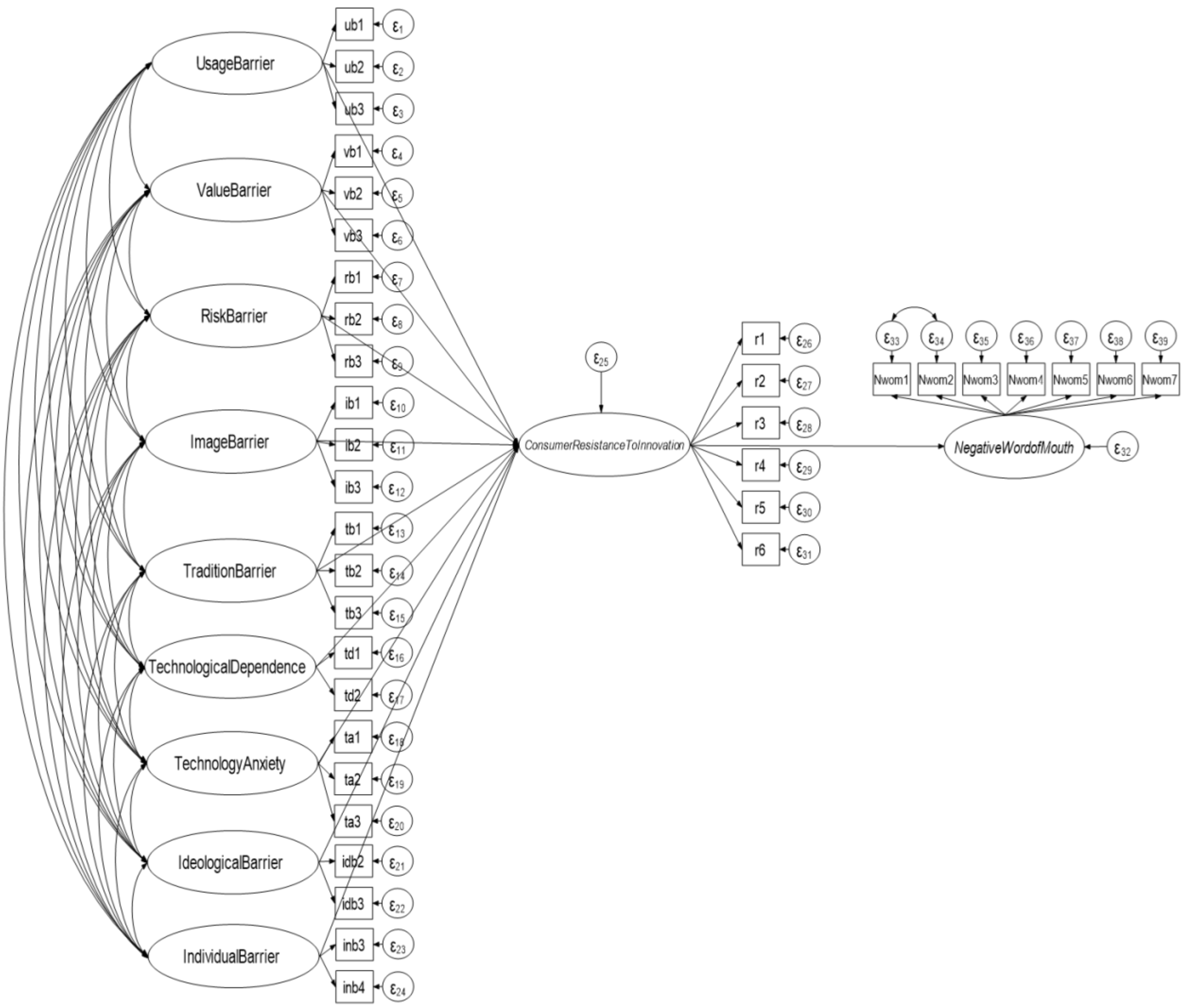


Figure 24: Structural model without control variables

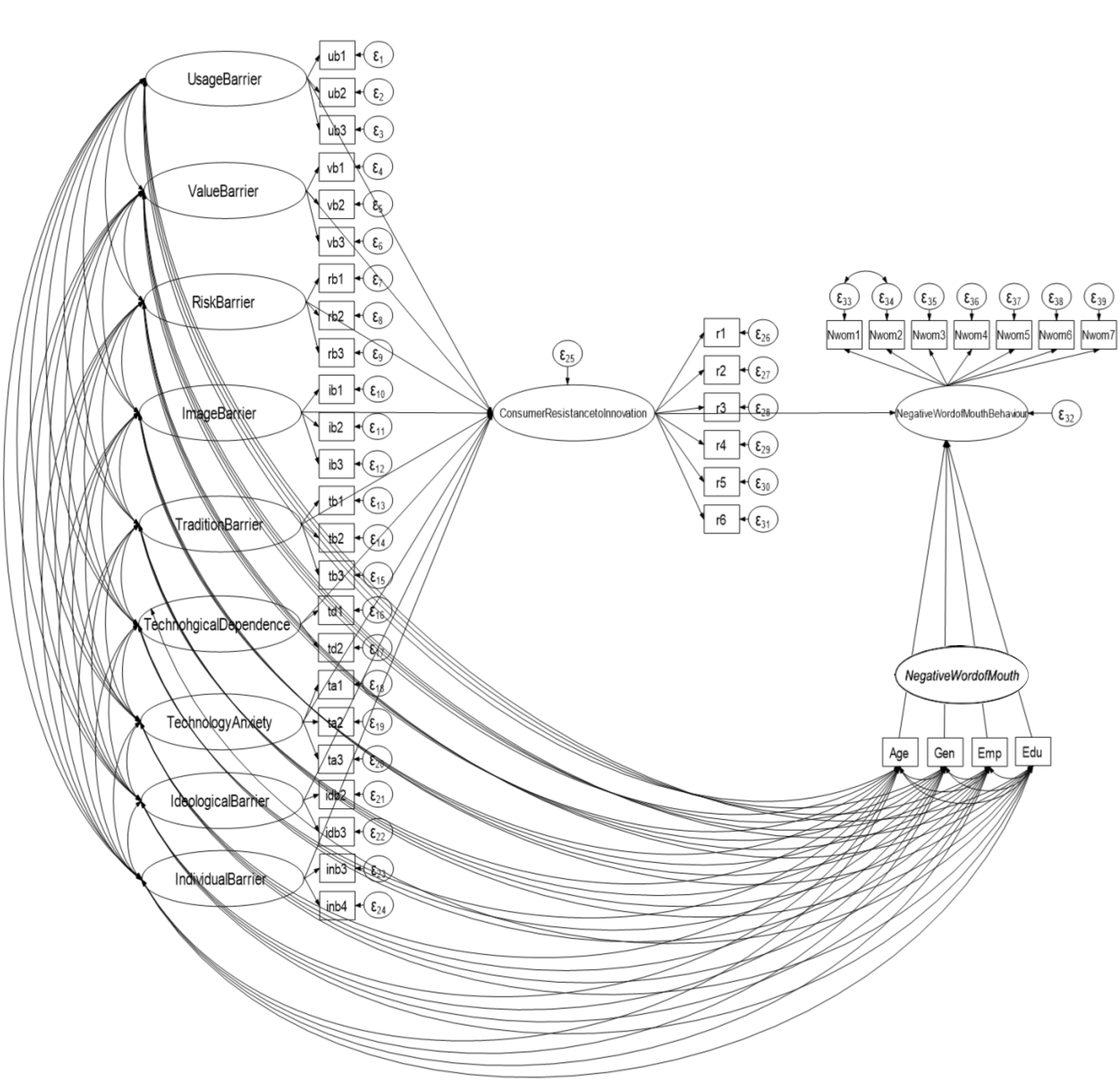


Figure 25: Structural model with control variables

5.6.2 Assessing structural model validity

In this step, the GOF statistics were assessed. Table 35 shows the results of the fit statistics, which indicate that the model fit statistics are adequate for both structural models (without and with control variables) as they satisfy their respective threshold values.

Table 35: Model fit statistics for the structural models

Model fit indices	χ^2 (df)	χ^2/df <3	RMSEA<.07 with CFI >.92	CFI >.90	TLI >.90
Without control variables	1580.260 (582)	2.715	.070	.927	.917
With control variables	1610.243 (690)	2.333	.061	.934	.922

The model fit statistics above indicate that the structural model with controls has better fit statistics than the structural model without controls. Hence, the control variables were retained for the further analysis of the hypotheses testing.

5.6.3 Hypotheses testing

This section presents the results for all the proposed hypotheses i.e., the direct effects, mediating effects, moderating effects, and moderated mediation effects. Since these hypotheses are directional, one-tailed test results are reported. This is because using two-tailed tests for directional hypotheses can lead to "inaccurate or mistaken empirical conclusions at a given level of significance α" (Cho and Abe, 2013, p. 1265).

a) Direct effects

Hypotheses H1(a) to (i) proposed that all the perceived barriers are positively related to consumer resistance to smart payment services. H2 proposed that consumer resistance to smart payment services is positively related to negative word of mouth. These hypotheses were tested at a significance level of 5%. The summarized results are presented in Table 36.

Table 36: Direct effects test results (with controls)

Hypo-theses	**Paths**	**Standard-ized estimates**
H1(a)	Perceived usage barrier → Consumer resistance to smart payment services	.193*
H1(b)	Perceived value barrier → Consumer resistance to smart payment services	-.041
H1(c)	Perceived risk barrier → Consumer resistance to smart payment services	.104*
H1(d)	Perceived image barrier → Consumer resistance to smart payment services	.200**
H1(e)	Perceived tradition barrier → Consumer resistance to smart payment services	-.012
H1(f)	Perceived technological dependence → Consumer resistance to smart payment services	.327**
H1(g)	Perceived technology anxiety → Consumer resistance to smart payment services	-.108
H1(h)	Perceived ideological barrier → Consumer resistance to smart payment services	.389**
H1(i)	Perceived individual barrier → Consumer resistance to smart payment services	.334**
H2	Consumer resistance to smart payment services → Negative word of mouth	.559**
Controls		
Age → Negative word of mouth		-.164
Gender → Negative word of mouth		-.118
Education level → Negative word of mouth		.258
Occupation status → Negative word of mouth		-.085

Note: Significant at ** $p < .01$; *$p < .05$
R-squared value of consumer resistance to smart payment services = .820
R-squared value of negative word of mouth = .581

The results indicate that perceived usage barrier ($\gamma = .193$, $p < .05$); perceived risk barrier ($\gamma = .104$, $p < .05$); perceived image barrier ($\gamma = .200$, $p < .01$); perceived technological dependence ($\gamma = .327$, $p < .01$); perceived ideological barrier ($\gamma = .389$, $p < .01$); and perceived individual barrier ($\gamma = .334$, $p < .01$) have statistically significant positive relationships with consumer resistance to smart payment services. Therefore, these render support for hypotheses H1(a), H1(c), H1(d), H1(f), H1(h) and H1(i).

However, the effects of the remaining three perceived barriers (perceived value barrier, perceived tradition barrier, and perceived technology anxiety) on consumer resistance to smart payment services were found to be statistically non-significant. Hence, hypotheses H1(b), H1(e) and H1(g) are not supported.

Regarding hypothesis H2, it was proposed that consumer resistance to smart payment services is positively related to negative word of mouth. The result indicates that consumer resistance to smart payment services has a significant positive impact on negative word of mouth (β = .559, p $\leq$ .001), thereby supporting hypothesis H2.

b) Mediation analysis

Mediation is hypothesized when an independent variable affects a dependent variable through an intervening variable, known as the mediating variable or mediator. A mediation process involving only one mediating variable is known as simple mediation, whereas the presence of more than one mediating variable is referred to as multiple mediation (Preacher and Hayes, 2008). Figure 26 demonstrates a simple mediation process.

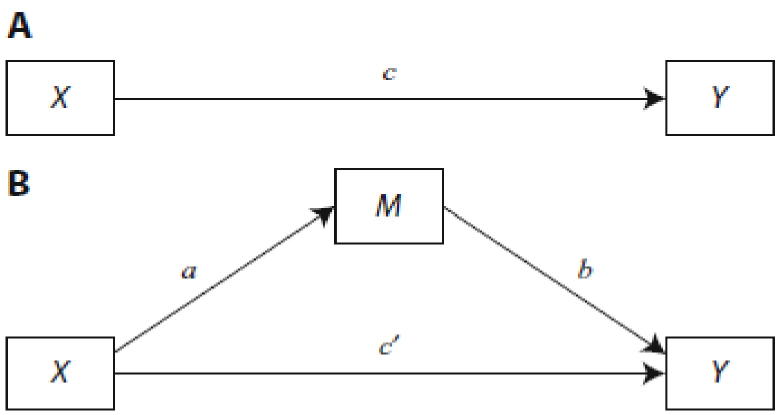


Figure 26: Simple mediation process (Preacher and Hayes, 2008)

Where *X* = independent variable

M = mediating variable

Y = dependent variable

a = effect of *X* on *M*

b = effect of M on Y partialling out the effect of X

In a simple mediation model, the causal effect of X can be divided into indirect and direct effects.

c = total effect of X on Y = sum of direct and indirect effects = $c' + ab$

In this study, following the approach in Preacher and Hayes (2008), the results of the hypothesized mediating effect of consumer resistance to smart payment services between perceived barriers and negative word of mouth are presented for H3(a) to (i). This approach to mediation analysis was adopted because prior research in the field of innovation has provided evidence of its application (e.g., Mani and Chouk, 2018; Stock et al., 2019; Weeth et al., 2020). Specifically, those perceived barriers which revealed a significant direct impact on consumer resistance to smart payment services (see section 5.6.3(a)) were included in the mediation analysis.

The structural model estimated the direct and indirect effects of all the perceived barriers on negative word of mouth (via consumer resistance to smart payment services). The analysis yielded an adequate model fit to the data (χ^2 = 841.124; df = 405; CFI = .959; TLI = .950; RMSEA = .055). To estimate the significance of the indirect effects, a non-parametric bootstrapping method with 5000 resamples at 95% confidence intervals proposed by Preacher and Hayes (2008) was used.

Indirect effects

The bootstrapping results indicated that perceived risk barrier (γ = .044, $p < .05$); perceived image barrier (γ = .092, $p < .01$); perceived technological dependence (γ = .107, $p < .05$), perceived ideological barrier (γ = .168, $p < .01$); and perceived individual barrier (γ = .154, $p < .01$) had statistically significant indirect effects on negative word of mouth (via consumer resistance to smart payment services). According to the bootstrapping analysis, since the significance of indirect effects is the only requirement for confirming mediation, the aforementioned results suggest that consumer resistance to smart payment services mediates the relationship between these perceived barriers and negative word of mouth. Hence, these results render support for H3(c), H3(d), H3(f), H3(h) and H3(i). The bootstrapping results also indicated that the indirect effect of perceived usage barrier on negative word of mouth (via consumer resistance to smart payment services) is statistically non-significant. Hence, consumer resistance to smart payment services does not mediate the relationship between perceived usage barrier and negative word of mouth, thus not supporting H3(a).

Direct effects

As a result of the inclusion of a mediator (i.e., consumer resistance to smart payment services) in the model, the results indicate statistically significant effects of perceived risk barrier ($\gamma = .104$, $p < .05$); perceived image barrier ($\gamma = .216$, $p < .01$); perceived ideological barrier ($\gamma = .396$, $p < .01$); and perceived individual barrier ($\gamma = .363$, $p < .01$) on consumer resistance to smart payment services. The results also indicate a statistically significant effect of consumer resistance to smart payment services on negative word of mouth ($\beta = .425$, $p < .01$).

The results also revealed statistically significant effects of perceived risk barrier ($\gamma = -.087$, $p < .05$); perceived image barrier ($\gamma = -.250$, $p < .01$); perceived ideological barrier ($\gamma = .298$, $p < .05$); and perceived individual barrier ($\gamma = -.180$, $p < .05$) on negative word of mouth. This suggests that consumer resistance to smart payment services partially mediates the relationship between perceived risk, image, ideological, individual barriers and negative word of mouth.

However, it was found that perceived technological dependence has a statistically significant effect on consumer resistance to smart payment services ($\gamma = .251$, $p < .01$) but a statistically non-significant effect on negative word of mouth. Since the results also revealed a statistically significant effect of consumer resistance to smart payment services on negative word of mouth (β = .425, p < .01), this implies that consumer resistance to smart payment services fully mediates the relationship between perceived technological dependence and negative word of mouth.

Further, the Sobel test was used to confirm the mediating role of consumer resistance to smart payment services. The results of the Sobel test support the analyses by confirming the existence of mediated relationships for perceived risk barrier (z-value = 4.341, $p \leq .01$), perceived image barrier (z-value = 4.517, $p \leq .01$), perceived technological dependence (z-value = 4.084, $p \leq .01$), perceived ideological barrier (z-value = 4.536, $p \leq .01$) and perceived individual barrier (z-value = 4.823, $p \leq .01$). Table 37 summarizes these results.

Table 37: Results of mediation analysis

Hypo-theses	**Path**	**Direct effects**			**Indirect effects**	**Total effects**	**Mediation result**
		X→M	M→Y	**X→Y**			
H3(a)	UB→R→NWOM	0.089	0.425**	0.178**	0.038	0.215*	No mediation
H3(c)	RB→R→NWOM	0.104**	0.425**	-0.087*	**0.044***	-0.043	Partial mediation
H3(d)	IB→R→NWOM	0.216**	0.425**	-0.250**	**0.092****	-0.158**	Partial mediation
H3(f)	TD→R→NWOM	0.251**	0.425**	0.031	**0.107***	0.138	Full mediation
H3(h)	IdB→R→NWOM	0.396**	0.425**	0.298*	**0.168***	0.466**	Partial mediation
H3(i)	InB→R→NWOM	0.363**	0.425**	-0.180*	**0.154****	-0.026	Partial mediation

Note: Significant at **$p < .01$, *$p < .05$; all values mentioned are standardized coefficients
Number of bootstrap samples: 5000
Total effect = direct effect (X→Y) + indirect effect (product of X→M and M→Y)
R-squared value of consumer resistance to smart payment services = .815
R-squared value of negative word of mouth = .813
UB = perceived usage barrier; RB = perceived risk barrier; IB = perceived image barrier; TD = perceived technological dependence; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth
X = all barriers; M = consumer resistance to smart payment services, Y = negative word of mouth

c) Moderation analysis

The interaction effects in terms of moderated relationships are conceptualized as a three-variable system. In this system, one variable is considered as the independent variable, the second as the outcome variable and the third as the moderator variable. Hence, when the effect of the independent variable on the outcome variable depends on the value of the moderator variable, it is said that an interaction effect exists (Jaccard and Turrisi, 2003). Furthermore, in the analysis of two-way interactions, the researcher investigates the effect of two independent variables on the dependent or outcome variable. Hence, within the two independent variables, one of them is considered as a focal independent variable, the effect of which on the outcome variable varies as a function of the second independent variable, considered as the moderator variable (Jaccard and Turrisi, 2003). Figure 27 demonstrates a moderated causal relationship representing a two-way interaction, where *X* is the focal independent variable, *Y* is the outcome or dependent variable, and *Z* is the moderator variable.

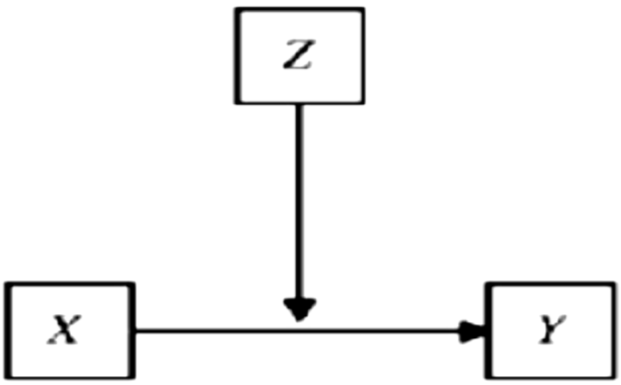


Figure 27: Two-way interaction (Jaccard and Turrisi, 2003)

In this study, two-way interactions were carried out in which perceived consumption values were considered as the moderator variables (*Z*), perceived barriers were the focal independent variables (*X*) and consumer resistance to smart payment services was the outcome variable (*Y*).

To test the moderating effects of perceived consumption values, SEM was employed in Stata 16, which included the effects of the focal constructs (perceived barriers and perceived consumption values), control variables (age, gender, education and employment) and the interaction terms (perceived barriers x perceived consumption values). Prior to the analysis, all moderators and predictive variables were standardized to minimize multicollinearity. In line with Heidenreich et al. (2017) and Stock et al. (2014), to investigate the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services, five separate interaction analysis models were run, which included either perceived functional value (performance) (i.e., H4(a) to (i)) or perceived functional value (convenience) (i.e., H5(a) to (i)) or perceived social value (i.e., H6(a) to (i)) or perceived emotional value (i.e., H7(a) to (i)) or perceived epistemic value (i.e., H8(a) to (i)).

The following sections present the results of the interaction effects between perceived barriers and perceived consumption values on consumer resistance to smart payment services.

i. Moderating effects of perceived functional value (performance)

H4(a) to (i) predicted that perceived functional value (performance) will moderate the relationship between perceived barriers and consumer resistance to smart payment services. The results indicate a statistically significant negative moderating effect of functional value (performance) on the relationship between perceived usage barrier and consumer resistance to smart payment services ($\gamma = -.071$, $p < .05$). Hence, the result suggests that perceived functional value (performance) buffers the effect of perceived usage barrier on consumer resistance to smart payment services, thereby confirming hypothesis H4(a).

The results also revealed a statistically significant negative moderating effect of functional value (performance) on the relationship between perceived individual barrier and consumer resistance to smart payment services ($\gamma = -.049$, $p < .05$). Hence, the result suggests that perceived functional value (performance) mitigates the effect of perceived individual barrier on consumer resistance to smart payment services. This renders support for hypothesis H4(i).

However, a statistically non-significant moderating effect of functional value (performance) was found on the relationship between other perceived barriers and consumer resistance to smart payment services. Thus, H4(b) to (h) were not supported.

Table 38 shows the results of the moderating effect of perceived functional value (performance). Figures 28 and 29 demonstrate the plots for significant two-way interactions at a high level (i.e., one standard deviation (SD) above the mean) and a low level (i.e., one SD below the mean of the moderator).

Table 38: Moderating effects of functional value (performance) on relationships between perceived barriers and consumer resistance to innovation

	Coefficient	***t*-Value**
Direct effects		
UB → R	.157**	2.83
VB → R	.061	1.25
RB → R	.152**	3.91
IB → R	.182**	4.25
TB → R	.046	1.12
TD → R	.183**	3.68
TA → R	.009	.17
IdB → R	.246**	4.62
InB → R	.274**	8.17
FV(P) → R	-.050	-1.20
Interaction effects		
UB x FV(P) → R	**-.071***	-1.65
VB x FV(P) → R	.071	1.41
RB x FV(P) → R	-.028	-.74
IB x FV(P) → R	-.029	-.79
TB x FV(P) → R	-.031	-.77
TD x FV(P) → R	-.030	-.66
TA x FV(P) → R	.131	2.27
IdB x FV(P) → R	.014	.30
InB x FV(P) → R	**-.049***	-1.67
Control variables		
Age → R	-.005	-1.51
Gender → R	-.074	-1.18
Employment status → R	.001	.05
Highest education level → R	.025	.57

Note: n = 356
Significant at **p < .01, *p < .05; All values mentioned are standardized coefficients
R-squared value of consumer resistance to smart payment services = .716
UB = perceived usage barrier; VB = perceived value barrier; RB = perceived risk barrier; IB = perceived image barrier; TB = perceived tradition barrier; TD = perceived technological dependence; TA = perceived technology anxiety; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; FV(P) = perceived functional value (performance)

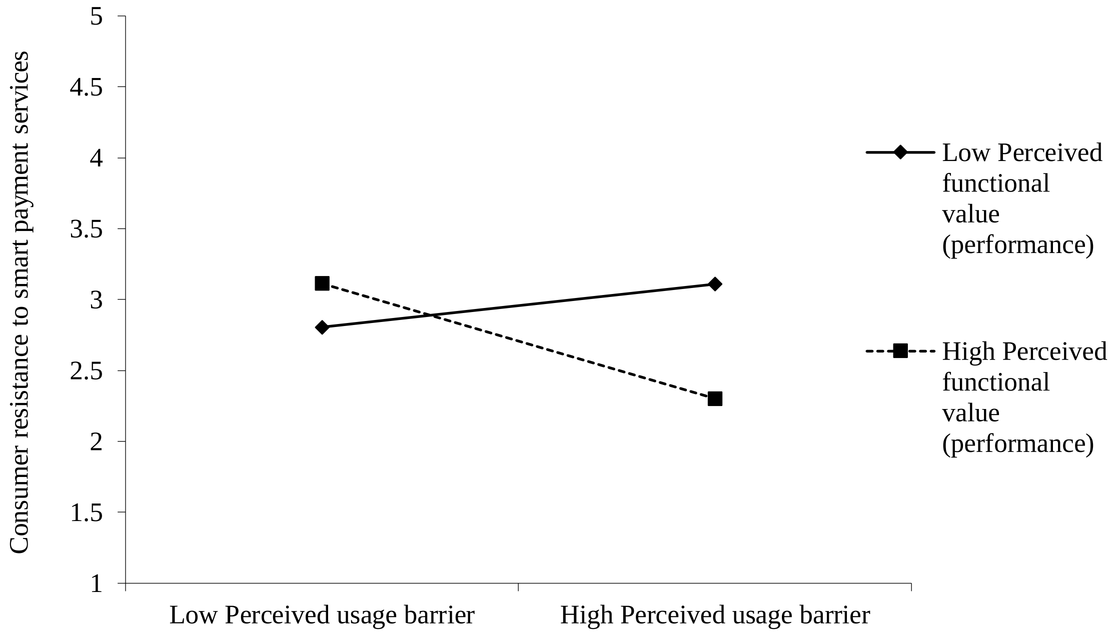


Figure 28: Moderating role of perceived functional value (performance) in the relationship between perceived usage barrier and consumer resistance to smart payment services

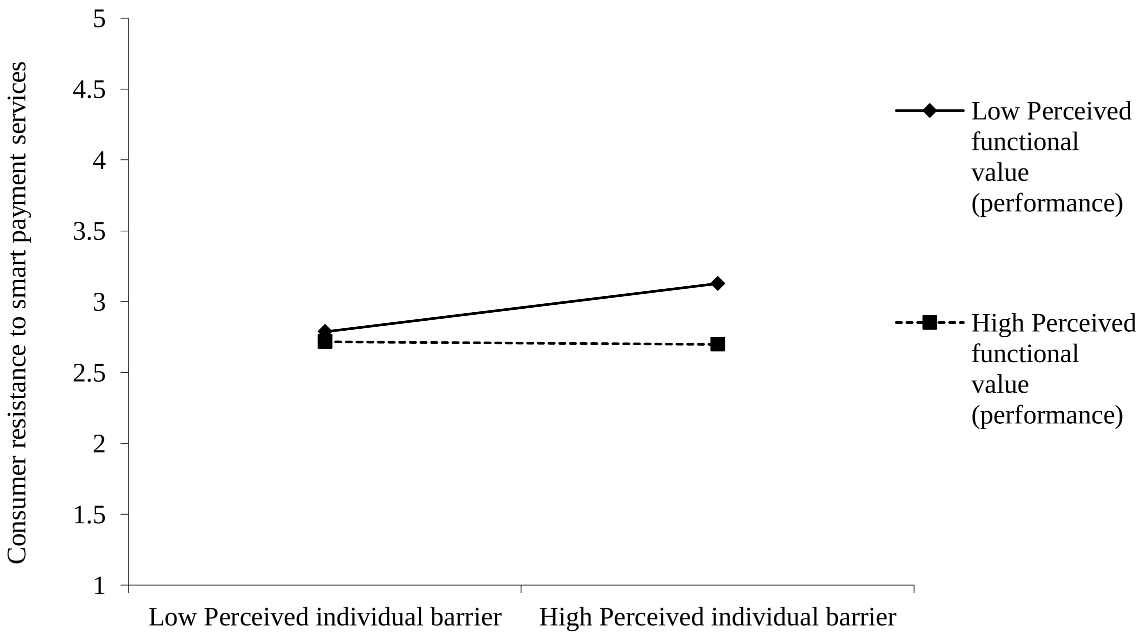


Figure 29: Moderating role of perceived functional value (performance) in the relationship between perceived individual barrier and consumer resistance to smart payment services

ii. Moderating effects of perceived functional value (convenience)

H5(a) to (i) predicted that perceived functional value (convenience) will moderate the relationship between perceived barriers and consumer resistance to smart payment services. The results indicate a statistically significant negative moderating effect of functional value (convenience) on the relationship between perceived risk barrier and consumer resistance to smart payment services ($\gamma = -.065$, $p < .05$). <u>This renders support for hypothesis H5(c</u>). Therefore, this result implies that functional value (convenience) mitigates the effect of perceived risk barrier on consumer resistance to smart payment services.

The results also indicate a statistically significant negative moderating effect of functional value (convenience) on the relationship between perceived image barrier and consumer resistance to smart payment services ($\gamma = -.064$, $p < .05$). <u>Hence, this confirms hypothesis H5(d</u>). Therefore, this result implies that functional value (convenience) mitigates the effect of perceived image barrier on consumer resistance to smart payment services.

However, a statistically non-significant moderating effect of perceived functional value (convenience) was found on the relationship between the other perceived barriers and consumer resistance to smart payment services. <u>Hence, H5(a), (b) and (e) to (i) are not supported</u>.

Table 39 below presents the results of the moderation effect of perceived functional value (convenience). Figures 30 and 31 present the plots for significant two-way interactions at a high level (i.e., one SD above the mean) and a low level (i.e., one SD below the mean) of the moderator.

Table 39: Moderating effects of functional value (convenience) on the relationships between perceived barriers and consumer resistance to smart payment services

	Coefficient	***t*-Value**
Simple effects		
UB → R	.134*	2.44
VB → R	.059	1.33
RB → R	.162**	4.40
IB → R	.099*	2.28
TB → R	.054	1.40
TD → R	.204**	4.14
TA → R	.037	.69
IdB → R	.208**	3.96
InB → R	.255**	7.86
FV(C) → R	-.145**	-3.61
Interaction effects		
UB x FV(C) → R	-.037	-.85
VB x FV(C) → R	.072	1.75
RB x FV(C) → R	**-.065***	-1.78
IB x FV(C) → R	**-.064***	-1.82
TB x FV(C) → R	-.058	-1.80
TD x FV(C) → R	.029	.67
TA x FV(C) → R	.089	1.82
IdB x FV(C) → R	.005	.14
InB x FV(C) → R	-.041	-1.30
Control variables		
Age → R	-.005	-1.87
Gender → R	-.061	-1.02
Employment status → R	-.003	-.12
Highest education level → R	.022	1.00

Note: n = 356

Significant at **p < .01, *p < .05; All values mentioned are standardized coefficients

R-squared value of consumer resistance to smart payment services = .732

UB = perceived usage barrier; VB = perceived value barrier; RB = perceived risk barrier; IB = perceived image barrier; TB = perceived traditional barrier; TD = perceived technological dependence; TA = perceived technology anxiety; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; FV(C) = perceived functional value (convenience)

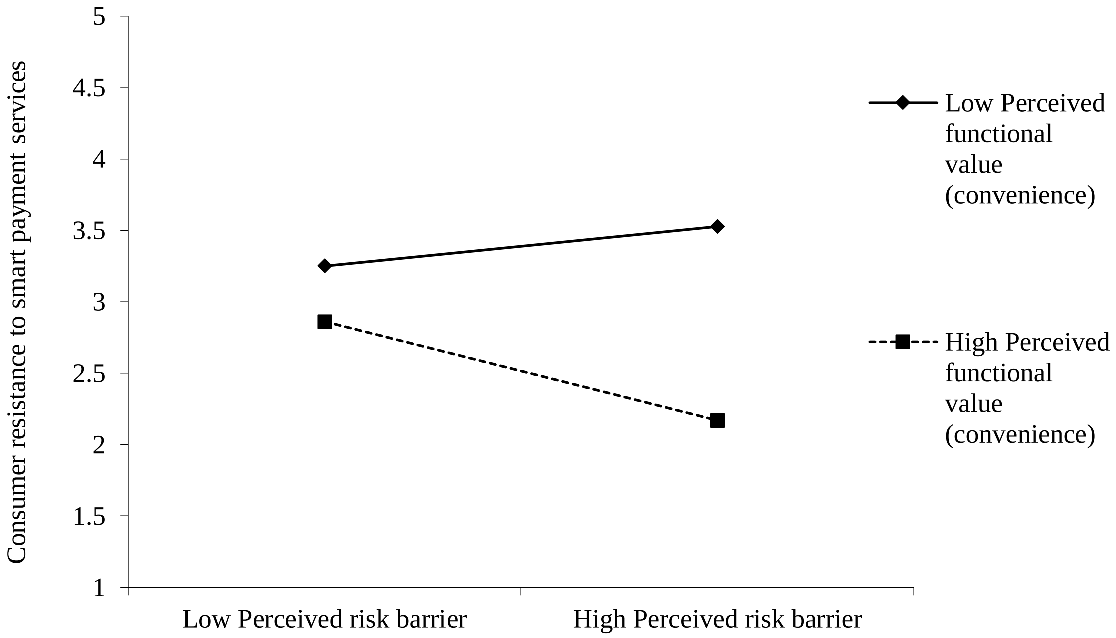


Figure 30: Moderating role of perceived functional value (convenience) in the relationship between perceived risk barrier and consumer resistance to smart payment services

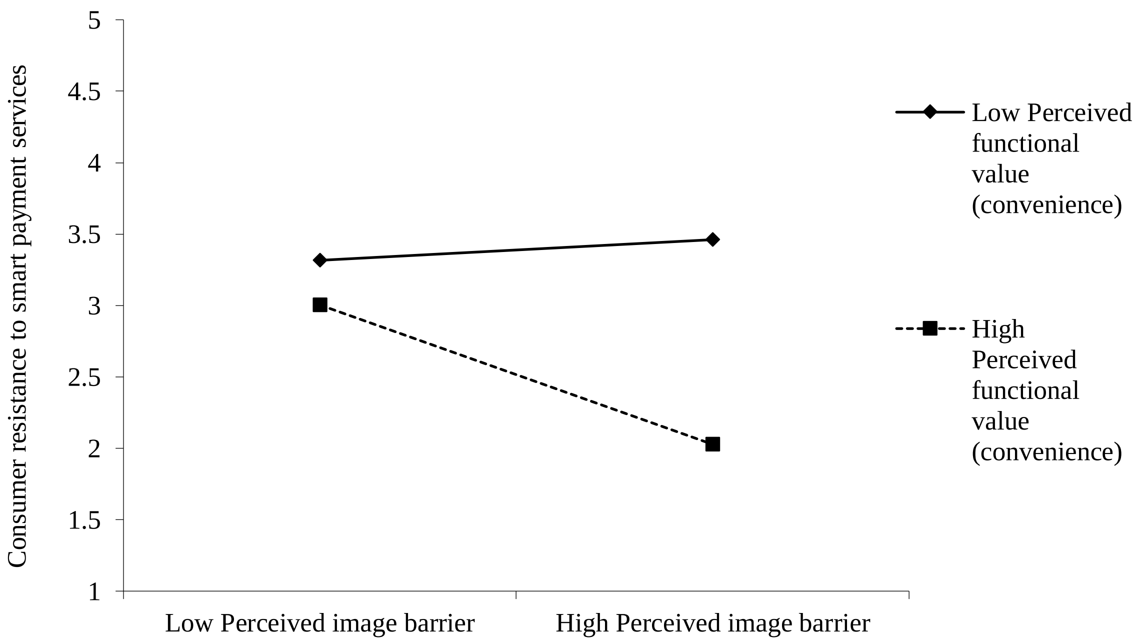


Figure 31: Moderating role of perceived functional value (convenience) in the relationship between perceived image barrier and consumer resistance to smart payment services

iii. Moderating effects of perceived social value

H6(a) to (i) predicted that perceived social value will moderate the relationship between perceived barriers and consumer resistance to smart payment services. The results indicated a statistically significant negative moderating effect of perceived social value on the relationship between perceived usage barrier and consumer resistance to smart payment services ($\gamma = -.089$, $p < .05$). This confirms support for hypothesis H6(a).

The results also indicated a statistically significant negative moderating effect of perceived social value on the relationship between perceived risk barrier and consumer resistance to smart payment services ($\gamma = -.080$, $p < .05$). This renders support for hypothesis H6(c).

The results revealed a statistically significant negative moderating effect of perceived social value on the relationship between perceived image barrier and consumer resistance to smart payment services ($\gamma = -.061$, $p < .05$), thereby confirming H6(d).

The results also revealed a statistically significant negative moderating effect of perceived social value on the relationship between perceived individual barrier and consumer resistance to smart payment services ($\gamma = -.056$, $p < .05$). Therefore, this confirms hypothesis H6(i).

Hence, these results imply that perceived social value reduces the effects of four types of perceived barrier (i.e., perceived usage barrier, perceived risk barrier, perceived image barrier and perceived individual barrier) on consumer resistance to smart payment services.

However, non-significant moderating effects of perceived social value were found on the relationships between other barrier perceptions and consumer resistance to smart payment services. Hence, H6(b), (e), (f), (g) and (h) are not supported.

Table 40 presents the results for the moderation effect of perceived social value. Figures 32, 33, 34 and 35 show the plots for significant two-way interactions at a high level (i.e., one SD above the mean) and a low level (i.e., one SD below the mean) of the moderator.

Table 40: Moderating effects of social value on the relationships between perceived barriers and consumer resistance to smart payment services

	Coefficient	***t*-Value**
Simple effects		
UB → R	.117*	2.16
VB → R	.091	1.89
RB → R	.147**	3.87
IB → R	.160**	3.85
TB → R	.019	.45
TD → R	.186**	3.62
TA → R	.085	1.54
IdB → R	.252**	4.84
InB → R	.254**	7.53
SV → R	-.006	-.14
Interaction effects		
UB x SV → R	**-.089***	-1.90
VB x SV → R	.052	1.20
RB x SV → R	**-.080***	-2.15
IB x SV → R	**-.061***	-1.64
TB x SV → R	-.013	-.34
TD x SV → R	-.048	-1.03
TA x SV → R	.174	3.73
IdB x SV → R	-.011	-.25
InB x SV → R	**-.056***	-1.80
Control variables		
Age → R	-.004	-1.33
Gender → R	-.067	-1.11
Employment status → R	-.003	-.11
Highest education level → R	.000	.00

Note: n = 356
Significant at **p < .01, *p < .05; All values mentioned are standardized coefficients
R-squared value of consumer resistance to smart payment services = .732
UB = perceived usage barrier; VB = perceived value barrier; RB = perceived risk barrier; IB = perceived image barrier; TB = perceived tradition barrier; TD = perceived technological dependence; TA = perceived technological anxiety; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; SV = perceived social value

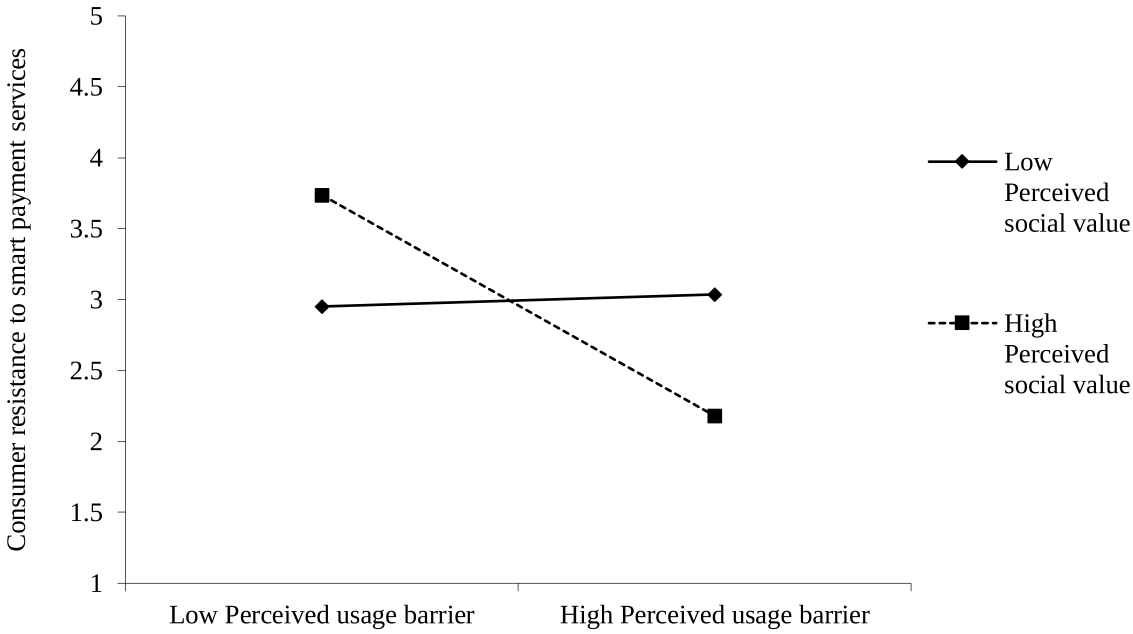


Figure 32: Moderating role of perceived social value in the relationship between perceived usage barrier and consumer resistance to smart payment services

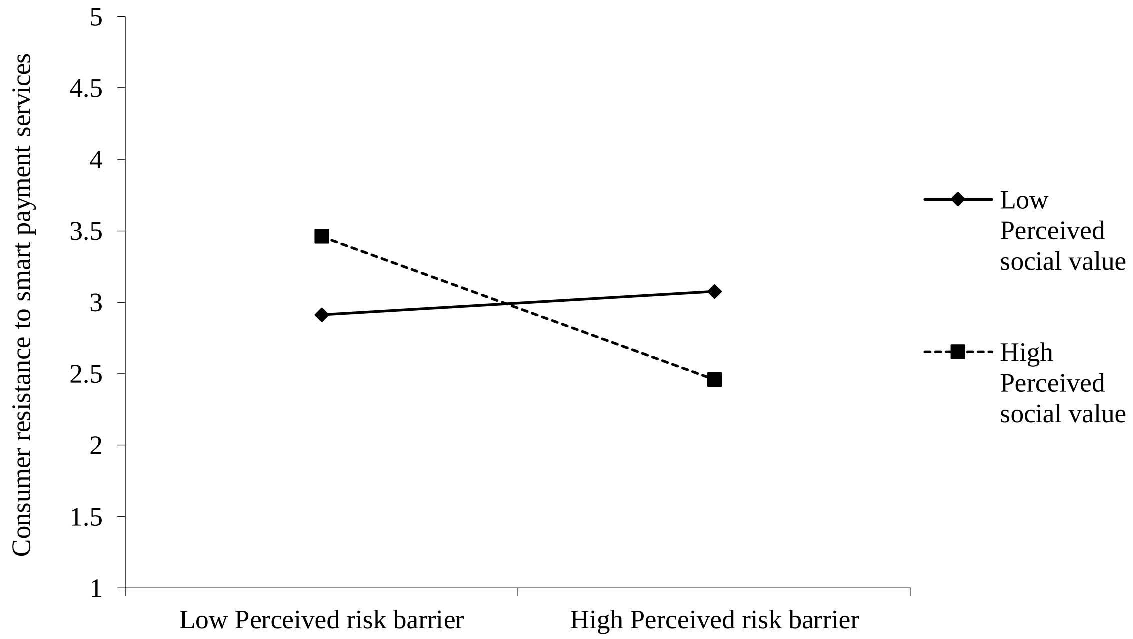


Figure 33: Moderating role of perceived social value in the relationship between perceived risk barrier and consumer resistance to smart payment services

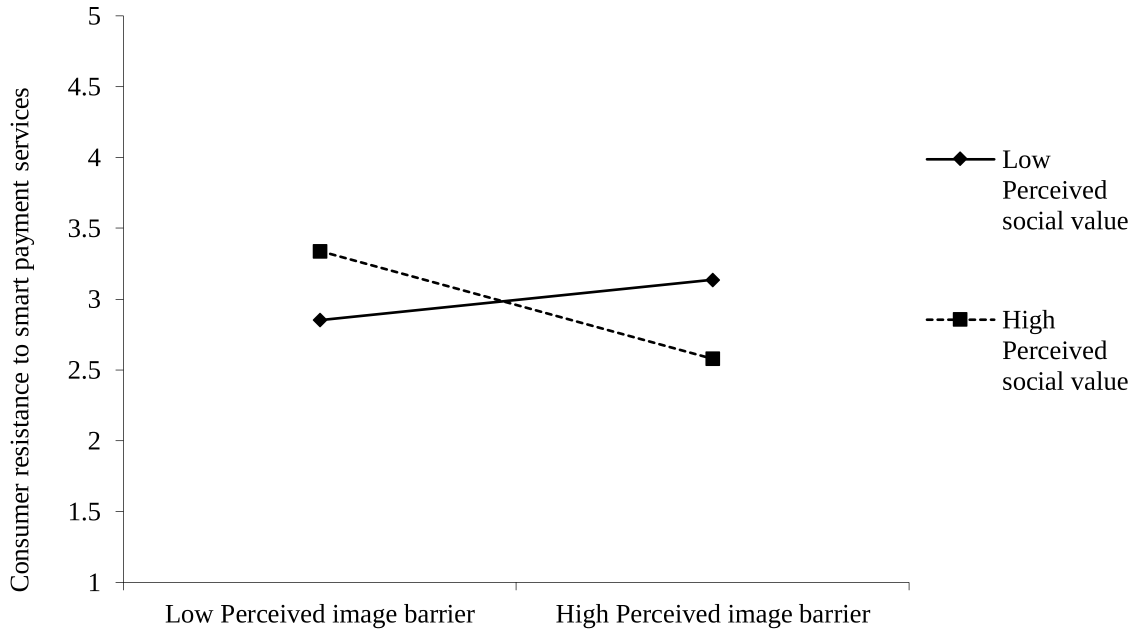


Figure 34: Moderating role of perceived social value in the relationship between perceived image barrier and consumer resistance to smart payment services

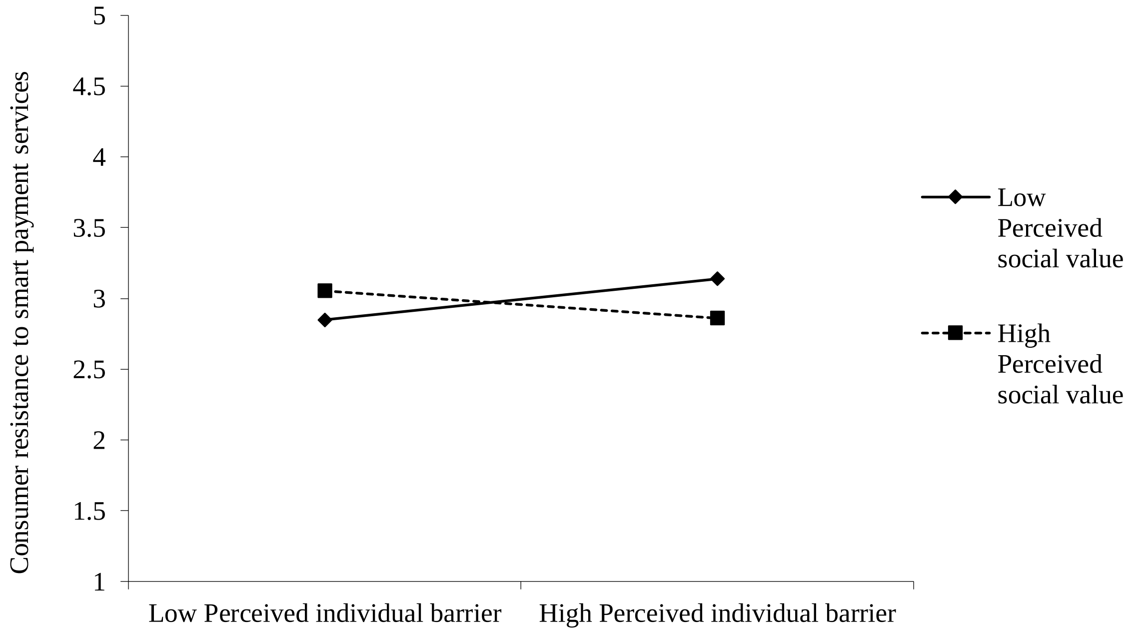


Figure 35: Moderating role of perceived social value in the relationship between perceived individual barrier and consumer resistance to smart payment services

iv. Moderating effects of emotional value

H7(a) to (i) proposed that perceived emotional value will moderate the relationship between perceived barriers and consumer resistance to smart payment services. The results indicate a statistically significant negative moderating effect of perceived emotional value on the relationship between perceived risk barrier and consumer resistance to smart payment services ($\gamma = -.078$, $p \leq .05$). This confirms support for hypothesis H7(c).

The results also revealed a statistically significant negative moderating effect of perceived emotional value on the relationship between perceived individual barrier and consumer resistance to smart payment services ($\gamma = -.064$, $p < .05$). Hence, hypothesis H7(i) is supported.

These results imply that perceived emotional value buffers the effects of perceived risk barrier and perceived individual barrier on consumer resistance to smart payment services.

However, a statistically non-significant moderating effect of perceived emotional value was found on the relationship between the other perceived barriers and consumer resistance to smart payment services, thereby rejecting H7(a), (b) and (e) to (h).

Table 41 shows the results for the moderating effects of perceived emotional value. Figures 36 and 37 demonstrate the plots for significant two-way interactions at a high level (i.e., one SD above the mean) and low level (i.e., one SD below the mean) of the moderator.

Table 41: Moderating effects of emotional value on the relationships between perceived barriers and consumer resistance to smart payment services

	Coefficient	***t*-Value**
Simple effects		
UB → R	.131*	2.43
VB → R	.061	1.29
RB → R	.120**	3.16
IB → R	.079*	1.78
TB → R	.067	1.65
TD → R	.251**	4.91
TA → R	.056	.99
IdB → R	.219**	4.13
InB → R	.231**	6.98
EV → R	-.145**	-.3.01
Interaction effects		
UB x EV → R	-.057	-1.25
VB x EV → R	.013	.31
RB x EV → R	**-.078***	-2.21
IB x EV → R	-.054	-1.46
TB x EV → R	-.031	-.87
TD x EV → R	.068	1.38
TA x EV → R	.112	2.28
IdB x EV → R	.003	.07
InB x EV → R	**-.064***	-2.11
Control variables		
Age → R	-.004	-1.51
Gender → R	-.086	-1.45
Employment status → R	.007	.25
Highest education level → R	.014	.33

Note: n = 356
Significant at **$p < .01$, *$p < .05$; All values mentioned are standardized coefficients
R-squared value of consumer resistance to smart payment services = .741
UB = perceived usage barrier; VB = perceived value barrier; RB = perceived risk barrier; IB = perceived image barrier; TB = perceived traditional barrier; TD = perceived technological dependence; TA = perceived technological anxiety; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; EV = perceived emotional value

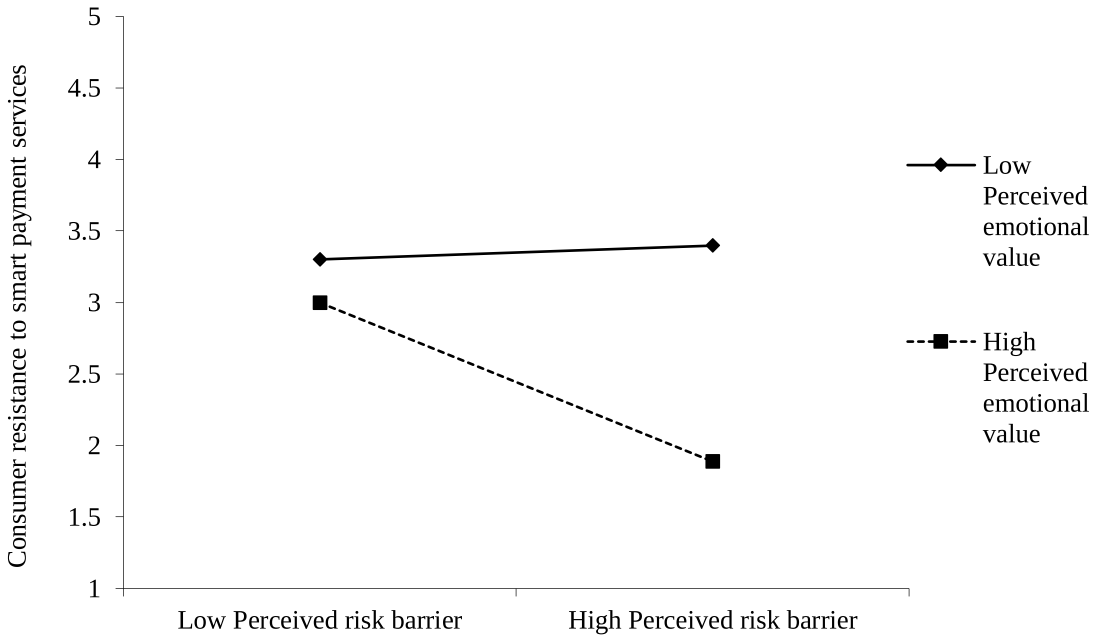


Figure 36: Moderating role of perceived emotional value in the relationship between perceived risk barrier and consumer resistance to smart payment services

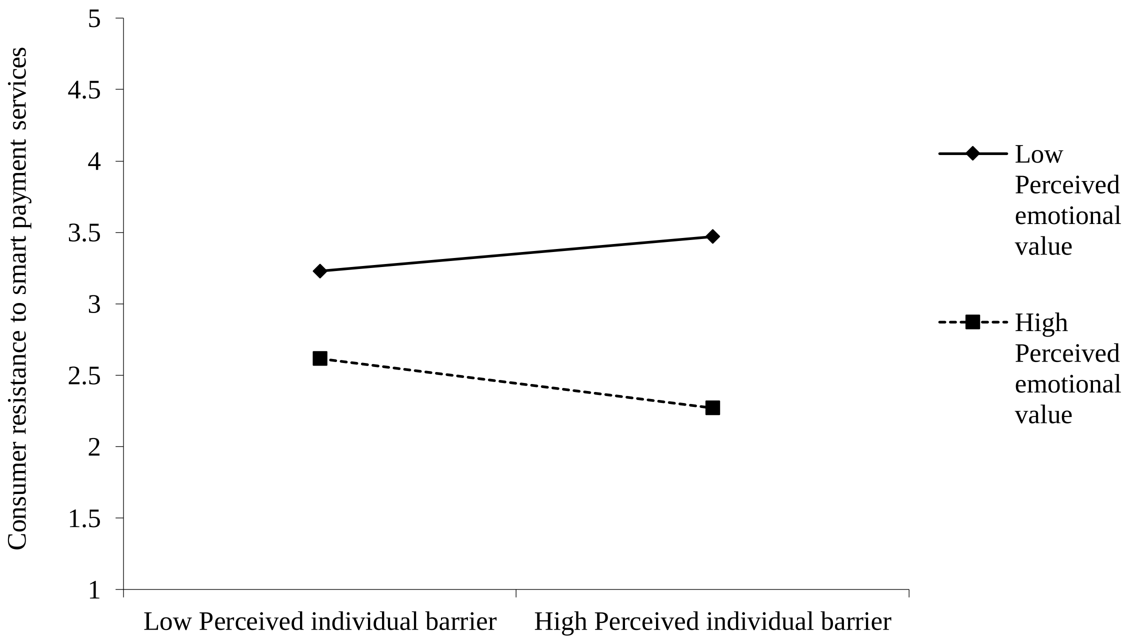


Figure 37: Moderating role of perceived emotional value in the relationship between perceived individual barrier and consumer resistance to smart payment services

v. Moderating effects of epistemic value

H8(a) to (i) predicted that perceived epistemic value will moderate the relationship between perceived barriers and consumer resistance to smart payment services. The results indicated a statistically significant negative moderating effect of perceived epistemic value on the relationship between perceived usage barrier and consumer resistance to smart payment services ($\gamma = -.083$, $p \leq .05$). This renders support for H8(a). Hence, this result suggests that perceived epistemic value mitigates the effect of perceived usage barrier on consumer resistance to smart payment services.

The results also revealed a statistically significant negative moderating effect of perceived epistemic value on the relationship between perceived risk barrier and consumer resistance to smart payment services ($\gamma = -.099$, $p \leq .01$). This result confirms hypothesis H8(c). Hence, this result suggests that perceived epistemic value mitigates the effect of perceived risk barrier on consumer resistance to smart payment services.

The results further indicated a statistically significant negative moderating effect of perceived epistemic value on the relationship between perceived image barrier and consumer resistance to smart payment services ($\gamma = -.085$, $p \leq .05$), thereby confirming support for H8(d). Hence, this result suggests that perceived epistemic value mitigates the effect of perceived image barrier on consumer resistance to smart payment services.

However, a statistically non-significant moderating effect of perceived epistemic value was found on the relationship between other perceived barriers and consumer resistance to smart payment services. Thus, H8(b) and (e) to (i) are not supported.

Table 42 shows the results for the moderating effects of perceived epistemic value. Figures 38, 39 and 40 demonstrate the plots for significant two-way interactions at a high level (i.e., one SD above the mean) and a low level (i.e., one SD below the mean) of the moderator.

Table 42: Moderating effects of epistemic value on the relationships between perceived barriers and consumer resistance to smart payment services

	Coefficient	***t*-Value**
Simple effects		
UB → R	.140**	2.58
VB → R	.071	1.48
RB → R	.134**	3.51
IB → R	.161**	3.91
TB → R	.038	.90
TD → R	.221**	4.36
TA → R	.058	1.09
IdB → R	.243**	4.77
InB → R	.259**	7.70
EpV → R	-.049	-1.03
Interaction effects		
UB x EpV → R	**-.083***	-1.72
VB x EpV → R	.012	.28
RB x EpV → R	**-.099****	2.69
IB x EpV → R	**-.085***	-2.43
TB x EpV → R	-.042	-1.21
TD x EpV → R	-.006	-.13
TA x EpV → R	.155	3.08
IdB x EpV → R	-.002	-.06
InB x EpV → R	-.036	-1.15
Control variables		
Age → R	-.004*	-1.66
Gender → R	-.055	-.92
Employment status → R	.002	.06
Highest education level → R	.038	.88

Note: n = 356
Significant at **p < .01, *p < .05; All values mentioned are standardized coefficients
R-squared value of consumer resistance to smart payment services = .736
UB = perceived usage barrier; VB = perceived value barrier; RB = perceived risk barrier; IB = perceived image barrier; TB = perceived tradition barrier; TD = perceived technological dependence; TA = perceived technological anxiety; IdB = perceived ideological barrier; InB = perceived individual barrier; R = consumer resistance to smart payment services; EpV = perceived epistemic value

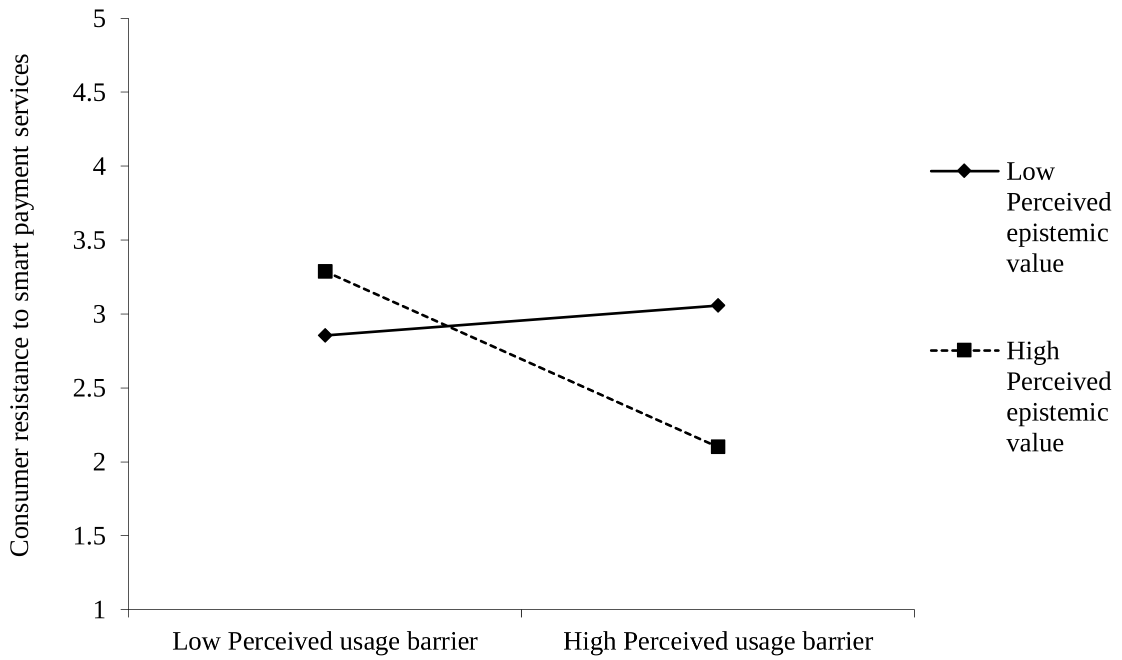


Figure 38: Moderating role of perceived epistemic value in the relationship between perceived usage barrier and consumer resistance to smart payment services

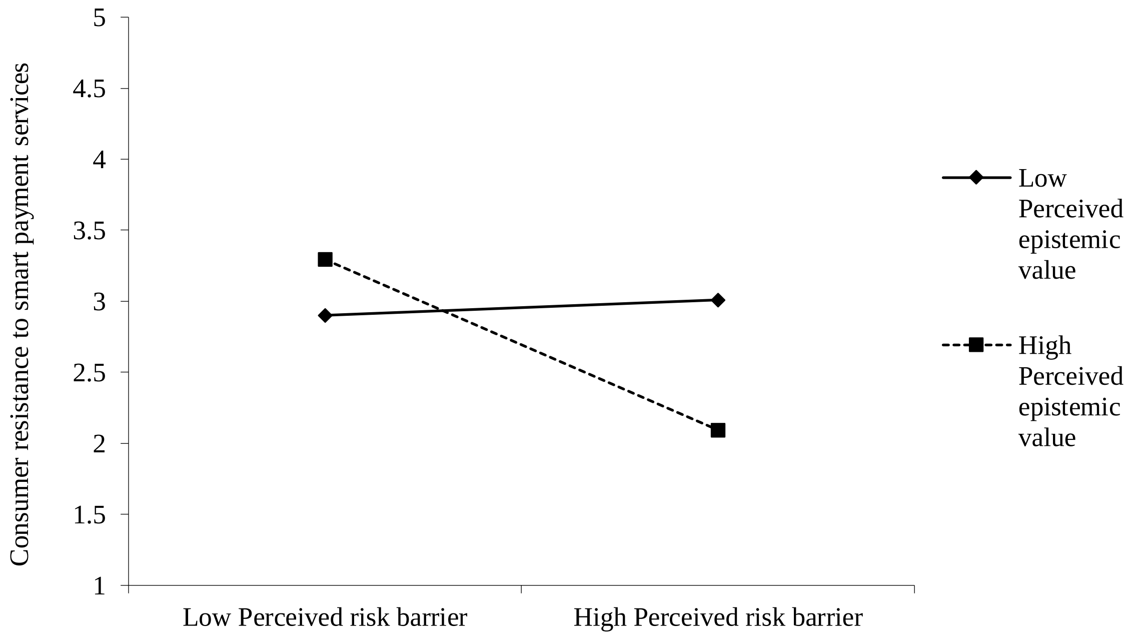


Figure 39: Moderating role of perceived epistemic value in the relationship between perceived risk barrier and consumer resistance to smart payment services

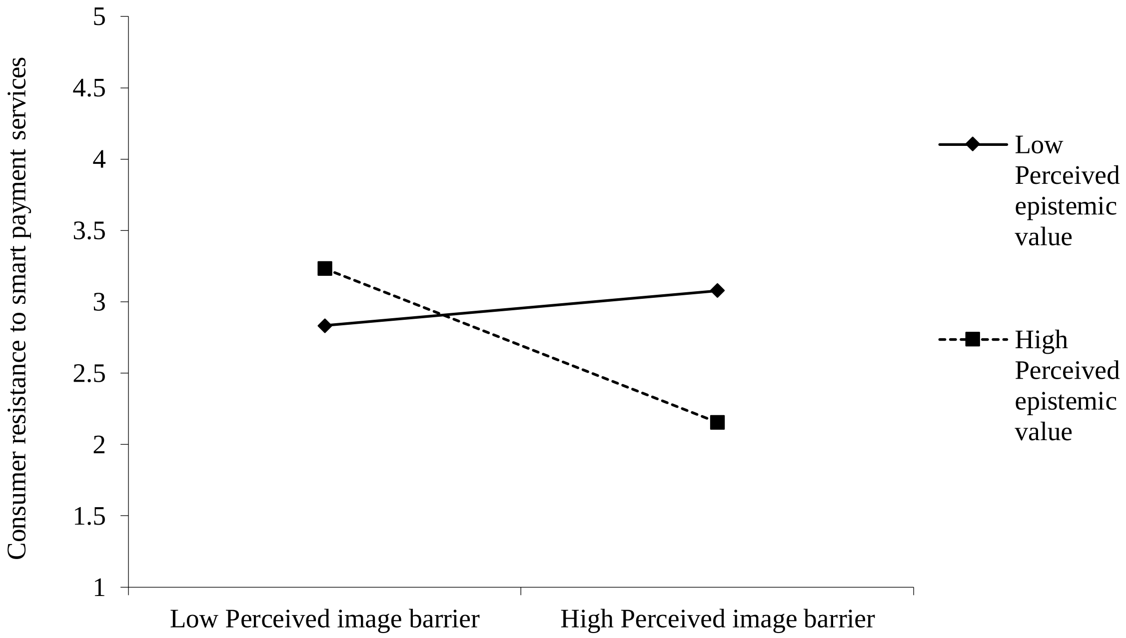


Figure 40: Moderating role of perceived epistemic value in the relationship between perceived image barrier and consumer resistance to smart payment services

d) Moderated mediation analysis

Research studies also consider complex models to determine whether the mediation effect or indirect effect varies among different contexts or values of the independent variables. Such a case can be presented in the way in which the strength of the indirect effect may vary linearly depending on the value of the other variables, such as a moderator variable(s), or when mediation relations are contingent on the level of a moderator. This type of effect is commonly termed a moderated mediation effect, which is generally calculated in terms of *conditional indirect effects* (Preacher et al., 2007).

Further, according to the model presented below (Figure 41), two types of conditional indirect effects can be hypothesized (Preacher et al., 2007):

a) A moderation effect is mediated by M, also known as mediated moderation.

b) When path a_1 is moderated by W (moderator) in a simple mediation model, also known as moderated mediation.

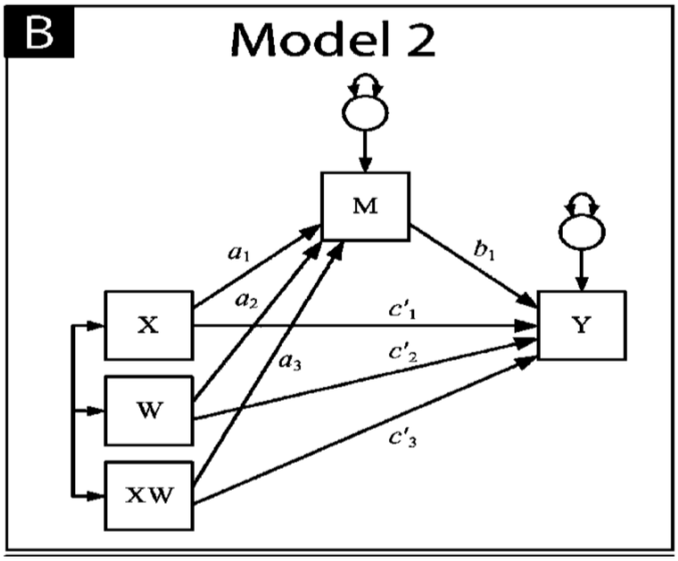


Figure 41: Path diagram showing conditional indirect effects (Preacher et al., 2007)

This study has proposed hypotheses H9(a) to (i), H10(a) to (i), H11(a) to (i), H12(a) to (i) and H13(a) to (i) based on the second case, i.e., when path a_1 (perceived barriers (X) → consumer resistance to smart payment services (M)) is moderated by perceived consumption values (W) in a simple mediation model with NWOM as the dependent variable (Y). When testing moderated mediation hypotheses, the moderation and mediation hypotheses need to receive empirical support (Preacher et al., 2007).

Therefore, the following results of the mediation analysis were found to be significant, as demonstrated in section 5.6.3(b):

H3(c) – Consumer resistance to smart payment services mediates the relationship between perceived risk barrier and NWOM.

H3(d) – Consumer resistance to smart payment services mediates the relationship between perceived image barrier and NWOM.

H3(f) – Consumer resistance to smart payment services mediates the relationship between perceived technological dependence and NWOM.

H3(h) – Consumer resistance to smart payment services mediates the relationship between perceived ideological barrier and NWOM.

H3(i) – Consumer resistance to smart payment services mediates the relationship between perceived individual barrier and NWOM.

Next, the following significant moderating effects were reported in section 5.6.3(c):

H4(a) – Perceived functional value (performance) moderates the relationship between perceived usage barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (performance) is high rather than low.

H4(i) – Perceived functional value (performance) moderates the relationship between perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (performance) is high rather than low.

H5(c) – Perceived functional value (convenience) moderates the relationship between perceived risk barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (convenience) is high rather than low.

H5(d) – Perceived functional value (convenience) moderates the relationship between perceived image barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived functional value (convenience) is high rather than low.

H6(a) – Perceived social value moderates the relationship between perceived usage barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived social value is high rather than low.

H6(c) – Perceived social value moderates the relationship between perceived risk barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived social value is high rather than low.

H6(d) – Perceived social value moderates the relationship between perceived image barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived social value is high rather than low.

H6(i) – Perceived social value moderates the relationship between perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived social value is high rather than low.

H7(c) – Perceived emotional value moderates the relationship between perceived risk barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived emotional value is high rather than low.

H7(i) – Perceived emotional value moderates the relationship between perceived individual barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived emotional value is high rather than low.

H8(a) – Perceived epistemic value moderates the relationship between perceived usage barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived epistemic value is high rather than low.

H8(c) – Perceived epistemic value moderates the relationship between perceived risk barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived epistemic value is high rather than low.

H8(d) – Perceived epistemic value moderates the relationship between perceived image barrier and consumer resistance to smart payment services, such that the relationship is weaker when perceived epistemic value is high rather than low.

Therefore, in following Preacher et al.'s (2007) recommendation, the following hypotheses can be tested for moderated mediation:

H9 – Perceived functional value (performance) moderates the indirect effect of (i) perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (performance).

H10 – Perceived functional value (convenience) moderates the indirect effects of (c) perceived risk barrier and (d) perceived image barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (convenience).

H11 – Perceived social value moderates the indirect effects of (c) perceived risk barrier, (d) perceived image barrier, and (i) perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived social value.

H12 – Perceived emotional value moderates the indirect effects of (c) perceived risk barrier and (i) perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived emotional value.

H13 – Perceived epistemic value moderates the indirect effects of (c) perceived risk barrier and (d) perceived image barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived epistemic value.

The model was estimated using SEM in Stata 16, which allowed for calculating the indirect effects of perceived barriers (independent variable) on negative word of mouth (NWOM) (dependent variable) via consumer resistance to innovation (mediator) across moderator (perceived consumption values) conditions (Little et al., 2007). The indirect effects were further assessed at three values of the moderator variable: mean, mean + 1 SD, and mean – 1 SD (Preacher et al., 2007). The bootstrapping procedure was run with 5000 resamples based on 95% bias-corrected confidence intervals. The following sections present the moderated mediation results for the aforementioned hypotheses.

i. Moderated mediation conditioned on functional value (performance)

Hypothesis H9(i) predicted that perceived functional value (performance) will moderate the indirect effect of perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (performance).

As shown in Table 43, the bootstrapping analyses at 95% CIs excluding zero revealed a significant indirect effect of perceived individual barrier on NWOM (via consumer resistance to smart payment services) at low (γ = .576, SE = .056, CI: .469 .690), mean (γ = .529, SE = .050, CI: .437 .633) and high values (γ = .481, SE = .071, CI: .351 .634) of perceived functional value (performance). These results imply that the conditional indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived functional value (performance) increases (see Figure 42), thereby providing support for hypothesis H9(i). The graph demonstrated in Figure 42 was plotted for further understanding of the moderated mediation results.

Table 43: Moderated mediation results conditioned on functional value (performance)

Moderator values	**Path**	**Conditional indirect effects**	**Bootstrap SE**	**LLCI**	**ULCI**
Low FV(P)		.576	.056	.469	.690
Medium FV(P)	InB→R→NWOM	.529	.050	.437	.633
High FV(P)		.481	.071	.351	.634

Note: bootstrap sample size = 5000 at 95% confidence interval (bias-corrected); SE = standard error
LLCI = lower-level confidence interval; ULCI = upper-level confidence interval
FV(P) = perceived functional value (performance); InB = perceived individual barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth
Low SV = mean – 1 standard deviation; Medium SV = mean; High SV = mean + 1 standard deviation
R-squared value of consumer resistance to smart payment services = .905
R-squared value of negative word of mouth = .540

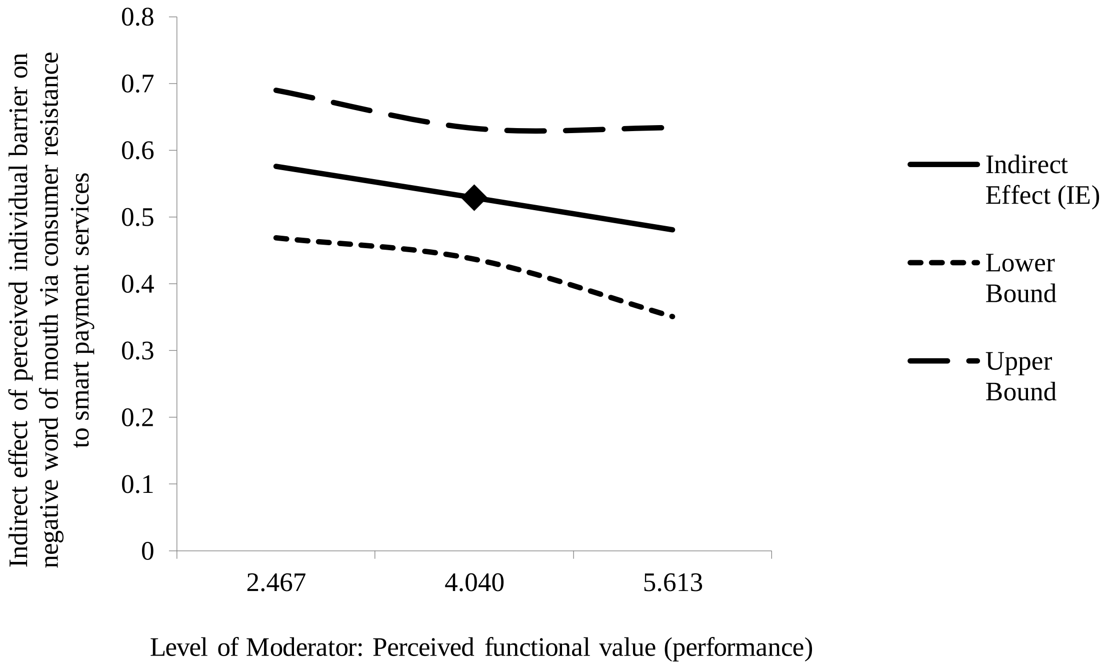


Figure 42: Conditional indirect effect of perceived individual barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on functional value (performance), with 95% confidence bands
Note: The square indicates the mean level of perceived functional value (performance)

ii. Moderated mediation conditioned on functional value (convenience)

Hypotheses H10(c) and (d) predicted that perceived functional value (convenience) will moderate the indirect effects of perceived risk barrier and perceived image barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived functional value (convenience).

As shown in Table 44, the bootstrapping analysis at 95% CIs excluding zero revealed a significant indirect effect of risk barrier on NWOM (via consumer resistance to smart payment services) at a low level of perceived functional value (convenience) (γ = .055, SE = .029, CI: .00 .115). But the indirect effects are not observed at the mean (CI: -.022 .066) and high levels (CI: -.086 .056) of perceived functional value (convenience) because the CIs contain zero. However, the graph in Figure 43 suggests that the conditional indirect effects of perceived risk barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived functional value (convenience) increases. This renders support for hypothesis H10(c).

Further, regarding hypothesis H10(d), the bootstrapping analyses at 95% CIs excluding zero revealed a significant indirect effect of perceived image barrier on NWOM (via consumer resistance to smart payment services) at low (γ = .121, SE = .028, CI: .064 .174), mean (γ = .099, SE = .023, CI: .053 .146) and high values (γ = .078, SE = .033, CI: .015 .146) of perceived functional value (convenience). These results imply that the conditional indirect effects of perceived image barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived functional value (convenience) increases (see Figure 43), thereby providing support for hypothesis H10(d).

Table 44 presents the results for hypotheses H10(c) and (d). The graphs in Figures 43 and 44 were plotted for further understanding of the moderated mediation results.

Table 44: Moderated mediation results conditioned on functional value (convenience)

Moderator values	**Path**	**Conditional indirect effects**	**Bootstrap SE**	**LLCI**	**ULCI**
Low FV(C)		.055	.029	.000	.115
Medium FV(C)	RB→R→NWOM	.019	.022	-.022	.066
High FV(C)		-.017	.037	-.086	.056
Low FV(C)		.121	.028	.064	.174
Medium FV(C)	IB→R→NWOM	.099	.024	.053	.147
High FV(C)		.078	.033	.015	.146

Note: bootstrap sample size = 5000 at 95% confidence interval (bias-corrected); SE = standard error
LLCI = lower-level confidence interval; ULCI = upper-level confidence interval
FV(C) = perceived functional value (convenience); RB = perceived risk barrier; IB = perceived image barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth
Low SV = mean – 1 standard deviation; Medium SV = mean; High SV = mean + 1 standard deviation
R-squared value of consumer resistance to smart payment services = .908
R-squared value of negative word of mouth = .540

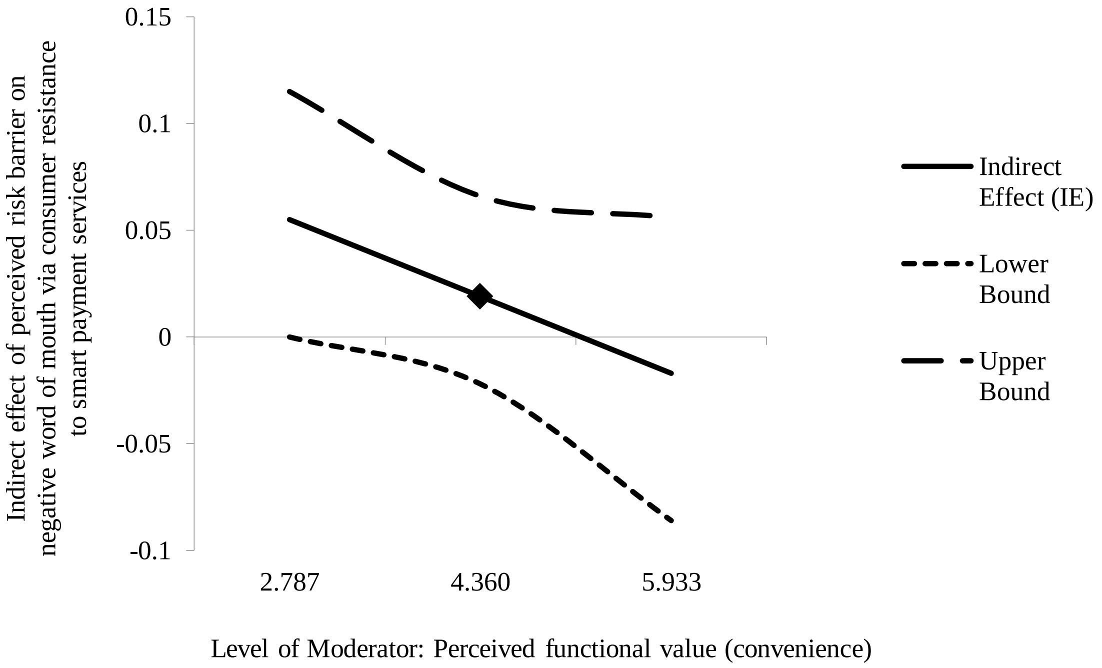


Figure 43: Conditional indirect effect of perceived risk barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on functional value (convenience) with 95% confidence bands

Note: The square indicates the mean level of perceived functional value (convenience)

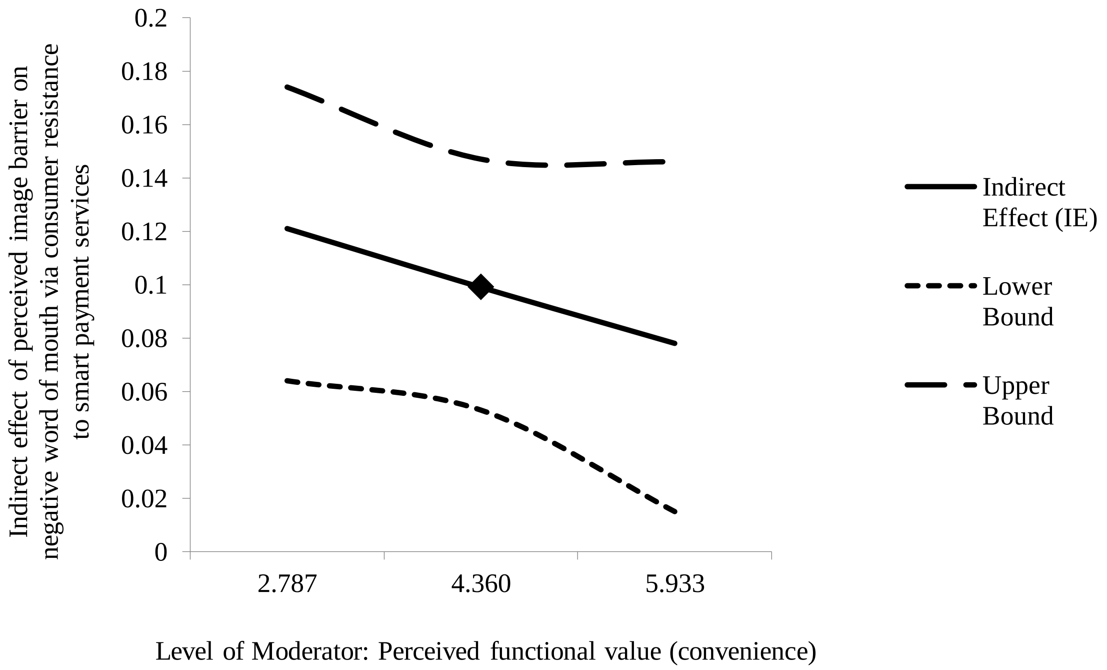


Figure 44: Conditional indirect effect of perceived image barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on functional value (convenience) with 95% confidence bands

Note: The square indicates the mean level of perceived functional value (convenience)

iii. Moderated mediation conditioned on social value

Hypotheses H11(c), (d) and (i) predicted that perceived social value will moderate the indirect effects of perceived risk barrier, perceived image barrier and perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived social value.

According to Table 45, the bootstrapping analysis at 95% CIs excluding zero revealed a significant indirect effect of perceived risk barrier on NWOM (via consumer resistance to smart payment services) only at a low level of perceived social value ($\gamma = .062$, SE = .028, CI: .008 .118). But the indirect effects are not observed at the mean (CI: -.027 .066) and high levels (CI: -.102 .049) of perceived social value because the CIs contain zero. However, the graph in Figure 45 suggests that the conditional indirect effects of perceived risk barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived social value increases. <u>This renders support for H11(c</u>).

Further, the bootstrapping analysis at 95% CIs excluding zero yielded significant indirect effects of perceived image barrier on NWOM (via consumer resistance to smart payment services) at all three levels of perceived social value: at a low level ($\gamma = .136$, SE = .026, CI: .086 .187), the mean value ($\gamma = .121$, SE = .023, CI: .078 .168) and a high level ($\gamma = .106$, SE = .032, CI: .047 .172). These results imply that the conditional indirect effects of perceived image barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived social value increases, <u>thereby indicating support for hypothesis H11(d</u>).

The bootstrapping analysis at 95% CIs excluding zero also indicated significant indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) at all three levels of perceived social value: at a low level ($\gamma = .583$, SE = .055, CI: .483 .702), the mean (γ = .537, SE = .051, CI: .441 .631) and a high level (γ = .491, SE = .068, CI: .365 .631). Hence, these results imply that the conditional indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived social value increases. This renders support for hypothesis H11(i).

Table 45 shows the results for hypotheses H11(c), (d) and (i). The graphs in Figures 45, 46 and 47 were plotted for further understanding of the moderated mediation results.

Table 45: Moderated mediation results conditioned on perceived social value

Moderator values	Path	Conditional indirect effects	Bootstrap SE	LLCI	ULCI
Low SV		.062	.028	.008	.118
Medium SV	RB→R→NWOM	.018	.023	-.027	.065
High SV		-.026	.038	-.101	.049
Low SV		.136	.026	.086	.187
Medium SV	IB→R→NWOM	.122	.023	.078	.168
High SV		.107	.032	.047	.172
Low SV		.583	.055	.483	.702
Medium SV	InB→R→NWOM	.537	.052	.441	.646
High SV		.491	.068	.365	.631

Note: bootstrap sample size = 5000 at 95% confidence interval (bias-corrected); SE = standard error
LLCI = lower-level confidence interval; ULCI = upper-level confidence interval
SV = perceived social value; RB = perceived risk barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth; IB = perceived image barrier; InB = perceived individual barrier
Low SV = mean – 1 standard deviation; Medium SV = mean; High SV = mean + 1 standard deviation
R-squared value of consumer resistance to smart payment services = .908
R-squared value of negative word of mouth = .541

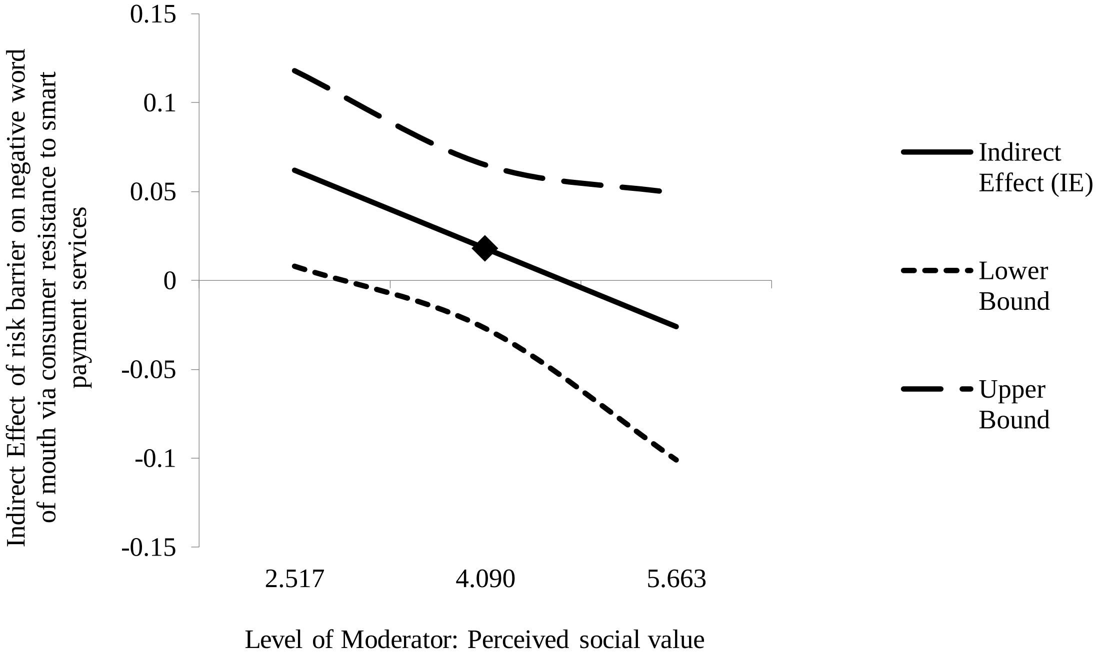


Figure 45: Conditional indirect effect of perceived risk barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived social value with 95% confidence bands

Note: The square indicates the mean level of perceived social value

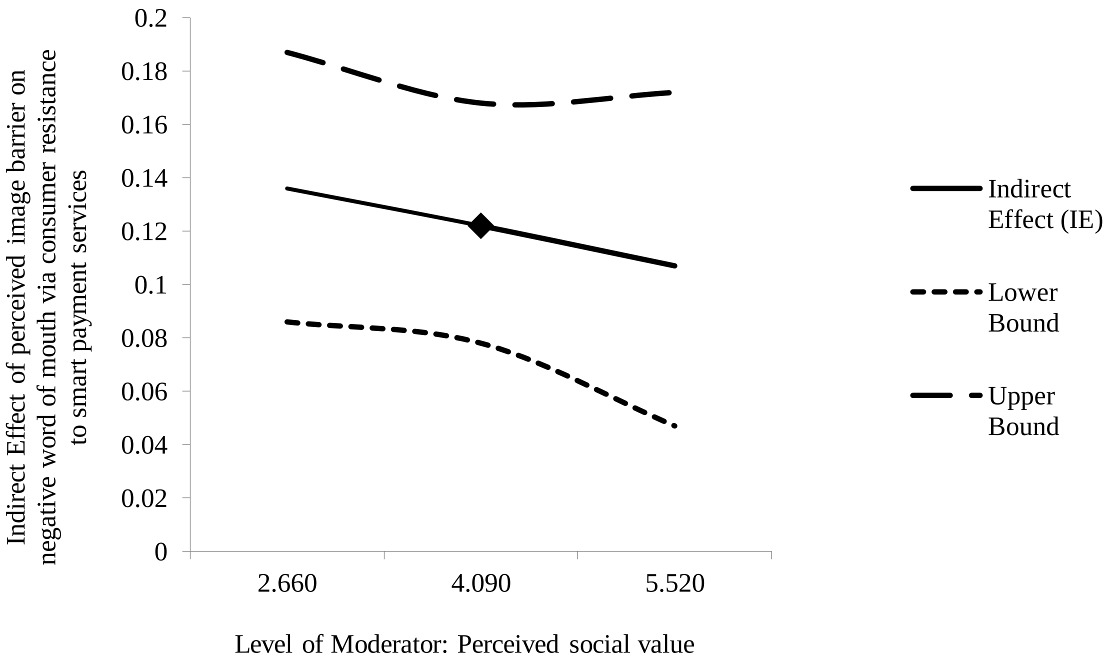


Figure 46: Conditional indirect effect of perceived image barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived social value with 95% confidence bands

Note: The square indicates the mean level of perceived social value

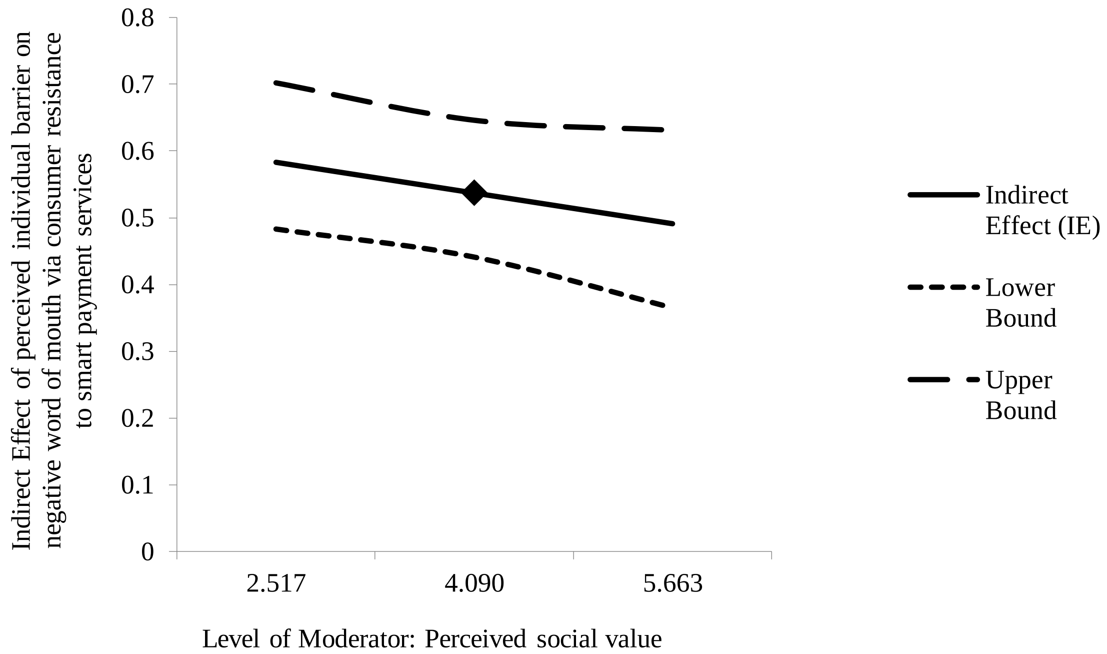


Figure 47: Conditional indirect effect of perceived individual barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived social value with 95% confidence bands

Note: The square indicates the mean level of perceived social value

iv. Moderated mediation conditioned on emotional value

Hypotheses H12(c) and (i) predicted that perceived emotional value will moderate the indirect effects of perceived risk barrier and perceived individual barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived emotional value.

According to Table 46, the bootstrapping analysis at 95% CIs excluding zero revealed a significant indirect effect of perceived risk barrier on NWOM (via consumer resistance to smart payment services) only at a low level of perceived emotional value (γ = .060, SE = .028, CI: .007 .116). But the indirect effects are not observed at the mean (CI: -.031 .056) and high levels (CI: -.107 .038) of perceived emotional value because the CIs contain zero. However, the graph in Figure 48 suggests that the conditional indirect effects of perceived risk barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived emotional value increases. This renders support for H12 (c).

The bootstrapping analysis at 95% CIs excluding zero further indicated significant indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) at all three levels of perceived emotional value: at a low level (γ = .572, SE = .053, CI: .474 .681), the mean (γ = .519, SE = .051, CI: .423 .622) and a high level (γ = .467, SE = .068, CI: .337 .603). Hence, these results imply that the conditional indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived emotional value increases. This provides support for hypothesis H12(i).

Table 46 presents the results for hypotheses H12(c) and (i). The graphs presented in Figures 48 and 49 provide additional understanding of the moderated mediation results.

Table 46: Moderated mediation results conditioned on perceived emotional value

Moderator values	**Path**	**Conditional indirect effects**	**Bootstrap SE**	**LLCI**	**ULCI**
Low EV		.059	.028	.007	.115
Medium EV	RB→R→NWOM	.012	.022	-.031	.056
High EV		-.036	.037	-.107	.038
Low EV		.527	.053	.474	.681
Medium EV	InB→R→NWOM	.519	.051	.423	.622
High EV		.468	.070	.337	.603

Note: bootstrap sample size = 5000 at 95% confidence interval (bias-corrected); SE = standard error
LLCI = lower-level confidence interval; ULCI = upper-level confidence interval
EV = perceived emotional value; RB = perceived risk barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth; InB = perceived individual barrier
Low EV = mean – 1 standard deviation; Medium EV = mean; High EV = mean + 1 standard deviation
R-squared value of consumer resistance to smart payment services = .909
R-squared value of negative word of mouth = .540

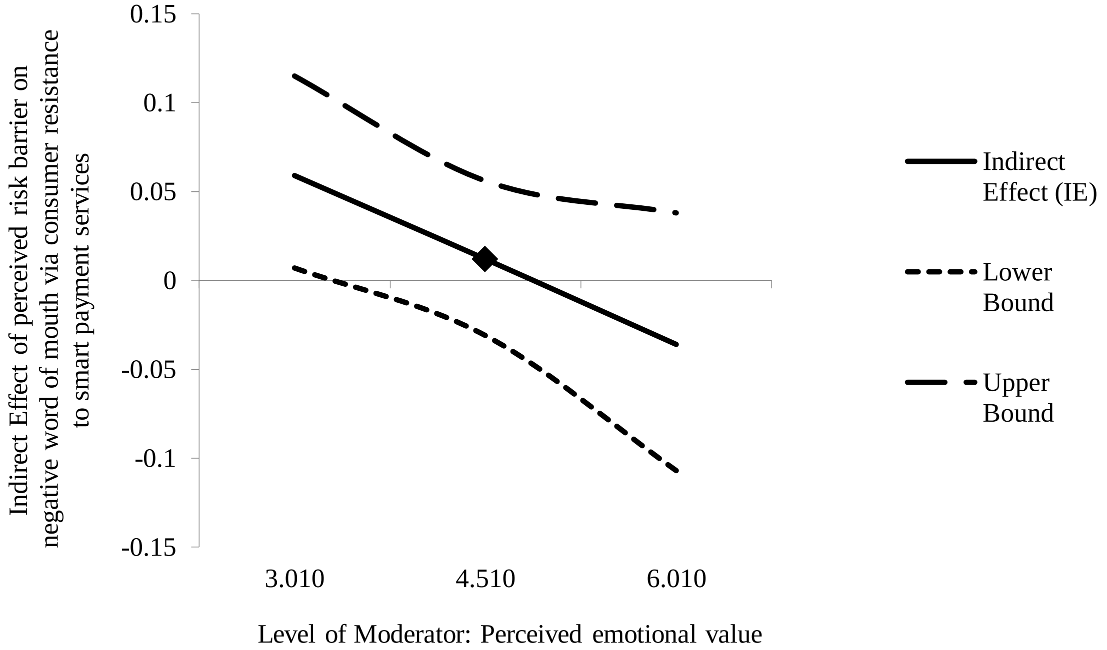


Figure 48: Conditional indirect effect of perceived risk barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived emotional value with 95% confidence bands
Note: The square indicates the mean level of perceived emotional value

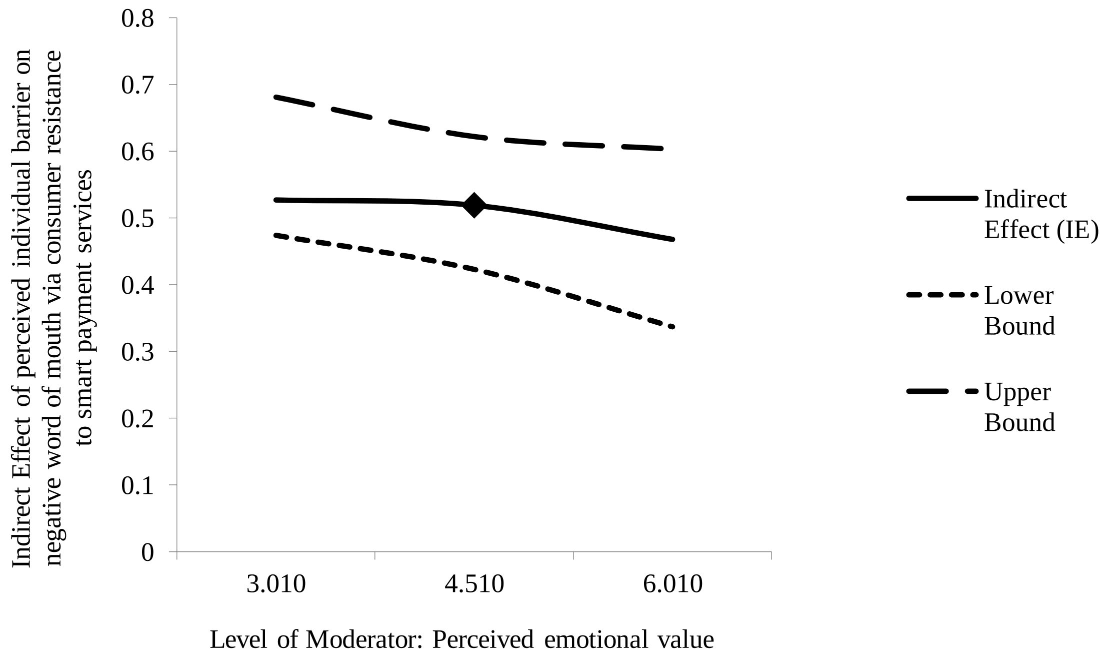


Figure 49: Conditional indirect effect of perceived individual barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived emotional value with 95% confidence bands
Note: The square indicates the mean level of perceived emotional value

v. Moderated mediation conditioned on epistemic value

Hypotheses H13(c) and (d) predicted that perceived epistemic value will moderate the indirect effects of perceived risk barrier and perceived image barrier on NWOM (via consumer resistance to smart payment services), such that the indirect effects are weaker at higher versus lower levels of perceived epistemic value.

According to Table 47, the bootstrapping analysis at 95% CIs excluding zero yielded a significant indirect effect of perceived risk barrier on NWOM (via consumer resistance to smart payment services) only at a low level of perceived epistemic value (γ = .068, SE = .027, CI: .017 .125). But the indirect effects are not observed at the mean (CI: -.031 .062) and high levels (CI: -.122 .046), of perceived epistemic value because the CI contain zero. However, the graph in Figure 50 suggests that the conditional indirect effects of perceived risk barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived epistemic value increases, <u>thereby supporting H13(c</u>).

The bootstrapping analysis at 95% CIs excluding zero further indicated significant indirect effects of perceived image barrier on NWOM (via consumer resistance to smart payment services) at a low level (γ = .145, SE = .026, CI: .096 .194), the mean (γ = .116, SE = .022, CI: .074 .161) and a high level (γ = .088, SE = .030, CI: .029 .147) of perceived epistemic value. Hence, the results imply that the conditional indirect effects of perceived image barrier on NWOM (via consumer resistance to smart payment services) become weaker as the level of perceived epistemic value increases. <u>This indicates support for hypothesis H13(d</u>).

Table 47 shows the results for hypotheses H13(c) and (d). The graphs presented in Figures 50 and 51 were plotted for further understanding of the moderated mediation results.

Table 47: Moderated mediation results conditioned on perceived epistemic value

Moderator values	Path	Conditional indirect effects	Bootstrap SE	LLCI	ULCI
Low EpV		.068	.027	.017	.125
Medium EpV	RB→R→NWOM	.012	.024	-.031	.062
High EpV		-.043	.042	-.122	.046
Low EpV		.144	.026	.096	.194
Medium EpV	IB→R→NWOM	.116	.022	.074	.161
High EpV		.088	.030	.029	.147

Note: bootstrap sample size = 5000 at 95% confidence interval (bias-corrected); SE = standard error
LLCI = lower-level confidence interval; ULCI = upper-level confidence interval
EpV = perceived epistemic value; RB = perceived risk barrier; R = consumer resistance to smart payment services; NWOM = negative word of mouth; IB = perceived image barrier
Low EpV = mean – 1 standard deviation; Medium EpV = mean; High EpV = mean + 1 standard deviation
R-squared value of consumer resistance to smart payment services = .911
R-squared value of negative word of mouth = .540

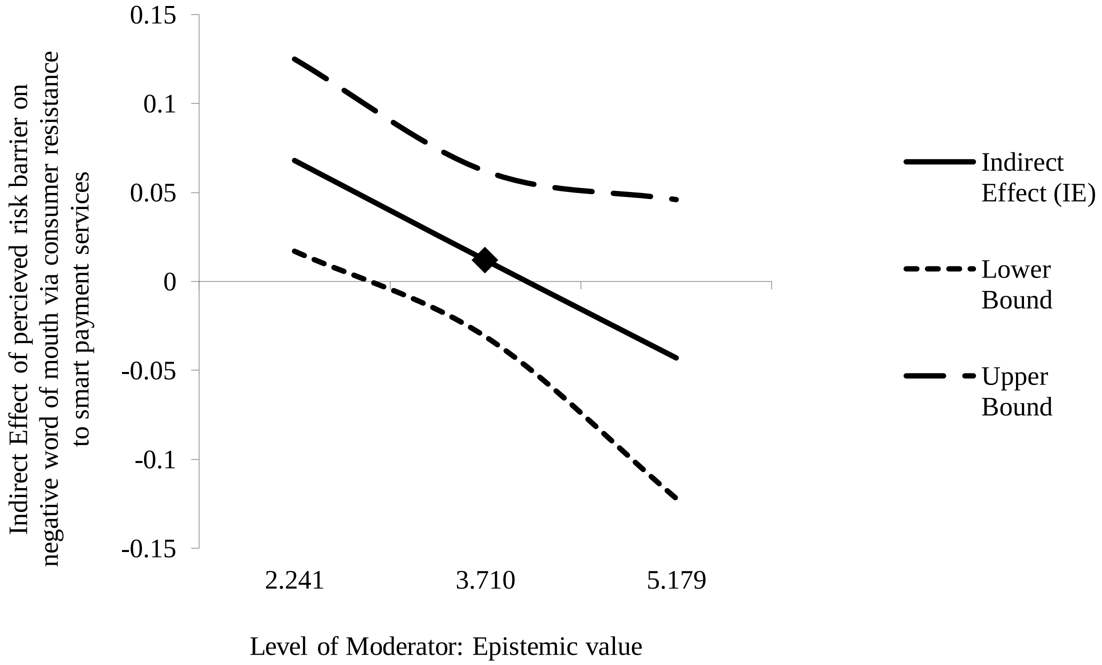


Figure 50: Conditional indirect effect of perceived risk barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived epistemic value, with 95% confidence bands
Note: The square indicates the mean level of perceived epistemic value

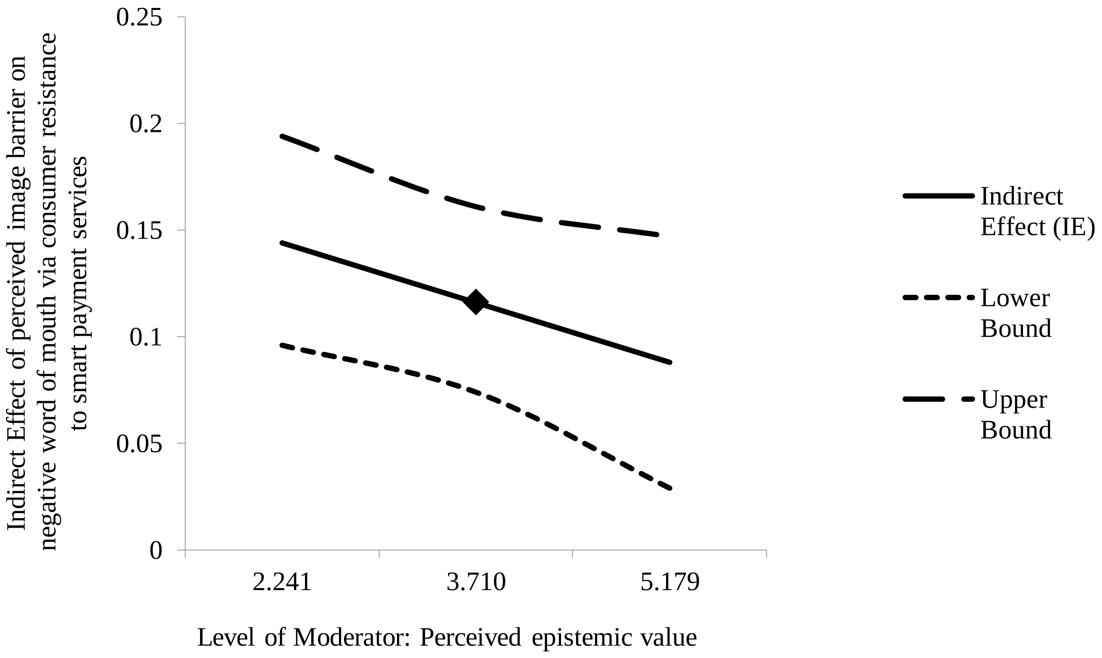


Figure 51: Conditional indirect effect of perceived image barrier on negative word of mouth via consumer resistance to smart payment services, conditioned on perceived epistemic value with 95% confidence bands
Note: The square indicates the mean level of perceived epistemic value

5.7 Conclusion

The quantitative data analysis was conducted on 356 consumer responses using IBM SPSS 27 and Stata 16 statistical softwares. The analysis consisted of a preliminary examination of the collected data along with factor analyses and descriptive analyses of the study constructs. This was followed by the testing of the hypotheses proposed in Chapter 3 that state the direct effect of perceived barriers on consumer resistance to smart payment services; the direct effect of consumer resistance to smart payment services on negative word of mouth; the mediating effect of consumer resistance to smart payment services between perceived barriers and NWOM; the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services; and finally, the moderated mediation effects (i.e., the conditional indirect effects) of perceived barriers on NWOM (via consumer resistance to smart payment services) depending on the perceived consumption values. A summary of the hypotheses results appears in Table 48.

Table 48: Summary of hypotheses results

Hypothesis (hypothesized sign)	**Result**
Direct effects	
H1(a): Perceived usage barrier → Consumer resistance to smart payment services (+)	S
H1(b): Perceived value barrier → Consumer resistance to smart payment services (+)	N.S.
H1(c): Perceived risk barrier → Consumer resistance to smart payment services (+)	S
H1(d): Perceived image barrier → Consumer resistance to smart payment services (+)	S
H1(e): Perceived tradition barrier → Consumer resistance to smart payment services (+)	N.S.
H1(f): Perceived technological dependence → Consumer resistance to smart payment services (+)	S
H1(g): Perceived technology anxiety → Consumer resistance to smart payment services (+)	N.S.
H1(h): Perceived ideological barrier → Consumer resistance to smart payment services (+)	S
H1(i): Perceived individual barrier → Consumer resistance to smart payment services (+)	S
H2: Consumer resistance to smart payment services → Negative word of mouth (+)	S
Mediating effect of consumer resistance to smart payment services	
H3(a): Perceived usage barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	N.S.
H3(b): Perceived value barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	N.S.*
H3(c): Perceived risk barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	S
H3(d): Perceived image barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	S
H3(e): Perceived tradition barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	N.S.*
H3(f): Perceived technological dependence → Consumer resistance to smart payment services → Negative word of mouth (+)	S
H3(g): Perceived technology anxiety → Consumer resistance to smart payment services → Negative word of mouth (+)	N.S.*
H3(h): Perceived ideological barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	S
H3(i): Perceived individual barrier → Consumer resistance to smart payment services → Negative word of mouth (+)	S
Moderating effects of perceived functional value (performance)	
H4(a): Perceived functional value (performance) x usage barrier → Consumer resistance to smart payment services (–)	S
H4(b): Perceived functional value (performance) x value barrier → Consumer resistance to smart payment services (–)	N.S.*
H4(c): Perceived functional value (performance) x risk barrier → Consumer resistance to smart payment services (–)	N.S.
H4(d): Perceived functional value (performance) x image barrier → Consumer resistance to smart payment services (–)	N.S.
H4(e): Perceived functional value (performance) x tradition barrier → Consumer resistance to smart payment services (–)	N.S.*

H4(f): Perceived functional value (performance) x technological dependence → Consumer resistance to smart payment services (–)	N.S.
H4(g): Perceived functional value (performance) x technology anxiety → Consumer resistance to smart payment services (–)	N.S.*
H4(h): Perceived functional value (performance) x ideological barrier → Consumer resistance to smart payment services (–)	N.S.
H4(i): Perceived functional value (performance) x individual barrier → Consumer resistance to smart payment services (–)	S
Moderating effects of perceived functional value (convenience)	
H5(a): Perceived functional value (convenience) x usage barrier → Consumer resistance to smart payment services (–)	N.S.
H5(b): Perceived functional value (convenience) x value barrier → Consumer resistance to smart payment services (–)	N.S.*
H5(c): Perceived functional value (convenience) x risk barrier → Consumer resistance to smart payment services (–)	S
H5(d): Perceived functional value (convenience) x image barrier → Consumer resistance to smart payment services (–)	S
H5(e): Perceived functional value (convenience) x tradition barrier → Consumer resistance to smart payment services (–)	N.S.*
H5(f): Perceived functional value (convenience) x technological dependence → Consumer resistance to smart payment services (–)	N.S.
H5(g): Perceived functional value (convenience) x technology anxiety → Consumer resistance to smart payment services (–)	N.S.*
H5(h): Perceived functional value (convenience) x ideological barrier → Consumer resistance to smart payment services (–)	N.S.
H5(i): Perceived functional value (convenience) x individual barrier → Consumer resistance to smart payment services (–)	N.S.
Moderating effects of perceived social value	
H6(a): Perceived social value x usage barrier → Consumer resistance to smart payment services (–)	S
H6(b): Perceived social value x value barrier → Consumer resistance to smart payment services (–)	N.S.*
H6(c): Perceived social value x risk barrier → Consumer resistance to smart payment services (–)	S
H6(d): Perceived social value x image barrier → Consumer resistance to smart payment services (–)	S
H6(e): Perceived social value x tradition barrier → Consumer resistance to smart payment services (–)	N.S.*
H6(f): Perceived social value x technological dependence → Consumer resistance to smart payment services (–)	N.S.
H6(g): Perceived social value x technology anxiety → Consumer resistance to smart payment services (–)	N.S.*
H6(h): Perceived social value x ideological barrier → Consumer resistance to smart payment services (–)	N.S.
H6(i): Perceived social value x individual barrier → Consumer resistance to smart payment services (–)	S
Moderating effects of perceived emotional value	
H7(a): Perceived emotional value x usage barrier → Consumer resistance to smart payment services (–)	N.S.
H7(b): Perceived emotional value x value barrier → Consumer resistance to smart payment services (–)	N.S.*
H7(c): Perceived emotional value x risk barrier → Consumer resistance to smart payment services (–)	S
H7(d): Perceived emotional value x image barrier → Consumer resistance to smart payment services (–)	N.S.

H7(e): Perceived emotional value x tradition barrier → Consumer resistance to smart payment services (–)	N.S.*
H7(f): Perceived emotional value x technological dependence → Consumer resistance to smart payment services (–)	N.S.
H7(g): Perceived emotional value x technology anxiety → Consumer resistance to smart payment services (–)	N.S.*
H7(h): Perceived emotional value x ideological barrier → Consumer resistance to smart payment services (–)	N.S.
H7(i): Perceived emotional value x individual barrier → Consumer resistance to smart payment services (–)	S
Moderating effects of perceived epistemic value	
H8(a): Perceived epistemic value x usage barrier → Consumer resistance to smart payment services (–)	S
H8(b): Perceived epistemic value x value barrier → Consumer resistance to smart payment services (–)	N.S.*
H8(c): Perceived epistemic value x risk barrier → Consumer resistance to smart payment services (–)	S
H8(d): Perceived epistemic value x image barrier → Consumer resistance to smart payment services (–)	S
H8(e): Perceived epistemic value x tradition barrier → Consumer resistance to smart payment services (–)	N.S.*
H8(f): Perceived epistemic value x technological dependence → Consumer resistance to smart payment services (–)	N.S.
H8(g): Perceived epistemic value x technology anxiety → Consumer resistance to smart payment services (–)	N.S.*
H8(h): Perceived epistemic value x ideological barrier → Consumer resistance to smart payment services (–)	N.S.
H8(i): Perceived epistemic value x individual barrier → Consumer resistance to smart payment services (–)	N.S.
Moderated mediation effects conditioned on perceived functional value (performance)	
H9(a): Perceived functional value (performance) x usage barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(b): Perceived functional value (performance) x value barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(c): Perceived functional value (performance) x risk barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(d): Perceived functional value (performance) x image barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(e): Perceived functional value (performance) x tradition barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(f): Perceived functional value (performance) x technological dependence → Consumer resistance to smart payment services→ Negative word of mouth	
H9(g): Perceived functional value (performance) x technology anxiety → Consumer resistance to smart payment services→	

Negative word of mouth	
H9(h): Perceived functional value (performance) x ideological barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H9(i): Perceived functional value (performance) x individual barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
Moderated mediation effects conditioned on perceived functional value (convenience)	
H10(a): Perceived functional value (convenience) x usage barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H10(b): Perceived functional value (convenience) x value barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H10(c): Perceived functional value (convenience) x risk barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H10(d): Perceived functional value (convenience) x image barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H10(e): Perceived functional value (convenience) x tradition barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H10(f): Perceived functional value (convenience) x technological dependence → Consumer resistance to smart payment services→ Negative word of mouth	
H10(g): Perceived functional value (convenience) x technology anxiety → Consumer resistance to smart payment services→ Negative word of mouth	
H10(h): Perceived functional value (convenience) x ideological barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H10(i): Perceived functional value (convenience) x individual barrier → Consumer resistance to smart payment services→ Negative word of mouth	
Moderated mediation effects conditioned on perceived social value	
H11(a): Perceived social value x usage barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H11(b): Perceived social value x value barrier → Consumer resistance to smart payment services→ Negative word of mouth	

H11(c): Perceived social value x risk barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H11(d): Perceived social value x image barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H11(e): Perceived social value x tradition barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H11(f): Perceived social value x technological dependence → Consumer resistance to smart payment services→ Negative word of mouth	
H11(g): Perceived social value x technology anxiety → Consumer resistance to smart payment services→ Negative word of mouth	
H11(h): Perceived social value x ideological barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H11(i): Perceived social value x individual barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
Moderated mediation effects conditioned on perceived emotional value	
H12(a): Perceived emotional value x usage barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H12(b): Perceived emotional value x value barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H12(c): Perceived emotional value x risk barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H12(d): Perceived emotional value x image barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H12(e): Perceived emotional value x tradition barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H12(f): Perceived emotional value x technological dependence → Consumer resistance to smart payment services→ Negative word of mouth	
H12(g): Perceived emotional value x technology anxiety → Consumer resistance to smart payment services→ Negative word of mouth	

H12(h): Perceived emotional value x ideological barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H12(i): Perceived emotional value x individual barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
Moderated mediation effects conditioned on perceived epistemic value	
H13(a): Perceived epistemic value x usage barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H13(b): Perceived epistemic value x value barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H13(c): Perceived epistemic value x risk barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H13(d): Perceived epistemic value x image barrier → Consumer resistance to smart payment services→ Negative word of mouth	S
H13(e): Perceived epistemic value x tradition barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H13(f): Perceived epistemic value x technological dependence → Consumer resistance to smart payment services→ Negative word of mouth	
H13(g): Perceived epistemic value x technology anxiety → Consumer resistance to smart payment services→ Negative word of mouth	
H13(h): Perceived epistemic value x ideological barrier → Consumer resistance to smart payment services→ Negative word of mouth	
H13(i): Perceived epistemic value x individual barrier → Consumer resistance to smart payment services→ Negative word of mouth	

Notes: S = supported; N.S. = not supported

* For these hypotheses, direct effects of perceived barriers on consumer resistance to smart payment services are non-significant. Hence, in the case of such non-significant barriers, the mediating and moderating results are likely to be non-significant.

Chapter 6 – Discussion and Managerial Implications

As the majority of innovation research has focused on investigating the success factors of an innovation in order to understand its adoption process (Heidenreich and Handrich, 2015), research emphasizing understanding the factors that may lead to consumers resisting innovations is sparse (Kaur, Dhir, Bodhi et al., 2020; Talwar et al., 2020). Further, the majority of the innovation resistance studies focus on the development of consumers' resistance towards innovation due to their barrier perceptions (e.g., Casidy et al., 2021; Mani and Chouk, 2018), and research has yet to gain empirical understanding of the role of some scarcely investigated barriers, how consumer resistance to innovation may be detrimental to the success of innovations and how these barrier perceptions can be mitigated to overcome consumer resistance to innovation.

Therefore, building on prior research that investigated the role of barriers in influencing consumer resistance to innovation (e.g., Joachim et al., 2018; Khanra et al., 2021; Laukkanen, 2016; Santos and Ponchio, 2021), this study addresses the gaps identified in the literature (as discussed in Chapter 2). Specifically, this study provides a comprehensive understanding of the phenomenon of consumer resistance to innovation by examining the following: 1) the mechanism of resistance in the context of service innovation (i.e., smart payment services); 2) the development of consumer resistance to smart payment services due to different barrier perceptions; 3) the detrimental impact of consumer resistance to smart payment services by empirically establishing its consequence in the form of NWOM; 4) the role of consumer resistance to smart payment services as an underlying mechanism that explicates the translation of perceived barriers into NWOM; and 5) the role of perceived consumption values in buffering the effects of barrier perceptions on consumer resistance to smart payment services and resulting NWOM.

6.1 Study findings

6.1.1 Key barriers leading to consumer resistance to innovation

The first aim of this study sought to examine the key antecedents (perceived barriers) of consumer resistance to innovation in the context of smart payment services. This study found that the barriers posited under the widely acknowledged innovation resistance theory (Ram and Sheth, 1989), that is, usage barrier, image barrier, and risk barrier, are perceived by consumers which lead to their resistance towards smart payment services.

Following the definition of complexity laid down by Rogers (2003) as the "degree to which an innovation is perceived as difficult to understand and use" (p. 257), the findings of this study indicate that consumers perceive smart payment services as being complex to use (usage barrier), which drives their resistance towards these services. This is because consumers perceive that a smart payment service involves complicated processes (e.g., wirelessly connecting smart devices with online/offline payment terminals) that are equipped by sophisticated technology (e.g., sensors and microprocessors) (Mani and Chouk, 2018). As such, despite being a part of a rapidly growing digital environment, consumers are still concerned about trying these smart services, which they perceive as complex (Chouk and Mani, 2019), thereby leading to their resistance. This finding agrees with those of other studies (e.g., Leong et al., 2020; Mani and Chouk, 2018) that demonstrate perceived complexity as one of the barriers leading to consumer resistance to innovation.

Further, consistent with priorsresearch (e.g., Juric and Lindenmeier, 2018; Mani and Chouk, 2018, 2019) and Ram and Sheth's (1989) model that finds perceived risk barrier to be a key cause of consumer resistance to innovation, this study found that perceived security risk leads to resistance to smart payment services. A possible explanation of this finding may be that as the use of a smart payment service involves connecting to online payment terminals, consumers are concerned about the risks of the exposure and theft of their private and sensitive data (e.g., credit/debit card details and transaction amounts), as well as their smart devices being vulnerable to hackers or other unauthorized third parties (Mani and Chouk, 2018, 2019), thereby influencing their resistance.

According to self-congruity theory (Sirgy, 1985), self-image congruence is a key psychological variable that explains consumers' decision-making mechanisms. Consistent with this theory, the findings also indicate that self-image incongruence (perceived image barrier) is a psychological barrier responsible for consumers' resistance towards smart payment services. This implies that consumers resist smart payment services because they perceive a conflict between their self-image and the image of the service innovation. Therefore, similar to prior research findings that underscore the significance of image congruency for innovation adoption (Anton et al., 2013) and resistance (Mani and Chouk, 2018), consumers perceive this service innovation to be highly non-essential and as not conforming with their lifestyle and think that this innovative payment service is only for tech-savvy individuals (Mani and Chouk, 2018).

However, inconsistent with prior research findings related to a value barrier influencing consumer resistance to innovation (e.g., Khanra et al., 2021), this study revealed that consumers' resistance towards smart payment services is not driven by high perceived price (perceived value barrier). This finding is in line with those of Mani and Chouk (2018) and Kleijnen et al. (2004) in which perceived costs or prices associated with mobile financial services were found to be unrelated to consumer attitudes such as resistance to the services. This finding can be explained by acknowledging that with the evolution of financial technologies, consumers do not have sufficient knowledge of the costs of smart payment services and hence is negligible for them (Koenig-Lewis et al., 2010).

The study findings also indicate that a need for human interaction (perceived tradition barrier) is not the reason for consumers' resistance to smart payment services. This finding is in line with that of Walker and Johnson (2006), who also found that the need for human contact does not influence the use of internet-based services such as online shopping. However, this finding is different from that of prior research in which lack of human interaction was found to be an essential influencer of consumer resistance (Laukkanen, 2016; Mani and Chouk, 2018). An explanation of this finding could be that due to the growing pace of digitization of financial services and the advantages these offer (e.g., convenience, access, speed and accuracy) (e.g., Collier and Kimes, 2013), prospective consumers are not primarily concerned about the lack of human interaction in the context of smart payment services.

Moreover, the study findings also revealed that the major reasons for consumer resistance towards smart payment services are the additional barriers (i.e., technological dependence, ideological barrier and individual barrier) that were recently introduced by Mani and Chouk (2018) in their extended Ram and Sheth's (1989) framework, but which have received limited attention in the innovation resistance research.

Attribution theory suggests that people attribute causes to events based on their cognitive perceptions, which influence their attitudes and behaviour (Kelley and Michela, 1980). In line with prior research in which attribution theory has been used to understand the influence of consumers' scepticism about firms' practices and messages on their attitude and behaviour (e.g., Skarmeas and Leonidou, 2013) and which demonstrates that general scepticism acts as a major factor driving consumer resistance to smart services (e.g., Chouk and Mani, 2019), this study found general scepticism (perceived ideological barrier) to be the major barrier driving consumer resistance towards smart payment services. This is possibly because as consumers are inexperienced with smart payment services, they still perceive this service innovation as completely novel. As such, they have developed scepticism or doubts about the service innovation's benefits as promised by the companies via various commercial sources, such as marketing discourses (e.g., advertisements), prescriptive discourses (e.g., demonstration videos) and prospective discourses (e.g., consultancy firm reports) (Chouk and Mani, 2019; Mani and Chouk, 2018). Moreover, this type of scepticism developed by consumers encourages them to think that smart payment services may not fulfil the purpose for which the firms introduced the service, causing them to raise questions about different aspects of the service innovation, such as: is the information provided during the promotion of the service true? or does the service really perform the way it has been promised by its providers? (Morel and Pruyn, 2003).

While Mani and Chouk (2017, 2018) did not find that any of the technology vulnerability barriers (technological dependence and technology anxiety) had a direct influence on consumer resistance, the current study found technological dependence to be another major barrier leading to consumers' resistance towards smart payment services. This finding is consistent with the proposition of the TAP index, which found that technological dependence was one of the factors hindering the adoption of technology by consumers (Ratchford and Barnhart, 2012). This finding can be explained such that as smart payment services involve frequent and intense human-machine interactions, potential consumers are concerned about becoming overdependent on the incorporated advanced technologies (e.g., NFC technology), as they are afraid that, without relying on such technology, they will not be able to manage any task (e.g., payment transactions) (Shu et al., 2011). Further, in line with Mani and Chouk's (2018) study, another technology vulnerability barrier (i.e., technology anxiety) was not found to be related to resistance to smart payment services. Possibly, because of the integration of various digital payment services (e.g., internet banking and mobile banking) in consumers' everyday life, they do not seem to be concerned about unfamiliarity with such digital technologies and hence are not apprehensive about such payment services.

This study also found that a perceived individual barrier (inertia) drives consumers' resistance towards smart payment services. This finding is consistent with the application of status quo bias theory (Samuelson and Zeckhauser, 1988), which explains the influence of inertia in inhibiting the use of a new product/service (Polites et al., 2012), and prior research findings (e.g., Mani and Chouk, 2018) showing inertia causing consumers' resistance towards smart banking services. This can be explained by the notion that as consumers perceive the use of smart payment services may lead to changes in their established habit of making payments via traditional payment methods, they resist smart payment services (Talke and Heidenreich, 2014). In addition, the long-term use of traditional payment methods may have influenced consumers to believe that these methods are superior to smart payment services, leading them to become irrationally attached to traditional payment methods (status quo satisfaction) and to neglect this service innovation (Heidenreich and Handrich, 2015).

In conclusion, the direct influences of different barrier perceptions on consumer resistance to smart payment services reveal the following key findings:

Key finding 1 – The *scarcely researched barriers* (i.e., ideological barrier, $\gamma = 0.389$**; individual barrier,** $\gamma = 0.334$**; and technological dependence,** $\gamma = 0.327$**) were found to be *major reasons* for consumer resistance to smart payment services compared to the extensively researched barriers (i.e., usage barrier,** $\gamma = 0.193$; **risk barrier,** $\gamma = 0.104$ **and image barrier,** $\gamma = 0.200$**).**

Key finding 2 – *Ideological barrier* (i.e., perceived scepticism, $\gamma = 0.389$**) was found to be the major cause of consumer resistance to smart payment services.**

Key finding 3 – The effects of commonly investigated barriers (i.e., perceived value barrier and tradition barrier) on consumer resistance to smart payment services were surprisingly found to be non-significant.

6.1.2 Consequences of consumer resistance to innovation

The second aim of this study was to empirically establish the detrimental effect of consumer resistance to smart payment services on negative word of mouth (NWOM). A limited amount of research has investigated the consequences of consumer resistance to innovation (Heidenreich and Handrich, 2015; Heidenreich and Kraemer, 2015), such as intention to adopt or use intention (e.g., Kim and Park, 2020; Kladkleeb and Vongura, 2019). In this respect, the findings of this study revealed that consumers' resistance towards smart payment services directly encourages them to share negative comments and opinions about the service innovation with other consumers.

Key finding 4 – NWOM is a key detrimental consequence of consumer resistance to smart payment services.

6.1.3 Mediating role of consumer resistance to innovation

The third aim of this study was to examine the mediating role of consumer resistance to smart payment services in the relationship between perceived barriers and NWOM. In this regard, this study uncovered the role of consumer resistance to smart payment services as an underlying mechanism that explicates how and why perceptions of different barriers transform into NWOM. Specifically, consumer resistance to smart payment services was found to partially mediate the relationship between perceived barriers (risk barrier, image barrier, ideological barrier, and individual barrier) and NWOM. This suggests that consumers' resistance to smart payment services is partially accountable for explaining why perceptions of security risk, inconsistency between self-image and the image of the innovation, scepticism towards the service provider's various discourses, and irrational satisfaction with traditional payment methods can lead to resistant consumers' engagement in negative opinion sharing about the smart payment service with others. It was also revealed that consumer resistance to smart payment services fully mediates the relationship between perceived technological dependence and NWOM. This implies that consumers' resistance towards smart payment services is the only reason that explains why their fear of becoming too dependent on incorporated advanced technologies can lead to sharing negative comments and opinions regarding the service innovation with other consumers.

These findings suggest that potential consumers who perceive barriers spread NWOM about smart payment services because they show resistance towards such services. This is further corroborated by the results of the direct effects of perceived barriers on NWOM. For instance, consistent with findings in the extant literature (e.g., Kaur, Dhir, Ray et al., 2020), although the direct effects of risk barrier, image barrier, and individual barrier on NWOM were found to be significant but negative, the indirect effects via resistance are all significantly positive (see Table 37 in section 5.6.3(b)).

However, perceived usage barrier was also found to have a positive influence on NWOM without consumer resistance to smart payment services acting as a mediator. This is possibly because perceived complexity poses challenges for inexperienced users of smart payment services and, as such, they spread NWOM in order to release their frustration (S. Talwar, Dhir et al., 2021).

Hence, an important finding is

Key finding 5 – Consumer resistance to smart payment services *mediates* the effects of perceived risk barrier, perceived image barrier, perceived technological dependence, perceived ideological barrier, and perceived individual barrier on NWOM, except for perceived usage barrier.

6.1.4 Moderating role of perceived consumption values

With respect to the fourth aim, by examining the moderating role of consumption values in the relationship between perceived barriers and consumer resistance to smart payment services, this study makes another important contribution to the innovation literature, as little is known about how the effects of perceived barriers on consumer resistance to innovation can be regulated (e.g., Mani and Chouk, 2018). In accordance with the contentions of prospect theory (Kahneman and Tversky, 1979) in behavioural research and prior studies (e.g., Chiu et al., 2014; Chung and Koo, 2015; Wong et al., 2021) explaining consumer decision making due to an integrative evaluation of gains and losses under situations associated with risks and uncertainties, the findings of this study demonstrate that consumption values buffer the effects of barrier perceptions on consumer resistance to smart payment services. Specifically, the study findings confirm the buffering role of perceived functional value (performance and convenience), perceived social value, perceived emotional value, and perceived epistemic value on the relationship between perceived barriers and consumer resistance to smart payment services.

a) Moderating role of perceived functional value (performance)

In terms of performance, this study found that perception of functional value suppresses the effects of two perceived barriers (i.e., usage barrier and individual barrier) on consumer resistance to smart payment services.

The findings revealed that functional value in terms of performance benefits buffers the effect of perceived usage barrier on consumer resistance to innovation. This implies that if smart payment services are expected to offer a consistent quality of service with a well-designed platform for performing necessary financial transactions, such expected utility buffers the effect of consumers' concerns regarding usage complexity (e.g., difficulty in performing the necessary financial transactions) of the service innovation on their resistance.

It was also found that perception of functional value (performance) reduces the effect of perceived individual barrier on consumer resistance to smart payment services. This indicates that if smart payment services are expected to offer a high-quality performance service with a well-designed platform for making necessary financial transactions, this can reduce inertia (i.e., consumers' preference for maintaining the status quo), consequently lowering their resistance towards smart payment services.

b) Moderating role of perceived functional value (convenience)

Further, in terms of convenience, this study found that perception of functional value suppresses the effects of two perceived barriers (i.e., risk barrier and image barrier) on consumer resistance to smart payment services.

First, the findings demonstrate that perceived functional value (convenience) dampens the effect of perceived risk barrier on consumer resistance to smart payment services. This finding can be explained as if the smart payment services are expected to offer a convenient and efficient way of making payments anytime and anywhere, the impact of consumers' concerns regarding security risks (such as the susceptibility of their personal and financial details to being hacked by unauthorized third parties) on their resistance to the service innovation can be reduced.

It was also found that perception of functional value (convenience) reduces the effect of perceived image barrier on consumer resistance to smart payment services. This indicates that if smart payment services are expected to offer a convenient and efficient service for making necessary financial transactions, this reduces the impact of incompatibility between resistant consumers' self-image and the image of the smart payment service on their resistance towards such service innovation.

c) Moderating role of perceived social value

The findings indicate that perceived social value buffers the effects of four perceived barriers (i.e., usage barrier, risk barrier, image barrier and individual barrier) on consumer resistance to smart payment services.

First, it was found that perceived social value buffers the effect of perceived usage barrier on consumer resistance to smart payment services. This implies that if smart payment services are expected to improve the social image/status and offer social acceptance/approval of consumers among significant others, this abates the effect of any concerns they may have regarding usage complexity (e.g., difficulty in performing the necessary financial transactions) of the service innovation on their resistance.

Second, the findings demonstrate that perceived social value dampens the effect of perceived risk barrier on consumer resistance to smart payment services. This finding implies that if smart payment services are expected to enhance social image/status and provide social acceptance/approval among significant others, such expected utility suppresses the effect of resistant consumers' concerns about the associated security risks (e.g., credit/debit card information being vulnerable to hacking) on their resistance towards the service innovation.

Third, the findings suggest that perceived social value suppresses the effect of perceived image barrier on consumer resistance to smart payment services. This implies that if smart payment services are expected to improve consumers' social status and offer social acceptance/approval among significant others, this can reduce the effect of incongruence between resistant consumers' self-image and the image of the smart payment services on their resistance towards the service innovation.

Last, it was also found that perceived social value reduces the effect of perceived individual barrier on consumer resistance to smart payment services. In other words, if smart payment services are associated with social status improvement and social approval attainment, this can buffer the effects of inertia (i.e., consumers' preference for maintaining the status quo), consequently reducing their resistance towards smart payment services.

d) Moderating role of perceived emotional value

The findings indicate that perceived emotional value buffers the effects of two perceived barriers (i.e., risk barrier and individual barrier) on consumer resistance to smart payment services.

The findings of this study revealed that the effect of perceived risk barrier on consumer resistance to smart payment services can be reduced by the perception of emotional value. This finding implies that consumers' expectation of pleasure, enjoyment, or comfort in using smart payment service abates the effect of concerns related to security risk (e.g., abuse of financial information by hackers or third-party organizations) on their resistance towards smart payment services.

It was also found that the effect of perceived individual barrier on consumer resistance to smart payment services can be buffered by perceived emotional value. In other words, consumers' expectation of emotional gains (i.e., pleasure, enjoyment or comfort) in using smart payment services can suppress the effect of consumers' inertia (i.e., preference for maintaining the status quo) on their resistance towards smart payment services.

e) Moderating role of perceived epistemic value

The findings indicate that perceived epistemic value buffers the effects of three perceived barriers (i.e., usage barrier, risk barrier and image barrier) on consumer resistance to smart payment services.

First, it was found that perceived epistemic value buffers the effect of perceived usage barrier on consumer resistance to smart payment services. This implies that if smart payment services can arouse curiosity about using these services and provide a novel experience among consumers, the impact of any concerns regarding usage complexity (e.g., difficulty in performing the necessary financial transactions) of the service innovation on their resistance can be reduced.

This study found that perceived epistemic value reduces the effect of perceived risk barrier on consumer resistance to smart payment services. This implies that if smart payment services can arouse curiosity about using these services and provide a novel experience among consumers, this can buffer the impact of their concerns about security risks (e.g., breach of confidential personal and financial information) on their resistance.

Furthermore, the findings also demonstrate that perceived epistemic value minimizes the effect of perceived image barrier on consumer resistance to smart payment services. In other words, if smart payment services can arouse curiosity about using these services and provide a novel experience among consumers, this can diminish the effect of conflict between resistant consumers' self-image and the image of smart payment services on their resistance towards the service innovation.

In conclusion, the effects of various perceived barriers on consumer resistance towards smart payment services can be buffered if resistant consumers perceive that smart payment services can offer certain consumption values. However, the findings revealed that perceived consumption values do not buffer the effects of technological dependence on consumer resistance to smart payment services. The finding can be explained by the idea that in today's digital world, as consumers are constantly interacting with different technologies in every aspect of their lives, the negative effects of technology overuse and addiction (e.g., technostress, Shu et al., 2011; social isolation, Davis, 2001) are likely to be unavoidable. The findings also revealed that perceived consumption values do not buffer the effects of ideological barrier (general scepticism) on consumer resistance to smart payment services. It is possible that consumers who receive conflicting information about smart services (such as smart payments) from commercial sources, as well as anti-market activist networks, form negative opinions about such services, which leads to their scepticism towards the service-related benefits promised by the service providers (Mani and Chouk, 2018). Therefore, technological dependence and ideological barrier were found to influence consumer resistance towards smart payment services irrespective of the consumption values perceived.

Hence, the key findings are as follows:

Key finding 6 – *Perceived social value* (compared with other consumption value perceptions) was found to be a *major mitigator* in buffering the effect of the *highest number of perceived barriers* (i.e., usage barrier, image barrier, risk barrier and individual barrier) on consumer resistance to smart payment services.

Key finding 7 – Among all the barriers considered, *only the effect of risk barrier* on consumer resistance to smart payment services was found to be buffered by *the majority of consumption values* (i.e., perceived functional value – convenience, perceived social value, perceived emotional value, and perceived epistemic value).

According to key finding 1 (see section 6.1.1), individual barrier ($\gamma = 0.334$) was found to be the second major barrier leading to consumer resistance to smart payment services; ideological barrier being the first major barrier ($\gamma = 0.389$). Building on this, the findings related to the moderating effect of consumption values revealed the following:

Key finding 8 – The effect of the *second major barrier* (i.e., *perceived individual barrier*) on consumer resistance to smart payment services was found to be buffered by *three consumption values* (i.e., perceived functional value – performance, perceived social value, and perceived emotional value).

6.1.5 Moderated mediation effects

When considering the mediating role of consumer resistance to smart payment services in the relationship between barriers and NWOM and the moderating role of perceived consumption values, this study also hypothesized moderated mediation effects. Therefore, the moderated mediation effects were analysed based on significant mediating and moderating effects. The findings show that perceptions of consumption values also play an important role in discouraging the spread of NWOM about smart payment services by resistant consumers. Hence, the findings demonstrate that the indirect relationship of perceived barriers with NWOM via consumer resistance to smart payment services is weaker when the consumption values perceived by consumers are higher.

a) Indirect effects conditioned on perceived functional value (performance)

The results revealed that the indirect effects of perceived individual barrier on NWOM (via consumer resistance to smart payment services) are weaker as consumers perceive higher functional value (performance). This suggests that consumers who resist smart payment services due to inertia (i.e., status quo preference) are less likely to share negative comments and opinions about this service innovation when high levels of performance and quality are expected to be gained from such services.

b) Indirect effects conditioned on perceived functional value (convenience)

The results show the conditional effects of perceived functional value (convenience) on the indirect relation between perceived risk barrier and NWOM (via consumer resistance to smart payment services), such that the indirect relationships are found only at low but not at average/high levels of perceived functional value (convenience). According to these results, consumers' resistance to smart payment services transmits the impact of associated security concerns with the service innovation onto negative opinion sharing only when they have low expectations of receiving convenient and efficient service experience from these payment services. This also indicates that consumers' high and average expectations of receiving convenient and efficient service experiences do not translate their security concerns into NWOM as they resist the service innovation.

It was further found that the indirect effect of image barrier on NWOM (via consumer resistance to smart payment services) is weaker when functional value (convenience) perception is high rather than low. This indicates that consumers who perceive smart payment services to be incompatible with their lifestyle and preferences and resist such innovation are less likely to criticize and denigrate the service innovation to others if they expect to derive a highly convenient and efficient service experience from the service innovation.

c) Indirect effects conditioned on perceived social value

The results show the conditional effects of perceived social value on the indirect relation between perceived risk barrier and NWOM, such that the indirect relationships are found only at low but not at average/high levels of perceived social value. These results suggest that consumer resistance to smart payment services transmits the effect of associated security concerns with the service innovation onto consumers' negative opinion sharing only when the expectations of attaining improved social status from smart payment services are low. This also indicates that high and average expectations of attaining improved social status do not transform consumers' security concerns into NWOM sharing as they resist such services.

It was further found that the indirect effect of image barrier on NWOM (via consumer resistance to smart payment services) is weaker when social value perception is high rather than low. This indicates that consumers who perceive smart payment services to be incompatible with their lifestyle and preferences and resist such innovation are less likely to criticize and denigrate the service innovation to others if they expect to derive high social status/image and peer approval from such a service innovation.

The study findings also demonstrate that the indirect effect of individual barrier on NWOM (via consumer resistance to smart payment services) is weaker when social value perception is high rather than low. This suggests that consumers who resist smart payment services due to inertia (i.e., status quo preference) are less likely to share negative comments and opinions about the service innovation when a high level of social status and peer approval is expected to be gained from such services.

d) Indirect effects conditioned on perceived emotional value

The results show the conditional effects of perceived emotional value on the indirect relation between perceived risk barrier and NWOM, such that the indirect relationships are found only at low but not at average/high levels of perceived emotional value. These results suggest that consumer resistance to smart payment services transmits the effect of associated security concerns with the service innovation onto consumers' negative opinion sharing only when the expectations of emotional benefits (e.g., pleasure, enjoyment or comfort) from smart payment services are low. Hence, this also indicates that higher and average expectations of attaining emotional benefits do not transform consumers' security concerns into NWOM as they resist such services.

The results revealed that the indirect effect of individual barrier on NWOM (via consumer resistance to smart payment services) is weaker when emotional value perception is high rather than low. This indicates that consumers who resist smart payment services due to inertia (i.e., status quo preference) are less likely to share negative comments and opinions about such services when high levels of emotional benefits (e.g., pleasure, enjoyment or comfort) are expected to be gained from using smart payment services.

e) Indirect effects conditioned on perceived epistemic value

The results show the conditional effects of perceived epistemic value on the indirect relation between perceived risk barrier and NWOM, such that the indirect relationships are found only at low but not at average/high levels of perceived epistemic value. These results suggest that consumer resistance to smart payment services transmits the effect of associated security concerns with such services onto consumers' negative opinion sharing only when the level of curiosity aroused and the novel service experience offered by the smart payment services are low. This also indicates that when smart payment services are expected to offer high and average levels of novelty and curiosity, consumers' security concerns do not transform into negative opinion sharing as they resist such services.

It was found that the indirect effect of image barrier on NWOM (via consumer resistance to smart payment services) is weaker when epistemic value perceptions are high rather than low. This indicates that consumers who perceive smart payment services to be incompatible with their lifestyle and preferences and resist such services are less likely to spread negative opinions and comments about such services among other consumers if they expect smart payment services to arouse high levels of curiosity and offer a highly novel service experience.

In conclusion, the key findings are as follows:

Key finding 9 – Higher perceptions of consumption values can *buffer* the impact of barriers on consumers' NWOM as they resist smart payment services.

Key finding 10 – The impact of risk barrier transforming into NWOM as consumers show resistance towards smart payment services becomes *negligible* when they perceive high functional value (convenience), social value, emotional value and epistemic value.

Key finding 11 – The impact of image barrier transforming into NWOM as consumers show resistance towards smart payment services is *reduced* when they perceive high functional value (convenience), social value, and epistemic value.

Key finding 12 – The impact of individual barrier transforming into NWOM as consumers show resistance towards smart payment services is *reduced* when they perceive high functional value (performance), social value, and emotional value.

Key finding 13 – *Social value* emerged as being *more vital* for consumers than other consumption values, not only in buffering the effects of barrier perceptions on their resistance towards smart payment services, but also in discouraging the spread of NWOM about such services.

6.2 Study contributions

This study presents several theoretical and managerial contributions to the field of innovation diffusion literature and the consumer resistance to innovation literature.

6.2.1 Theoretical contributions

In response to research gap 1, this study explored the phenomenon of consumer resistance to innovation in an integrated approach by investigating the direct effects of different types of barriers on consumer resistance to smart payment services. Previous research in the field of consumer resistance to innovation has extensively examined functional barriers (i.e., usage barrier, value barrier and risk barrier), as well as the psychological barriers (i.e., image barrier and tradition barrier) that are posited under Ram and Sheth's (1989) model or innovation resistance theory. Recent literature proposed an extension to Ram and Sheth's (1989) model (Mani and Chouk, 2018) that highlighted certain barriers, such as technology vulnerability barriers (technological dependence and technology anxiety), ideological barriers and individual barriers (e.g., Juric and Lindenmeier, 2018; Mani and Chouk, 2017, 2018), the research on which is still sparse. To address this research gap, this study clarifies the direct effects of these sparsely researched barriers – factors explaining consumers' predisposition to prefer the status quo (individual barrier), barriers specific to digital technologies (i.e., technology vulnerability barriers) and consumers' personal convictions towards smart payment services (i.e., ideological barrier) – and adds important empirical evidence to the growing research field of consumer resistance to innovation. More importantly, these sparsely researched barriers were found to be major reasons for consumer resistance to smart payment services, in contrast to the extensively investigated functional and psychological barriers that have largely been major barriers in previous studies (Chen and Kuo, 2017; Laukkanen et al., 2008; Leong et al., 2020; Mani and Chouk, 2018). Furthermore, as an extension of the previous research, this study has demonstrated that integrating Ram and Sheth's (1989) model with other theories and concepts, such as self-congruity theory (Sirgy, 1985), attribution theory (Kelley and Michela, 1980), the TAP index (Ratchford and Barnhart, 2012) and status quo bias theory (Samuelson and Zeckhauser, 1988), can be relevant for providing a better understanding of the formation of consumer resistance to innovation such as smart payment services.

In response to research gap 2, it was found that previous studies had only explored the consequences of consumer resistance to innovation in the form of adoption intention, use intention or continual intention to use (e.g., Hong, 2020; Kang and Kim, 2009; Rahman et al., 2021; Sivathanu 2019). However, empirical research lacks the exploration of any further harmful consequences of consumer resistance to innovation (Heidenreich and Handrich, 2015;

Heidenreich and Kraemer, 2015), such as NWOM. Moreover, only a small amount of research exists that has conceptualized the link between consumer resistance to innovation and NWOM (e.g., Van Tonder, 2017). In this respect, this study contributes to the innovation diffusion literature (Rogers, 2003) by empirically demonstrating NWOM as a key detrimental consequence of consumer resistance to smart payment services. Previous research has also highlighted that negative opinion leaders and resistance leaders can have a major influence on their direct social ties (friends and peers) as well as those beyond their personal environment (i.e., at the societal level) by sharing negative information and comments about innovations, consequently turning potential adopters into late adopters or even non-adopters (Hietschold et al., 2020; Jahanmir and Cavadas, 2018). In addition, the term laggards is used to refer to non-adopters of innovation or innovation-resistant consumers who show almost no opinion leadership about innovations (Rogers, 2003). Therefore, by providing empirical evidence of the link between consumer resistance to smart payment services and NWOM, this study contributes to the innovation diffusion literature by suggesting that laggards also show opinion leadership in a negative form by spreading NWOM about smart payment services among other consumers.

In response to research gap 3, this study extends prior research examining the relationship between perceived barriers and word of mouth (e.g., Kaur, Dhir, Singh et al., 2020; M. Talwar et al., 2021) by demonstrating the mediating role of consumer resistance to smart payment services in the relationship between perceived barriers and NWOM. Research has demonstrated a direct relationship between barrier perceptions and WOM/NWOM (e.g., Kaur, Dhir, Ray et al., 2020, b; M. Talwar et al., 2021, S. Talwar, Dhir et al., 2021). However, these studies have reported equivocal findings. For instance, M. Talwar et al. (2021) reported a positive relationship between barrier perceptions and NWOM, while Kaur, Dhir, Ray et al. (2020) reported a positive relationship between barriers and WOM, and Kaur, Dhir, Singh et al. (2020) found a neutral relationship between barriers and intention to recommend. In this regard, this research clarifies these inconsistent findings in the innovation literature by highlighting the key role of consumer resistance to smart payment services as an underlying mechanism that provides a better understanding of how and why barrier perceptions lead consumers to spread NWOM about smart payment services. This contribution is further supported by study findings that demonstrated a direct negative influence of some barriers on NWOM; however, the indirect effects of these barriers on NWOM via consumer resistance to smart payment services were found to be positive. Therefore, this indicates that consumer resistance to smart payment services is the means by which barrier perceptions are translated into NWOM.

In response to research gap 4, this study attempted to provide a deeper understanding of the relationship between perceived barriers and consumer resistance to smart payment services by examining the moderating role of consumption values. This is because little has been done to investigate factors that may regulate the relationship between barriers and consumer resistance to innovation (e.g., Mani and Chouk, 2018). Studies have only considered the integration of innovation adoption paradigm with innovation resistance paradigm for investigating the relative influences of factors driving and inhibiting a particular attitude or behavioural intention, such as resistance or adoption intention (e.g., Chouk and Mani, 2019; Claudy et al., 2015; Dhir et al., 2021; Ma and Lee, 2020; Sivathanu, 2018). These studies have adopted either behavioural reasoning theory (Westaby, 2005) or dual factor concepts (Cenfetelli, 2004) as their theoretical underpinning to investigate this type of integration. In this respect, drawing on a novel theoretical underpinning that is, prospect theory; (Kahneman and Tversky, 1979), this study contributes to the innovation resistance literature by investigating the joint effects of perceived consumption values (gains) and barriers (losses) to explain the formation of consumers' decision to resist smart payment services.

Furthermore, research in the innovation resistance literature examining marketing strategies implemented by firms for mitigating consumer resistance to innovation is scarce (e.g., Laukkanen et al., 2009; Reinhardt et al., 2017; Rodríguez Sánchez et al., 2020; Weinmann et al., 2016; Yeatts et al., 2017). Therefore, by exploring the buffering role of consumption values, this study also contributes to the limited research that investigates the strategies suggested for mitigating consumer resistance to innovation. Specifically, this study extends the stream of research that emphasizes the importance of consumption values in the adoption process (e.g., Arruda Filho et al., 2020; Chiu et al., 2014), by demonstrating the potential of perceived consumption values to mitigate the effect of barrier perceptions on consumer resistance to smart payment services. Moreover, this research demonstrates that the indirect effect of perceived barriers on NWOM via consumer resistance to smart payment services becomes weaker (and even negligible) when high consumption values are perceived (see Figures 42 to 51). Table 49 presents a summary of the theoretical contributions of this study.

Table 49: Summary of theoretical contributions

Literature	Contributions

Innovation resistance	• Investigation of direct impact of sparsely explored barriers – ideological barrier, technology dependence, individual barrier
	  ○ These barriers were found to be the major reasons for consumer resistance to smart payment services.
	  ○ Integration of innovation resistance theory with other theories to explain consumer resistance to smart payment services.
	• Mediating role of consumer resistance to smart payment services in the relationship between perceived barriers and NWOM
	  ○ Consumer resistance to smart payment services is the underlying mechanism that explicates why and how barrier perceptions transform into NWOM.
	• Investigation of the moderating role of consumption values
	  ○ Application of a new theoretical underpinning i.e., prospect theory.
	  ○ New set of factors (i.e., consumption value perceptions) acting as mitigators of the effect of barriers on consumer resistance to smart payment services.

	○ Role of consumption value perceptions in decreasing the indirect effect of barrier perceptions on NWOM (via consumer resistance to smart payment services).
Innovation diffusion	• Investigation of NWOM as a detrimental consequence of consumer resistance to smart payment services ○ Laggards are innovation-resistant consumers who also show negative opinion leadership.

Contextual contributions

Contextually, this study responds to the call for research into innovation resistance in the service innovation context (i.e., smart payment services), as the majority of the existing innovation research conducted in the context of service innovation focuses on success factors to explain the innovation adoption process (e.g., Choudrie et al., 2018; Evanschitzky et al., 2015; Klein et al., 2022; Storey et al., 2016). Therefore, as smart payment services are a technologically advanced innovation which is likely to disrupt consumers' status quo, different reasons (i.e., perceived barriers) for resistance to the service innovation were found in this study. It was also found that such reasons can lead to negative opinion sharing about smart payment service by laggards when they resist this service innovation. However, the study also found that consumption values can be derived from smart payment services by resistant consumers that can potentially mitigate their barrier perceptions, consequently reducing their resistance as well as negative opinions about these services.

6.2.2 Managerial implications

The findings of this research have important managerial implications in terms of providing useful insights into managing innovations successfully. A major concern of the companies offering smart payment services is to reduce consumer resistance towards this service offering via the implementation of various strategies. The study findings suggested that consumers perceive various barriers that lead to their resistance towards smart payment services.

Therefore, managerial implications should be directed at how innovators and marketing managers can minimize perceived barriers in order to reduce resistance towards smart payment services and the resulting NWOM by resistant consumers.

a) Implications related to barrier-minimizing strategies

The findings suggest that usage complexity is the only barrier that has a direct positive influence on consumers' resistance as well as NWOM. In this respect, it is critical that innovators should focus on making their smart payment services easier to use. Usage simplicity can be incorporated in the form of software improvements such as developing user-friendly smartphone apps that can support different smart payment services with simplified setup procedures (e.g., Palmié et al., 2020). This will be helpful in reassuring those consumers who perceive that specific technical skills are required for using smart payment services.

The findings further identify that consumers resist and consequently spread NWOM about smart payment services when they are concerned about the associated security risk. In this respect, service providers need to reinforce the security measures of smart payment services by collaborating with reputable cybersecurity firms. Such collaborations and enhanced security features should then be communicated via advertising campaigns. Service providers should also promote the service innovation by presenting testimonials from existing users of smart payment services in order to convince resistant consumers about the safety regarding the processing of users' private and financial information while using such a service innovation.

The results demonstrate that conflict between consumers' self-image and the image of the innovation leads to their resistance towards a smart payment service and consequent sharing of NWOM. To this end, service providers should market such services as an important aspect of a modern digitalized lifestyle in their marketing and persuasion messages. This will be helpful in convincing consumers who are resistant to smart payment services that they do not need to be ‘tech-savvy’ to use them.

Consumers were further found to be afraid of becoming overly dependent on technology and losing control of their tasks, leading to their resistance to smart payment services and consequent NWOM sharing. Therefore, to reduce technological dependence, financial institutions, as well as service providers, should reassure consumers that the incorporated technology (i.e., NFC; Forum NFC, 2011) offers an alternative mode of payment and hence they have full autonomy to select their preferred payment methods.

According to the findings, scepticism regarding the service innovation’s benefits as promised by the company via multiple commercial sources (e.g., advertisements, demonstration videos and consultancy firm reports) is a source of consumer resistance to smart payment services, as well as NWOM. To this end, smart payment service providers could highlight the maturity of the technology employed and underscore their competence in delivering the smart payment service as promised. This can be accomplished by implementing such strategies that can communicate the promised benefits of smart payment services in a real-life situation. For instance, during the launch of a new product (e.g., smartphone), the event organizers could instruct consumers in the various innovative features of their branded smart payment system through real-life demonstrations (e.g., Eng and Quaia, 2009), thereby reducing resistance as well as the sharing of NWOM among sceptical consumers.

Last, the findings suggest that consumers resist and spread NWOM about smart payment services due to inertia. Hence, in order to overcome this individual barrier, the competitive benefits offered by smart payment services over traditional payment methods (e.g., hygiene benefits of contactless payments, Shishah and Alhelal, 2021; convenience on public transport, Liébana-Cabanillas et al., 2019) should be promoted by the companies offering such payment services, thereby encouraging behavioural change in consumers.

b) Implications related to maximizing consumption value perceptions

This investigation found that perceived consumption values can be helpful in mitigating the effects of barrier perceptions on consumer resistance to innovation and minimizing the resulting NWOM sharing. Accordingly, the study findings advise practitioners to maximize the consumption values that can be offered by smart payment services, thus reducing consumers' resistance and the consequent NWOM sharing regarding this service innovation.

Incorporating functional value

The findings suggest that if smart payment services can offer a convenient way of making payments, as well as enhanced performance and quality of service, this will minimize the effects of barrier perceptions on consumer resistance to innovation and the resulting NWOM. In this respect, service providers offering their smart payment services on various online platforms and physical POS terminals should install user-friendly and convenient payment check-out systems (e.g., de Luna et al., 2019). Further, the organizations offering such services could organize software development conferences at which innovators could brainstorm and suggest novel ideas focusing on improving the performance of these services, thereby making the smart payment system more secure, easier to use and more compatible with the lifestyle of the consumers, specifically for digital immigrants. Further, such functional modifications could be disseminated via social media influencers to ensure consumers develop positive perceptions regarding the service innovation (e.g., Singh et al., 2020).

Incorporating social value

The findings demonstrate that if a smart payment service offers an improvement in the social image/status and social acceptance/approval of consumers among significant others, it abates the effect of barrier perceptions on their resistance towards smart payment services and the resulting NWOM. In respect to these findings, smart payment service providers should focus on facilitating the acceptance and penetration of smart payment services within society to enhance the social value of the innovation. To accomplish this, service providers could develop partnerships with different retailers that accept smart payment methods to facilitate the penetration into customers' local communities and social life (e.g., Ng et al., 2021). For instance, facilitating smart payment services at local coffee shops and providing promotional offers (e.g., discounts) for using a particular smart payment service could encourage visiting customers to use the service innovation more frequently, who can then further recommend such payment services to their social group. Innovators could also implement modifications to a smart payment system that enhance the users' social connectedness with their social group. For instance, as a smart payment service is an application within a smart device (e.g., smartphones and smart watches), modifications facilitating the sharing of digital money via SMS text (paired with a smart payment service app) to friends could enhance the users' belongingness to their social groups. Hence, such modifications can help users in perceiving a service innovation as being better than traditional payment methods, thereby reducing resistance and the spreading of negative remarks by non-users. Smartphone brands such as Apple and Google that offer their own smart payment services (e.g., Apple Pay and Google Pay) should also promote such services using mass media and social media to advertise smart payment services as a mark of an up-to-date digital citizen, thereby highlighting the social value gained from adopting such technology (i.e., enhanced social self-concept as a digital innovation user), specifically for those who find it difficult to fit these innovative services within their own lifestyle.

Incorporating emotional value

The study findings suggest that if a smart payment service offers a fun and enjoyable service experience, this can mitigate the effects of barrier perceptions on consumer resistance and the consequent NWOM sharing. In this respect, smart payment service providers could collaborate with different brands to reward frequent users of smart payment services with gift coupons while shopping at these brands' online stores and/or physical stores, thereby providing an enjoyable service experience. Further, to make the use of this service innovation more fun and exciting, the innovators could incorporate achievement-related gamification features, such as progress bars or badge collecting (Koivisto and Hamari, 2019; Xi and Hamari, 2019), within the smart payment service application. These features can make use of this service innovation more entertaining in contrast to traditional payment methods, thereby reducing resistance towards smart payment services and, ultimately, leading to a reduction in NWOM spreading about the service innovation.

Incorporating epistemic value

The study findings suggest that if smart payment services can arouse curiosity among consumers about using the service innovation and offer a novel service experience, this can reduce the impact of barriers on consumer resistance and NWOM towards the service innovation. To accomplish this, the companies/brands offering smart payment services could provide novel forms of biometric authentication (e.g., iris scans or facial recognition) to reduce security concerns. Another novel experience could be provided to consumers by pairing smart payment services with virtual reality (VR) and/or augmented reality (AR) technologies. Through such technologies, innovators could bring a novel experience to consumers to illustrate how the service innovation can be used during online/offline shopping scenarios. Such an innovative AR/VR walkthrough might generate curiosity among consumers, especially non-users, and encourage them to adopt this service innovation, thereby lowering their resistance and NWOM sharing towards the service innovation (e.g., Willems et al., 2017). Table 50 presents a summary of the managerial implications of this study.

Table 50: Summary of managerial implications

Barrier-minimizing strategies	
Usage barrier	Making smart payment services easier to use by incorporating software improvements such as developing user-friendly smartphone apps that can support different smart payment services with simplified setup procedures.
Risk barrier	Reinforcing the security measures of smart payment service by collaborating with reputable cybersecurity firms. Communicating security updates via advertising campaigns. Promoting the service innovation by presenting testimonials from existing users of smart payment services (e.g., safety regarding the processing of users' private and financial information).
Image barrier	Service providers marketing such smart payment services as an important aspect of the modern digitalized lifestyle in their marketing and persuasion messages.
Technological dependence	Communicating to consumers that the incorporated technology (i.e., NFC) is an alternative method of payment ensuring users have full autonomy in selecting payment methods.
Ideological barrier	Highlighting the maturity of the technology employed and underscoring service providers' competence in delivering the smart payment service as promised. Implementing strategies that can communicate the promised benefits of smart payment services via a real-life demonstration at product launch events.
Individual barrier	Promoting certain competitive benefits that smart payment services can offer compared to traditional payment methods (the hygiene benefits of their contactless nature, convenience on public transportation, etc.).
Value-maximizing strategies	
Functional value	Instalment of user-friendly and convenient payment terminals/ check-out systems on various online platforms and in physical retail outlets. Software development conferences to brainstorm and suggest novel ideas focusing on improving the performance of these services. Functional modifications can be disseminated via influencer marketing techniques.

Social value	Service providers developing partnerships with different retailers that accept smart payment methods to facilitate the penetration into customers' local communities and social life. Innovation modifications to enhance users' social connectedness with their social group (e.g., sharing digital money via SMS text to friends). Using mass media and social media to advertise smart payment services as a mark of an up-to-date digital citizen to highlight the social value gained from adopting such technology.
Emotional value	Rewarding frequent users of a smart payment service with gift coupons while shopping at the brands' stores, providing an enjoyable service experience. Incorporating achievement-related gamification features (e.g., progress bars or badge collecting).
Epistemic value	Novel and more secure biometric authentication for transaction approval (e.g., iris scans and facial recognition). Application of AR and/or VR technologies to provide a walkthrough of the entire process of using a smart payment service to arouse curiosity.

Chapter 7 – Limitations, Future Research and Conclusion

This research provides valuable insights into the mechanism of consumer resistance to innovation by understanding its development due to different barrier perceptions, its consequence in the form of NWOM, as well as how it can be mitigated by the perception of the consumption values offered by a service innovation. However, there are limitations to this study, which can present implications for future research. Hence, this chapter outlines the limitations and opportunities for future research.

7.1 Limitations and future research directions for antecedents of consumer resistance to innovation and control variables

This study examined the indirect effects of perceived barriers highlighted under Ram and Sheth's (1989) model and its extension (Mani and Chouk, 2018; Ram and Sheth, 1989) on NWOM (via consumer resistance to innovation).

Limitations – Prior research investigated the role of negative emotions in influencing resistance towards innovation (e.g., Rieple and Snijders, 2018). Such negative emotions can lead to the formation of emotional barriers (e.g., pleasure barrier, arousal barrier and dominance), which can lead to innovation resistance (Castro et al., 2019; Santos and Ponchio, 2021). Talke and Heidenreich (2014) also highlighted different functional and psychological barriers that consumers may perceive when their personal needs are not satisfied by the attributes of the innovation (e.g., trialability barrier and compatibility barrier) and/or the innovation may conflict with a consumer's group-related values and social norms (e.g., information barrier and norm barrier). Therefore, these barriers have not been considered in this study. Further, following prior research in the field of consumer resistance to innovation, the current study controlled for demographic variables of the respondents: age, gender, education level and current employment status (e.g., Casidy et al., 2021; Joachim et al., 2018). However, recent innovation resistance studies have investigated the impact of variables such as 'trust in innovation' (Kaur, Dhir, Ray et al., 2020; S. Talwar, Dhir et al., 2021) and 'availability of the product/service' (Sadiq et al., 2021) on consumer resistance to innovation and WOM/NWOM. The effect of these variables has not been considered in this study.

Future research directions – Future research could examine the indirect effects of the emotional, functional, and psychological barriers highlighted by Castro et al. (2019) and Talke and Heidenreich (2014) on NWOM via consumer resistance to innovation. Therefore, by understanding the indirect translation of these barriers into NWOM, marketers may be able to develop more effective communication strategies that encourage consumers to develop positive emotions towards an innovation, ensure the innovation's consistency with consumers' needs and group values, and thereby reduce the possibility of spreading NWOM. Further, since trust violations may result in NWOM (Goles et al., 2009) and the availability of a product/service can influence consumers' resistance towards that product/service (Sadiq et al., 2021), future studies could control for the effects of these variables in addition to respondents' demographic variables.

7.2 Limitations and future research directions for consequences and mediating mechanisms

This study examined a research model to investigate NWOM as a harmful consequence of consumer resistance to innovation. This research also sheds light on the mediating role of consumer resistance to innovation, which explains the translation of barrier perceptions into NWOM.

Limitations – The literature suggests that, in addition to NWOM, consumer resistance to innovation may lead to other detrimental consequences, such as consumer boycotts. Consumer boycotts can be further categorized into marketing policy boycotts and political boycotts (Yener and Taşçıoğlul, 2020). Hence, the present study did not investigate consumer boycotting as a consequence of consumer resistance to innovation.

Research has highlighted the concept of consumers' 'leapfrogging intention', a temporary form of innovation rejection in which consumers resist a newly introduced product/service innovation, skip several generations of that innovation, and, finally, upgrade to a technologically advanced generation (Goldenberg and Oreg, 2007; Heidenreich et al., 2022). Previous research has also highlighted that consumer resistance to innovation can be delineated into three distinct forms based on how it is expressed by consumers and, as such, consumers may reject, postpone and/or oppose an innovation (Szmigin and Foxall, 1998). Hence, the present study did not examine the mediating role of consumers' leapfrogging intention and the three forms of resistance.

<u>Future research directions</u> – Current research lacks proper empirical investigation of how consumer resistance can lead to consumer boycotts. Hence, future research could look more deeply into understanding the psychology of resistant consumers who may participate in different types of boycotts (e.g., marketing policy boycotts and political boycotts). This investigation may assist organizations to devise appropriate response strategies (e.g., Rauschnabel et al., 2016) towards such social movements.

Limited research attention has been paid to consumers' leapfrogging intention and the three forms of resistance referred to above, as prior research has mainly investigated their antecedents (e.g., Chen et al., 2019; Heidenreich et al., 2022). Future research could investigate how different barriers (as considered in this study) may translate into behavioural consequences (e.g., NWOM or consumer boycotts) when consumers show leapfrogging intention and/or the three forms of resistance towards an innovation. Such an investigation may help marketers to tailor their strategies to address different groups of resistant consumers (i.e., rejectors, opponents and postponers), thereby reducing their NWOM sharing. Further, marketers will also be able to understand the various reasons behind leapfrogging that transform into NWOM, helping them to devise communication strategies such as highlighting the superiority of the newly introduced product/service generation in contrast to the current product/service generation (e.g., Heidenreich and Kraemer, 2016). Consequently, consumers may develop positive perceptions about newly introduced products/services and this will reduce the possibility of leapfrogging and other adverse consequences.

7.3 Limitations and future research directions for context and methodology

This study highlights the significance of consumption values in mitigating the effects of barriers on consumer resistance to innovation and the resulting NWOM.

Limitations – As stated above, consumer resistance to innovation can be delineated into three distinct forms based on how it is expressed by the consumers (i.e., consumers may reject, postpone and/or oppose an innovation) (Szmigin and Foxall, 1998). Consumer leapfrogging intention is also an emerging concept that has received little attention in the innovation resistance literature. Since this study did not consider the three forms of consumer resistance to innovation and consumer leapfrogging intention, the effects of consumption values in mitigating these three forms and intention were not examined.

Future research directions – Future research could explore the role of consumption values in buffering the effects of different barrier perceptions on the three forms of consumer resistance to innovation and consumer leapfrogging intention. This type of investigation could be useful for innovators when designing such innovations as they might be more likely to fulfil the utilitarian, hedonic and symbolic needs of, and invoke curiosity among, different types of resistant consumers (i.e., rejectors, opponents and postponers and those who intend to leapfrog). Further, previous research has also highlighted two sub-dimensions of social value: conspicuous value and status value (e.g., Ajitha and Sivakumar, 2017). Future research could consider the role of these two sub-dimensions of social value in mitigating the effects of barriers perceived in a luxury service innovation context.

Limitations – The current study focused only on the smart services context in the finance industry, which may affect the generalizability of the study findings. Further, the participants of this study were recruited from a single country (i.e., the USA). This neglects a cross-cultural context and those nations in which innovation resistance research is scarce. In addition, according to Figure 2 (see section 4.4.2), global statistics have indicated low penetration rates of smart payment services in countries such as Russia, Japan and Spain. Hence, resistance towards smart payment services by consumers of these countries has not been considered in this study. Finally, this research employed a survey-based methodology to illustrate the psychological process of consumer resistance to innovation, thus providing an opportunity to employ other methodological approaches and designs.

Future research directions – To further enhance the generalizability of the research findings, future research could re-test the research model with other innovation contexts, such as tourism (smart keys in hotels), smart health and home automation (smart home appliances). Further, a limited number of studies have paid attention to investigating consumer resistance to innovation in African and Latin American nations, as well as in a cross-cultural context. Since consumers' responses to innovation could be culture-specific (e.g., Yu and Chantatub, 2016), replicating the research model in a cross-cultural context (e.g., developing vs developed countries) or in African and Latin American countries or in specific countries (e.g., Russia, Japan and Spain) where smart payment service penetration rate is still low (according to Figure 2, section 4.4.2) may offer new insights into the drivers, inhibitors, and consequences of consumer resistance to smart payment services. Last, other methodological approaches (e.g., in-depth interviews or experiments) could be employed to enhance the understanding of consumer resistance to innovation, as well as to extend the findings of this study. Future research could also employ a longitudinal research design to explore changes in consumers' resistance over time because, even after initial resistance, the actual outcome could ultimately result in adoption (Ram, 1987).

For example, a longitudinal study design could explore if consumption values offered by a smart payment service ultimately resulted in the adoption of the service innovation by resistant consumers and/or if these consumers altered their NWOM into positive WOM.

7.4 Conclusion

A review of the existing literature on consumer resistance to innovation was conducted that revealed three research gaps. Based on the research gaps identified, the research objectives for this study were to:

a) understand the development of consumer resistance to innovation due to different barrier perceptions;
b) provide a deeper understanding of the detrimental impact of consumer resistance to innovation by empirically establishing its consequence in the form of negative word of mouth (NWOM);
c) understand the role of consumer resistance to innovation as an underlying mechanism that explicates the translation of perceived barriers into NWOM;
d) understand the interplay of perceived barriers and consumption values in the formation of consumer resistance to innovation by investigating the role of perceived consumption values in buffering the effects of barrier perceptions on consumer resistance to innovation, as well as the resulting NWOM; and
e) understand the mechanism of resistance in the context of service innovation (i.e., smart payment services).

To accomplish the above-stated objectives, research hypotheses were proposed to test:

a) the direct relationships between perceived barriers and consumer resistance to smart payment services;
b) the mediating effect of consumer resistance to smart payment services between perceived barriers and NWOM;

c) the moderating effects of perceived consumption values on the relationship between perceived barriers and consumer resistance to smart payment services; and

d) the moderated mediation effects in order to examine the indirect effects of perceived barriers on NWOM (via consumer resistance to smart payment services) conditioned on perceived consumption values.

Further, drawing on multiple theoretical perspectives, that is, extension of Ram and Sheth's model (Mani and Chouk, 2018), the theory of consumption values (Sheth et al., 1991) and prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), a research model was developed to test the proposed hypotheses. A quantitative methodological approach was adopted that consisted of data collection through an online survey and which examined the responses of 356 non-users of smart payment services who have reasonable knowledge of the service innovation.

This was followed by quantitative data analysis, which included data coding, preliminary examination of the data, validation of the research model via EFA and CFA, and testing the proposed hypotheses using SEM.

Next, interesting findings were obtained for each of the stated research objectives. With respect to the first research objective, the findings revealed different barrier perceptions responsible for consumers' resistance towards smart payment services. In particular, those barrier perceptions were found to be major drivers of consumer resistance, which has been much less widely researched in the literature compared to those barriers that have been extensively researched (i.e., functional and psychological barriers; Ram and Sheth, 1989). The major barriers identified were those which are specific to advanced technological innovations of the current digital age (i.e., technological dependence); consumers' personal convictions against innovation (i.e., ideological barrier); and factors related to consumers' tendency to prefer the current situation or status quo satisfaction (i.e., individual barrier).

In respect to the second and third research objectives, the findings explored NWOM as the detrimental consequence of consumer resistance to smart payment services. Further, the findings regarding the mediating role of consumer resistance to smart payment services indicated that it is an underlying mechanism that explicates how and why barrier perceptions transform into NWOM. Specifically, consumer resistance to smart payment services was found to be a partial mediator between the majority of the barrier perceptions considered (i.e., risk barrier, image barrier, ideological barrier and individual barrier) and NWOM. The relationship between technological dependence and NWOM was found to be fully mediated by consumer resistance to smart payment services.

In respect to the fourth research objective, the findings revealed the role of consumption value perceptions as mitigators of the effects of barrier perceptions on consumer resistance. Specifically, perceived functional value, social value, emotional value, and epistemic value were found to buffer the effects of perceived usage barrier, risk barrier, individual barrier, and image barrier on consumer resistance to innovation. Furthermore, moderated mediation analysis was conducted that revealed that the indirect effects of perceived risk barrier, image barrier and individual barrier on NWOM (via consumer resistance to smart payment services) become weaker and even negligible (in the case of perceived risk barrier) when high consumption values are perceived.

Last, this study highlighted theoretical contributions to the innovation literature. Specifically, the innovation resistance and innovation diffusion literature, together with its contextual contribution (i.e., studying consumer resistance to an innovation phenomenon in a service innovation context). The managerial implications of barrier minimizing and consumption value maximizing strategies were also discussed. The study concluded by proposing future research directions derived from the study limitations.

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Appendices

Appendix A: Ethical Approval Application Form

Ethics ETH1819-0019: Mr Iman Jana

Date Created	10 Jun 2019
Date Submitted	12 Jun 2019
Date of last resubmission	13 Jun 2019
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Category	Professional Services Staff
Supervisor	Dr Neeru Malhotra
Project	“Understanding the Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values”
Faculty	Social Sciences
Department	Essex Business School
Current status	Signed off under Annex B

Ethics application

Project overview

Title of project

“Understanding the Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values”

Do you object to the title of your project being published?

No

Applicant(s)

Mr Iman Jana

How would you like to submit your application?

Supervisor(s)

Dr Neeru Malhotra

Dr Hongfei Liu

Proposed start date of research

07 Jul 2019

Expected end date

07 Aug 2019

Will this project be externally funded?

No

Will the research involve human participants?

Yes

Will the research use collected or generated personal data?

Yes

Will the research involve the use of animals?

No

Will any of the research take place outside the UK?

No

Project details

Brief outline of project

1. The purpose of the research is investigate about the opinions of the consumers on the various barriers and consumption values that they may perceive while choosing a service innovation.

2. An online questionnaire designed in Qualtrics will be used for recording the responses of the participants to find out the significant barriers and consumption values perceived by the participants.

3. Depending on the results of online survey, insights will be drawn to understand the phenomenon of consumer resistance to innovation.

Participant details

Who are the potential participants?

Potential participants include people having age 18 years and above.

How will they be recruited?

The participants will be provided with a link of the online survey via Amazon Mechanical Turk (M-Turk).

Recruiting materials

Will participants be paid or reimbursed?

Yes

If yes, how will they be paid?

The participants will be paid via Amazon Mechanical Turk (M-Turk)

How much will the participants be paid?

£0.97

Could potential participants be considered to be vulnerable (e.g. children, mentally ill)?

No

If yes, please explain how the participants could be considered vulnerable and why vulnerable participants are necessary for the research.

Could potential participants be considered to feel obliged to take part in the research?

No

If yes, please explain how the participants could feel obliged and why they are still necessary for the research.

Will the research involve individuals below the age of 18 or individuals of 18 years and over with a limited capacity to give informed consent?
No

Is a DBS Check Required?

No

If yes, has the DBS check been completed?

No

If a DBS check is not required, please explain why.

DBS check is not required as the potential participants will not include any children or vulnerable adults.

Informed consent

How will consent be obtained?

Written

If consent will be obtained in writing, please attach an example of written consent for approval.
If consent will be obtained orally, please explain why.

Please upload a copy of the script that will be used to obtain oral consent.

If no script is available to upload please explain why.

Who will be obtaining and recording consent?

Researcher - Iman Jana

Please indicate at what stage in the data collection process consent will be obtained.

The consent will be obtained upon submission of the online questionnaire (as explained in the statement of consent).

If consent will not be obtained, explain why.

Please attach a participant information sheet.

Have you reviewed the information provided by the REO on participant information and consent?
Yes

Confidentiality and anonymity

Will you be maintaining the confidentiality and anonymity of participants whose personal data will be used in your research?
Yes

If yes, describe the arrangements for maintaining anonymity and confidentiality.

Participants will be identified by participant ID numbers which will be assigned in the data entry sheet. Participant IDs will not be disclosed in any form.

Personal data collected through this questionnaire will be aggregated and individuals will not be individually identifiable in any reports or publications from this research.

If you are not maintaining anonymity and confidentially, please explain your reasons for not doing so.

Data access, storage and security

Describe the arrangements for storing and maintaining the security of any personal data collected as part of the project.
1. Personal data related to participants age, gender, education, occupation and email address will be collected.

2. The personal data will be collected only for the analysis purpose.

3. Personal data will be maintained in a password secured file.

4. The identifiable data kept in password secured file will only be accessible to me and my supervisors.

5. Data will be destroyed, after the completion of the PhD studies and related academic publications.

Please provide details of all those who will have access to the data.

Researcher and Supervisors

Data sharing

Do you intend to share or archive data generated from this project once it is complete?

If yes, please describe briefly.

Please indicate the means by which you intend to share/archive your data:

If you chose other, please provide more details.

If you do not intend to share data please provide specific reasons why the data will not be made available.

Risk and risk management

Are there any potential risks (e.g. physical, psychological, social, legal or economic) to participants or subjects associated with the proposed research?
No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Are there any potential risks (e.g. physical, psychological, social, legal or economic) to the researchers working on the proposed research?
No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Are there any potential reputational risks to the University as a consequence of undertaking this proposal?
No

If yes, please provide full details and explain what risk management procedures will be put in place to minimise the risks.

Risk Assessment documents

Are there any other ethical issues that have not been addressed which you would wish to bring to the attention of the reviewer(s) of your application?

Attached files

Research Project Proposal.docx
Consent form for online questionnaire.docx
Participant information sheet.docx

Working Title

"Understanding the Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values"

Objectives

1. To understand the mechanism of consumer resistance in the context of service innovation (i.e., smart payment services).
2. To understand the development of consumer resistance to smart payment services due to different barrier perceptions,
3. To provide a deeper understanding of the detrimental impact of consumer resistance to smart payment services by empirically establishing its consequence in the form of negative word-of-mouth (NWOM),
4. To understand the role of consumer resistance to smart payment services as an underlying mechanism that explicates the translation of perceived barriers into NWOM, and
5. To understand the interplay of perceived barriers and consumption values in the formation of consumer resistance to smart payment services by investigating the role of perceived consumption values in buffering the effects of the barrier perceptions on consumer resistance to smart payment services, as well as the resulting NWOM.

Research questions

1. Which barriers significantly influence the consumers' resistance towards smart payment service?
2. Is NWOM a detrimental consequence of resistance shown by the consumers towards smart payment service?
3. Does consumers' resistance towards smart payment service explains the translation of their barrier perceptions into NWOM?
4. Can consumption values offered by smart payment service significantly diminish the effect of the barriers on consumers' resistance towards smart payment service and the resulting NWOM?

Proposed Methodology

Data collection Method- Online survey; Sampling method- Convenience sampling;
Sample – Non users of smart payment services having 18 years of age and above.

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[FIRST page of online questionnaire]

Title of Project - **“Understanding The Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values”**

Dear participant,

This questionnaire is investigating various barriers and values that you may face while making decision to choose an innovative service such as *Smart Payment Service.*

This research is being carried out by **Iman Jana** under the supervision of **Dr Neeru Malhotra** and **Dr Hongfei Liu**.

You will not be asked to provide your name, but you may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated and you will not be individually identifiable in any reports or publications from this research. All information collected will be kept securely and will only be accessible by me and my supervisors.

For more information about your rights as a participant in this research please download a copy of the participant information sheet which can be found at this link https://www.essex.ac.uk/-/media/documents/directories/reo/participant-information- and-consent.pdf

We would be very grateful for your participation in this study. If you need to contact us in future, please contact me **(ij18343@essex.ac.uk)** or **Dr Neeru Malhotra (n.malhotra@essex.ac.uk) or Dr Hongfei Liu (hongfei.liu@essex.ac.uk).** You can also contact us in writing at: EBS, University of Essex, Colchester CO4 3SQ.

Yours, Iman Jana

Statement of Consent

By submitting a completed version of this questionnaire, you are consenting to the following:

- I agree to participate in the research project being carried out by Iman Jana
- This agreement has been given voluntarily and without coercion.
- I have been given full information about the study and contact details of the researcher(s).
- I have read and understood the information provided above
- I have had the opportunity to ask questions about the research and my participation in it

[LAST page of online questionnaire]

Thank you for your participation in this study.

You are reminded that by submitting a completed version of this questionnaire you are agreeing to participate in this research.

If you have any queries, please contact me **(ij18343@essex.ac.uk)** or **Dr Neeru Malhotra (**n.malhotra@essex.ac.uk**) or Dr Hongfei Liu (**hongfei.liu@essex.ac.uk**).** You can also contact us in writing at: EBS, University of Essex, Colchester CO4 3SQ.

Yours, Iman Jana

University of Essex

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Participant Information Sheet for Research Project: "Understanding The Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values"

Dear participant,

I, *Iman Jana*, am currently carrying out a piece of research entitled, *"Understanding The Mechanism of Consumer Resistance to Innovation: The Moderating Role of Consumption Values"* under the supervision of *Dr Neeru Malhotra and Dr Hongfei Liu.*

We are investigating about your opinions on the various barriers and values that you may perceive while choosing an innovative service.

This information sheet provides you with information about the study and your rights as a participant.

What does taking part in the research involve?
You will be asked about your level of agreement or disagreement on few statements related to the various barriers and values that you may perceive in the context of a Service Innovation. All your responses will be recorded through an online questionnaire.

Do I have to take part?
Naturally, there is no obligation to take part in the study. It's entirely up to you. If you do decide to take part you will be given this information sheet to keep and be asked to give consent to take part. If publications or reports have already been disseminated, these cannot be withdrawn, however, these will only contain anonymised or aggregated data. If you wish to withdraw from the study at any time, please contact the researcher on the details below.

Will my taking part in this study be kept confidential?
All information collected will be kept securely and will only be accessible by me and my supervisors. However, this research forms part of my studies at the University of Essex and therefore may be subject to scrutiny by other University staff in determining the outcome of my degree. You will not be asked to provide your name, but you may be asked to provide some demographic information such as your age, education, gender, occupation and email address for analysis purposes. Data collected through this online questionnaire will be aggregated and you will not be individually identifiable in any reports or publications from this research.

What happens if something goes wrong?
If you are harmed by taking part in this research project, there are no special compensation arrangements. Regardless of this, if you wish to complain, or have any concerns about any aspect of the way you have been treated during the course of this study then you should immediately inform the student and/or their supervisor (details below). If you are not satisfied with the response, you may contact the Essex Business School Research Ethics Officer, Dr Maria Hudson (mhudson@essex.ac.uk).

We would be very grateful for your participation in this study. If you need to contact us in future, please contact me (ij18343@essex.ac.uk) or Dr Neeru Malhotra (n.malhotra@essex.ac.uk) or Dr Hongfei Liu (hongfei.liu@essex.ac.uk). You can also contact us in writing at: EBS, University of Essex, Colchester CO4 3SQ.

You are welcome to ask questions at any point.
Yours,
Iman Jana

Appendix B: Final Questionnaire

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About the Research
This survey is a part of an academic research project focusing on the exploration of your perceptions towards *Smart Payment Service*. If you don't know anything about *Smart Payment Service,* it doesn't matter, as a description will be provided. We are interested in your own personal opinion and there are no "right" or "wrong" answers, but it will be appreciated if you could be as precise and honest in your answers as possible.

This research is being undertaken by *Iman Jana* at Essex Business School and conforms with Ethical Guidelines. Your responses will not be identified by name, or any other means, and will be completely anonymous and confidential.This survey contains questions regarding your personality traits, understanding and perception towards *Smart Payment Service* and behavioural patterns of consumption and will take approximately 15 minutes to complete. You have the right to withdraw from completing this survey at any point of time. If you withdraw, your response will be deleted and not be used in this research.

Payment
Upon completion of the survey, you will be given a *completion ID at* the end of the survey. Please paste that *completion ID* into the box on Amazon Mechanical Turk to receive credit for taking our survey. For payment enquiries, please contact *ij18343@essex.ac.uk* via Amazon Mechanical Turk or via email: *ij18343@essex.ac.uk*.

Important: Please read the information in the survey carefully and answer **ALL** the questions. Only **valid** responses with **ALL the answers attempted** will get paid.

Have you ever used any of the *Smart Payment Services such as Apple Pay, Google Pay, Samsung Pay, Fitbit Pay, LG Pay*? These services can be used for contactless payments at shops, restaurants, for train

- ○ Yes
- ○ No

In this question, we are interested to know your personal knowledge about the *Smart Payment Service*.

Please rate the statement to indicate the extent to which you agree or disagree with that statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I have knowledge about Smart Payment Services.	○	○	○	○	○	○	○

Dear participant,

This questionnaire is investigating various barriers and values that you may face while making decision to choose an innovative service such as *Smart Payment Service*. This research is being carried out by Iman Jana under the supervision of Dr Neeru Malhotra and Dr Hongfei Liu.

You will not be asked to provide your name, but you may be asked to provide some demographic information for analysis purposes. Data collected through this questionnaire will be aggregated and you will not be individually identifiable in any reports or publications from this research. All information collected will be kept securely and will only be accessible by me and my supervisors.

For more information about your rights as a participant in this research please download a copy of the participant information sheet which can be found at this link https://www.essex.ac.uk/-/media/documents/directories/reo/participant-information-and-consent.pdf

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Yours,

Iman Jana

Statement of Consent

By submitting a completed version of this questionnaire, you are consenting to the following:

- I agree to participate in the research project being carried out by Iman Jana
- This agreement has been given voluntarily and without coercion.
- I have been given full information about the study and contact details of the researcher(s).
- I have read and understood the information provided above
- I have had the opportunity to ask questions about the research and my participation in it

Please indicate your consent if you are willing to participate.

○ Yes, I am over 18, understand the above information and agree to participate.

○ No, I do not want to participate.

Please read the below statements carefully and state your agreement or disagreement for each statement regarding the smart payment services.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Learning to use smart payment service will not be easy for me	○	○	○	○	○	○	○
Smart payment service will not be easy to use	○	○	○	○	○	○	○
It will not be easy to get results that I desire from smart payment service	○	○	○	○	○	○	○
I think that the fees of the smart payment service will be high	○	○	○	○	○	○	○
I think that smart payment service will be costly	○	○	○	○	○	○	○
I think that the smart payment service will be expensive	○	○	○	○	○	○	○
Please click only on the answer 'Agree'.	○	○	○	○	○	○	○
The risk of an unauthorized third party overseeing the payment process through smart payment service will be high.	○	○	○	○	○	○	○
The risk of abuse of usage information (credit/debit card details) will be high when using smart payment service	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The risk of abuse of billing information (e.g., credit/debit card number, transaction amount) will be high when using smart payment service	○	○	○	○	○	○	○
I identify with the typical image of a smart payment service user	○	○	○	○	○	○	○
I fit in with the typical image of a smart payment service user	○	○	○	○	○	○	○
The image of the typical smart payment service user reflects the kind of person I am	○	○	○	○	○	○	○
Human contact in making payments makes the process enjoyable for the customer	○	○	○	○	○	○	○
I like interacting with the person who provides smart payment service	○	○	○	○	○	○	○
Personal attention by the service employee is very important to me.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I'm afraid of becoming dependent on the technology							
The technology will reduce my autonomy							
I think my social life will suffer from my use of the technology							
I have avoided technology because it is unfamiliar to me							
I hesitate to use most forms of technology for fear of making mistakes I cannot correct							
I feel apprehensive about using technology							
I am skeptical toward smart payment service							
I do not think smart payment service will be successful							
I doubt that smart payment services can actually do what their service providers promise							
I generally consider the change as a negative thing							
I'd rather do the same old things than try new ones							

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In my opinion, traditional payment services are satisfactory so far	○	○	○	○	○	○	○
Overall, I consider that my needs of making payments have been met by existing traditional payment services.	○	○	○	○	○	○	○
In this statement, do not select any answer except 'Somewhat disagree'.	○	○	○	○	○	○	○
Smart payment services have consistent quality	○	○	○	○	○	○	○
Smart payment services are well designed	○	○	○	○	○	○	○
Smart payment services have an acceptable standard of quality.	○	○	○	○	○	○	○
Smart payment services will perform consistently	○	○	○	○	○	○	○
Using smart payment service is an efficient way to make payments at anytime and anyplace	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Using smart payment service is convenient at anytime and anyplace	○	○	○	○	○	○	○
Using smart payment service will make my life easier	○	○	○	○	○	○	○
Using smart payment service will fit in with the pace of my life	○	○	○	○	○	○	○
Using smart payment service would help me feel acceptable	○	○	○	○	○	○	○
Using smart payment service would improve the way I am perceived	○	○	○	○	○	○	○
Using Smart payment service would make a good impression on other people.	○	○	○	○	○	○	○
Using smart payment service would give me social approval	○	○	○	○	○	○	○
Smart payment service is one that I would enjoy	○	○	○	○	○	○	○
Smart payment service would make me want to use it	○	○	○	○	○	○	○
Smart payment service is one that I would feel relaxed about using	○	○	○	○	○	○	○
Smart payment service would make me feel good	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Smart payment service would give me pleasure	O	O	O	O	O	O	O
Do not select the option 'Strongly agree' in this statement. Select any other option.	O	O	O	O	O	O	O
When the things get boring, using smart payment service will give me new stimuli	O	O	O	O	O	O	O
Using Smart payment service will continually give me new activities and changing contents	O	O	O	O	O	O	O
Smart payment service will help me to experience novelty and change in my daily routine	O	O	O	O	O	O	O
In sum, a possible use of smart payment services would cause problems that I don't need	O	O	O	O	O	O	O
I would be making a mistake by using smart payment services.	O	O	O	O	O	O	O
The use of smart payment services would be connected with too many uncertainties.	O	O	O	O	O	O	O

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The smart payment services are not for me.	○	○	○	○	○	○	○
I'm opposed to the use of smart payment services.	○	○	○	○	○	○	○
I'm opposed to the discourses extolling the benefits of smart payment services.	○	○	○	○	○	○	○
The correct answer for this statement is 'Disagree'. Please select 'Disagree' only.	○	○	○	○	○	○	○
I spread negative comments about the smart payment service	○	○	○	○	○	○	○
I share negative opinions about the smart payment service	○	○	○	○	○	○	○
I write negative remarks about the smart payment service on discussion forums	○	○	○	○	○	○	○
I take active part in negative discussions related to the smart payment service	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I rave about the dark side of the smart payment service to others.							
I denigrate the smart payment service to my friends							
I tell my friends not to use the smart payment service, when they look for a similar service							
It is sometimes hard for me to go on with my work if I am not encouraged							
There have been times when I was quite jealous of the good fortune of others							
No matter who I am talking to, I am always a good listener							
I don't get irritated by people who ask favours of me							

Please mention your age.

State your gender.

- ○ Male
- ○ Female

Which statement best describes your current employment status? Select all that apply.

- ☐ Employed full time
- ☐ Employed part time
- ☐ Unemployed looking for work
- ☐ Unemployed not looking for work
- ☐ Retired
- ☐ Student

What is your highest education level?

- ○ Less than high school
- ○ High school graduate
- ○ Graduate
- ○ Postgraduate
- ○ Doctorate

This is a first part of a large research project. We may launch follow-up studies in the next 12 months. If you are interested in participating into our future research, please provide your email address below. We will email you the survey link on MTurk.

Please provide your MTurk ID below.

Your completion ID is ${e://Field/Random%20ID}

Copy this ID to paste into MTurk. Failing to provide this ID may cause potential payment issues.

*__**Reminder:**__ To receive payment for participating, click "Accept HIT" in the Mechanical Turk window, enter this completion code, and then click "Submit". After you have done that, please click the "continue" button to finish up the questionnaire.

We thank you for your time spent taking this survey.

Your response has been recorded.

Powered by Qualtrics

Thank you for your participation in this study.

You are reminded that by submitting a completed version of this questionnaire you are agreeing to participate in this research.

If you have any queries, please contact me **(ij18343@essex.ac.uk)** or Dr. Neeru Malhotra **(n.malhotra@essex.ac.uk)** or Dr Hongfei Liu **(hongfei.liu@essex.ac.uk).** You can also contact us in writing at: EBS, University of Essex, Colchester CO4 3SQ.

Yours,

Iman Jana