The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty

Abstract

Smart shopping malls integrate a range of smart technologies such as artificial intelligence, virtual reality and augmented reality. However, there is a lack of research on the personalisation-privacy paradox in the context of consumer interaction with smart technologies in shopping malls. Integrating the trust-commitment theory, the privacy calculus theory and interface design literature, this study develops a model for customer interactions with smart technologies in shopping malls. The model examines the mediating effects of personalisation and the moderating effects of consumer privacy concerns on the relationships between consumer interactions with smart technologies and shopping mall loyalty. Data were collected from 1,139 millennial customers patronising two smart shopping malls in the United Kingdom and United Arab Emirates. The findings highlight the significant mediating effects of personalisation on the positive relationships between dimensions of consumer interactions with smart technologies (interface design, trust, consumer peer interaction and relationship commitment) and shopping mall loyalty. In addition, our findings reveal a personalisation-privacy paradox, with consumer privacy concerns, unlike prior research, not exerting a moderating role in our proposed model. This study contributes to the literature by proposing a model on consumer interaction with smart technologies in shopping malls, addressing the roles of personalisation and privacy concerns.

Keywords: Smart shopping malls; human-computer interaction; personalisation; trust-commitment theory; privacy calculus theory; personalisation-privacy paradox

1. Introduction

Smart shopping malls are based on a complex integration of virtual and physical environments, allowing customers to use smart technologies as part of their shopping experience (Ameen et al., 2020a). These intelligent technologies such as artificial intelligence (AI), virtual reality (VR), augmented reality (AR) and biometrics (Morgan, 2018) benefit customers, mall owners and retailers. For example, a number of shopping malls around the world have introduced chatbots to interact with and assist customers (JCDecaux, 2019). These changes offer many benefits to consumers in the forms of personalised notifications, entertainment, awareness of promotions and sales, face recognition, wayfinding and an optimised environment (Fujitsu, 2019; Morgan, 2018). In these smart shopping malls, a personalised shopping experience can play an important role in increasing loyalty among shoppers. However, consumer privacy concerns can also shape their behaviour and how they interact with smart technologies.

A line of research focusses on the decline in consumers' interests in shopping malls (Calvo-Porral & Lévy-Mangin, 2019). This decline has been compounded by the global exogenous shock, the COVID-19 pandemic, causing disruption to consumer shopping habits (Ameen, Hosany & Tarhini, 2021; Sheth, 2020). As countries seek to adjust to the challenges and new realities (e.g. social distancing) brought about as a direct response to COVID-19, the use of smart technologies in shopping malls is more significant than before. For example, the shopping mall smart technology-enabled personalisation, such as smart wayfinding maps, monitoring customer foot traffic, robot assistant, smart mirrors and AI-enabled chatbots available on smartphones, allow customers to shop quickly and avoid crowded areas, thus enabling a safer shopping experience (Kalany, 2019).

An emerging body of research focus on in-store smart retail technology (e.g. Foroudi et al., 2018; Roy et al., 2018; Fazal-e-Hasan et al., 2021). In particular, Riegger et al. (2021) identify the lack of research and importance to study technology-enabled personalisation in providing smart experiences At the same time, Wang et al. (2019) note that privacy concerns over who controls their data and how their data are used by companies shape consumers' shopping behaviour. While recent studies focus on consumer interaction with smart technologies in the context of in-store experiences, little is known about how shoppers interact with smart technologies in a broader context (i.e., smart shopping malls) and the relevance of the personalisation-privacy paradox in explaining shopping mall loyalty.

Accordingly, drawing on the trust-commitment theory (Morgan & Hunt, 1994), the privacy calculus theory (Culnan & Armstrong, 1999) and interface design literature (e.g., Miles et al., 2000; Cheng, Wu & Leiner, 2019), we propose a model integrating consumer interactions with smart technologies in shopping malls via social media platforms (e.g. interface design, trust, consumer-peer interactions, relationship commitment) and shopping mall loyalty. Furthermore, we analyse the mediating role of personalisation and the moderating effects of consumer privacy concerns on the relationship between consumer interactions and shopping mall loyalty. The proposed model was tested in a cross-national context, using two samples of young shoppers in two smart shopping malls in the United Kingdom (UK) and the United Arab Emirates (UAE). Our analysis also examines the similarities and differences in shoppers' interactions with smart technologies at these two shopping malls. The UK and UAE were chosen as they are at the forefront of the digital retailing revolution yet customer profiles and location context are different. Previous studies emphasised the relevance of national differences in how customers perceive services they receive in shopping malls (Thomas & Carraher, 2014; Diallo et al., 2018).

The contribution of this research is fourfold. First, we propose a model that acknowledges the complex nature of customers' interactions with smart technologies in shopping malls. Second, our study analyses the role of personalisation as a mediator in understanding the relationship between customer interaction with smart technologies and loyalty. Personalisation has been previously studied in the context of online shopping (e.g. Carrozzi et al., 2019; Theodosiou et al., 2019) and shopping mall experiences (Mathwick et al., 2001; Keng et al., 2007), but its role as a mediator remains unexplored. Hence, our results offer important implications for theory building, as mediation provides insights into how and why a relationship between two variables exists (Baron & Kenny, 1986). Third, we explore the moderating effects of consumer privacy concerns on the relationships between smart technologies interaction-related factors, personalisation and shopping mall loyalty. While recent studies (e.g. Volchek et al., 2021) examine the privacy-personalisation paradox, the moderation-mediation effects have not been studies in the context of consumer interactions with smart technologies in shopping malls. Fourth, collecting data from customers patronising leading smart shopping malls in two countries allows a more in-depth understanding of shopping experiences in a cross-national context. In terms of the practical implications, the findings assist experts and management teams of shopping malls to provide a better smart shopping experience to their customers and enhance loyalty. In particular, we offer useful recommendations for shopping mall management teams in terms of how customers' interaction with smart technologies can strengthen personalisation during shopping experiences, which in turn enhances their loyalty to the mall.

2. Literature review

2.1 Shopping malls and smart technologies

A smart mall assimilates the Internet of Things (IoT) functionality both inside and outside the mall's buildings, and uses data shared by customers to provide valuable insights for retailers and mall management teams (Idsolve, 2020). The customer experience can begin with eye scanners at the mall entrance, which recall information about the customer's previous purchases, offering customers personalised short cuts to specific stores around the mall (Morgan, 2018). Secure wireless connectivity (Wi-Fi) is key to managing a connected smart mall. The IoT, big data, AI, analytics and marketing tactics enabled in smart shopping malls have revolutionised customer experiences. For example, customers who receive personalised notifications, can be made aware of promotions and sales, join loyalty schemes, use wayfinding technology and make the most of an optimised environment (Kalany, 2019). In smart shopping malls, retailers use smart technologies such as smart virtual beauty applications and AI-enabled chatbots (Ameen et al., 2021; Ameen et al., 2020b). Recent studies focus on specific smart retail technologies (e.g. Fazal-e-Hasan et al., 2021; Foroudi et al., 2018). However, Fazal-e-Hasan et al. (2021) recommend studying smart retail technologies more broadly as the use of one type of smart retail technology may limit the robustness of proposed models. In reality, a smart shopping experience integrates different types of smart technologies at different touchpoints.

Previous studies in the area of human-computer interaction highlight the significance of integrating advanced technologies in shopping malls. For example, Van Kerrebroeck, Brengman and Willems (2017) point out the benefits of using smart technologies such as VR to escape crowding and increase mall satisfaction. Bertacchini, Bilotta and Pantano (2017) further explain that a robot companion acts as an intelligent shopping assistant. However, despite attempts to study the integration of smart technologies in shopping malls, research in this area is still in its infancy (Ameen et al., 2020a) and little is known about how shoppers develop loyalty to smart shopping malls taking into consideration the mediating role of personalisation and moderating effect of privacy concerns.

2.2 The personalisation-privacy paradox and shopping mall loyalty

Personalisation refers to “the degree to which information is tailored to meet the needs of the individual user” (Bilgihan et al., 2016, p. 110). It entails using data mining techniques to tailor a service to customers so that it meets their needs and preferences and increases their interest in shopping (Chung & Shin 2008). It can be based on customer demographics, preferences, context and content (Carrozzi et al., 2019). The human-computer interaction and marketing literature acknowledge that personalisation plays a significant role in enhancing the shopper experience (e.g. Foroudi et al., 2018; Carrozzi et al., 2019; Theodosiou et al., 2019). However, research has not yet studied the mediating effect of personalisation on the smart shopping mall experience.

In addition, the literature acknowledges that consumers can have privacy concerns while using technology for shopping (Limbu, Wolf & Lunsford, 2011). This is because consumers share personal and financial data with shopping malls and retailers during all interactions with technology and they expect a confidential treatment of their information (Martin & Murphy, 2017). Bart et al. (2005) describe privacy as consumers' perceptions about the protection of individually identifiable information when interacting with retailers' digital technologies for shopping purposes. The introduction of new technologies in shopping malls and among retailers such as AI, VR, AR and robotics are likely to increase customers' concerns of privacy due to a lack of knowledge and experience in terms of how these technologies gather and use personal data (Deane, 2018). Hence, shoppers' privacy concerns can have a significant effect on customers' interactions with smart technologies and the extent to which they provide personal information in shopping malls.

The paradoxical value of personalisation triggers consumer concerns over their personal information being tracked, stored and shared (Ohkubo, Suzuki & Kinoshita, 2005). While consumers are interested in a fast smart technologies-enabled personalised shopping experience, they are also concerned about the privacy of their data and the amount of data they share (Riegger et al., 2021). Although personalisation offers significant benefits for shoppers, it involves disclosing personal information (Roussos, Peterson, & Patel, 2003). Previous studies reveal customers feel their privacy have been invaded once they realise that shopping lists are personalised based on browsing and purchasing history (Roussos et al., 2002). In addition, previous research confirms that if privacy concerns are sufficiently addressed, it is possible consumer assessments of personalisation will be more positive (Lee & Cranage, 2011). However, there is a gap in research in understanding whether and how the trade-off between personalisation and privacy can lead to smart shopping mall loyalty.

Shopping mall loyalty refers to a "shopper's attitudinal predisposition consisting of intentions to continually patronize the mall in terms of repeated shopping at the mall and willingness to recommend the mall" (Chebat, El Hedhli & Sirgy, 2009, p. 54). Loyalty reflects customers' commitment to the mall and their intention to revisit it and provide positive recommendations (Diallo et al., 2018). According to Adkins et al. (2002), the concept of loyalty is based on behavioural loyalty (which focuses on repurchase and patronage behaviour) and attitudinal loyalty (which focuses on the customer's evaluation of how closely the mall meets their expectations). A true loyal customer is one who holds a relatively positive attitude towards the retailer and the mall and has a high level of repeat purchase behaviour (El-Adly & Eid, 2016). Previous studies have emphasised that shopping mall loyalty provides significant benefits for malls and retailers by increasing their market share, the sustainability of their competitive advantage (Rabbanee et al., 2012) and the profitability from long-term customers. Despite its importance, loyalty and its antecedents in the context of smart shopping malls remains poorly understood (El-Adly & Eid, 2016). In other words, little is known in terms of how consumer interaction with smart technologies influence shopping mall loyalty.

3. Conceptual framework and hypotheses development

The future of retailing is in embracing a variety of smart technologies to engage customers, with a convergence of the online and offline domains (Grewal, et al., 2020). The trust-commitment theory explains that trust and relationship commitment are key to the process of developing relationships between customers and retailers online (Morgan & Hunt, 1994). The theory integrates the factors that can be applied to virtual environments; namely, privacy, trust, relationship commitment and customer-peer interaction. Wang et al. (2019) explained that trust helps to build a committed relationship between customers and retailers online and on social media. The authors highlight the role of privacy issues, including privacy control, which may raise concerns – in particular, that consumers have a low level of control over how retailers use their data. Hajli (2015) also emphasised the significance of consumer-peer interaction, as consumers share their shopping experiences and interact with others on social commerce platforms to exchange information about products and services. Furthermore, existing studies on human-computer interaction emphasise the significant impact of interface design on usability (e.g., Cheng et al., 2019; Hong et al., 2017). The interface design of smart technologies can determine whether shoppers think that the technology is personalised or not.

The widely accepted explanation of the privacy paradox comes from the privacy calculus theory (Culnan & Armstrong, 1999) to describe the cognitive process behind the privacy-related behaviour of an individual (Vimalkumar et al., 2021). The theory sees privacy in economic terms, postulating that humans conduct a subjective cost-benefit analysis when requested to provide information in exchange for a product or service and disclosure occurs when they think benefits will outweigh the risks of privacy loss (Jozani et al., 2020). Prior studies (e.g. Gutierrez et al., 2019; Kim et al., 2019) on human-computer interaction examine consumer privacy concerns through the lens of the privacy calculus theory.

The proposed model (Figure 1) combines the trust-commitment theory (Morgan & Hunt, 1994), the privacy calculus theory (Culnan & Armstrong, 1999) and interface design literature (e.g., Miles et al., 2000; Cheng et al., 2019). The integration and extension of these theories offers novel insights into our understanding of customer interactions with smart technologies in shopping malls and the role personalisation-privacy paradox in explaining shopping mall loyalty. The model hypothesises personalisation as mediator and consumer privacy concerns as a moderator. In addition, previous studies highlight the relevance of interface design, trust, consumer-peer interaction and relationship commitment (Park & Kim, 2018; Trivedi & Trivedi, 2018; Wang et al., 2019). However, the mediating role of personalisation and moderating influence of consumer privacy concerns on the relationship between these factors and loyalty have not been studied, specifically in the context of smart shopping malls.

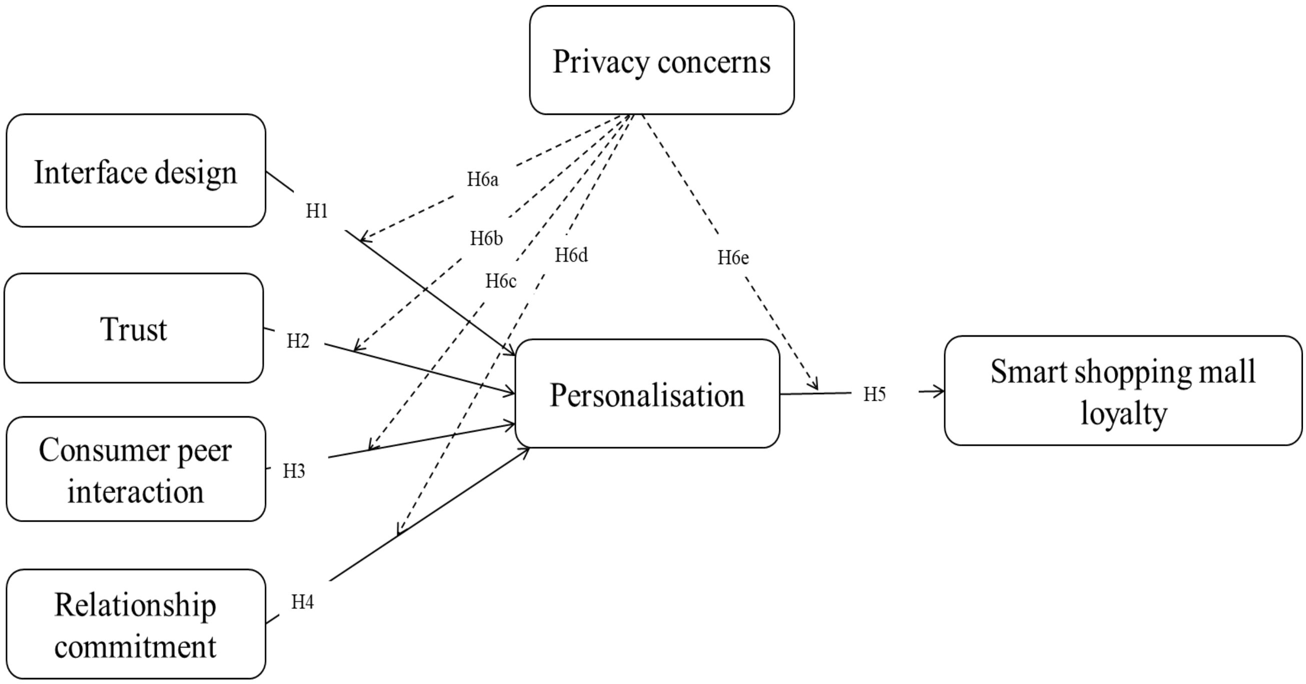

Figure 1. The proposed model

3.1 Interface design

The design of the technology interface – whether it is mobile, online, AI-enabled service, virtual reality or a smartboard – has a significant impact on customers' intention to shop (Ariff et al., 2013). The interface design used in the virtual environment of a smart shopping mall is different from that of an ordinary shopping mall. A user interface consists of a physical medium and content presentation interface elements (Miles et al., 2000). Existing studies on consumers' interaction with different technologies for shopping purposes have highlighted the importance of providing a clear, userfriendly design and understanding customers' needs and preferences (Ariff et al., 2013; Ameen et al., 2020c; Cheng et al., 2019) for more effective personalisation. A rich yet specific interface increases shoppers' perceptions of personalisation (Wilson, 2018). In other words, personalising the user experience requires a high-quality interface design. Hence, we hypothesise:

H1. Interface design has a positive relationship with personalisation.

3.2 Trust

In an online context, trust has been defined as an attitude of confident expectation that one's vulnerabilities will not be exploited (Corritore, Kracher & Wiedenbeck, 2003; Lee et al., 2015). From a marketing perspective, in contrast with traditional commerce, where the sole object of a customer's trust is the seller or the company they represent, in electronic commerce the customer has to trust not only the website but also the brand, and they must be sure that the technology used by the company. These points highlight the complicated nature of trust in digital commerce exchanges and in collecting data about consumers. Personalisation involves gathering customer data in order to understand their behaviour, needs and preferences (Bleier & Eisenbeiss, 2015). However, for malls and brands to be able to use this data for personalisation purposes, it is essential that customers trust that their data will be kept safe (Briggs, Angeli & Simpson, 2004). Customers are unlikely to reveal confidential information to an organisation that they do not trust (Aguirre et al., 2015). Customer trust is required in order for the personalisation process to be initiated (Bleier & Eisenbeiss, 2015). Trust also influences the effectiveness of a personalised experience (Aguirre et al., 2015). The following hypothesis is proposed:

H2. Trust has a positive relationship with personalisation.

3.3 Consumer-peer interaction

Consumer-peer interaction is defined as consumers' social relationships with their peers (Wang et al., 2019). This factor is present in trust-commitment theory, and it acknowledges the power of social interactions between consumers in shopping and connecting to brands (Morgan & Hunt, 1994). Consumers interact with each other on social commerce platforms (social media) to exchange information about products and services (Papagiannidis & Bourlakis, 2015). This helps shopping malls and retailers to obtain rich data about customers' shopping experience and preferences, which they can then use to create more personalised content on social platforms and while shopping in malls (Lee, 2017; Wang et al., 2019). Consumers interact with others on social commerce platforms to exchange information about products and services. This helps shopping malls and retailers to obtain rich data about customers' shopping experience and preferences, which they can then use to create more personalised content on social platforms and while shopping in malls (Lee, 2017). Understanding customers' needs and preferences through the collection of data on social media is essential for a more personalised customer shopping journey (Malthouse & Li, 2017; Zadeh et al., 2019). Social customer relationship management makes it possible to carry out more precise analysis based on conversations on social media; this helps malls to provide programmes and activities that more accurately match customers' interests and preferences. Hence, we hypothesise:

H3. Consumer-peer interaction has a positive relationship with personalisation.

3.4 Relationship commitment

Relationship commitment refers to the enduring desire to maintain a valued relationship, and this factor plays a key role in determining customers' behavioural intention (Moorman, Zaltman & Deshpande, 1992). It is present in trust-commitment theory (Morgan & Hunt, 1994). Morgan and Hunt (1994) explained that consumers can become more interested in interacting with retailers and building relationships with them. This sort of relationship has been found to be important in technology-mediated communications between brands and customers (Park & Kim, 2018; Wang et al., 2019). According to Morgan and Hunt (1994), when a consumer believes that an ongoing relationship with a retailer is important, they will devote maximum effort to maintaining it and will continue to shop there. Similarly, consumers can develop their commitment to their relationship with smart shopping malls through the use of different technologies in the virtual environment. Relationship commitment is an outcome of satisfactory interactions between customers and shopping malls and retailers over the long term (Wang et al., 2016). When customers are committed to the relationship, they assume that there are no alternatives that would provide similar benefits, which makes them less likely to shift to online shopping. Customer brand relationship has a positive influence on consumers' perceptions of personalisation (Hayes et al., 2021). Consumers who are highly committed to their relationships with their favourite brands, stores and shopping malls may have a strong perception of personalisation. Hence, we hypothesise:

H4. Relationship commitment has a positive relationship with personalisation.

3.5 Personalisation

Personalisation via the use of technologies is an important factor in providing customers a positive shopping experience (Trivedi & Trivedi, 2018). Previous studies show a positive relationship between personalisation and loyalty (Ball, Coelho & Vilares, 2006). Fang (2019) further investigates the direct relationship between personalisation and loyalty. Findings indicate that consumers tend to evaluate their experiences as being memorable and unique, which eventually increases their loyalty. Personalising customers' experience is even more important in building shopping mall loyalty, as it results in memorable experiences. Hence, we propose:

H5. Personalisation has a positive relationship with smart shopping mall loyalty.

3.6 The moderating effects of privacy concerns

Prior studies suggest that the evolution of privacy follows the advancements of information technology and its dimensions are subject to change with the evolution of markets and technologies (Smith, Dinev & Xu, 2011). However, technological advancements in the last decade have significantly changed the perception of privacy and have raised unique issues in relation to the role of third-party, the degree of user involvement in privacy settings, and the commercialisation of user data (Jozani et al., 2020). Pizzi and Scarpi (2020) found that within the context of interactions with smart retail technologies, consumers' privacy perceptions can play a significant role in shaping their behaviour in terms of intentions and word-of-mouth. A few studies explored the moderating effects of privacy concerns in online shopping environments (e.g., McCole, Ramsey & Williams, 2010; Li et al., 2017). In this study, we expect consumer privacy concerns (high vs low levels) to moderate the relationships proposed in our model.

Consumers with a high (versus low) level of privacy concerns are likely to perceive personalised offerings to be less of a value than consumers with a low level of privacy concerns (Awad & Krishnan, 2006). Accordingly, the relationship between interface design and personalisation would be stronger among consumers with a low level of privacy as they pay more attention to information available on the user interface. We also propose that consumer privacy concerns will moderate the influence of trust on personalisation and this effect will be higher among consumers with low level of privacy concerns. Consumers with high level of privacy concerns exhibits a low level of trust in how their data is handled and who controls it (Taylor, Davis & Jillapalli, 2009). The impact of trust on personalisation would be higher among those with a low level of privacy concerns. In addition, low level of privacy concerns can increase the effects of consumer peer interactions via social media on personalisation. Individuals are more open to interact on social media when they have lower levels of privacy concerns (Jozani et al., 2020). Furthermore, in line with recent research on consumer-brand relationship, personalisation and privacy concerns (Hayes et al., 2021), we argue that high levels of privacy concerns moderate the relationship between consumers' commitment to their relationships with smart shopping malls smart shopping malls and perception of personalisation. We also propose that consumers with a low level of privacy concerns will perceive personalisation to impact on their loyalty to smart shopping malls. A high level of privacy concerns decreases the magnitude of this relationship because consumers are less concerned about personalisation (Awad & Krishnan, 2006). Accordingly, we propose the following hypotheses on the moderating role of privacy concerns:

H6. A low (versus high) level of privacy concerns enhances the relationships between interface design (H6a), trust (H6b), consumer peer interaction (H6c), relationship commitment (H6d) and personalisation. Consumer privacy concerns (low versus high levels) also moderate the relationship between personalisation and smart shopping mall loyalty (H6e)

3.7 The mediating effects of personalisation

In this study, we hypothesise that personalisation mediates the relationships between the factors interface design, trust, consumer-peer interaction and relationship commitment, and shopping mall loyalty. A high-quality personalised interface can lead to more recommendations and revisits to the mall (Cyr, 2014). In addition, trust can have an indirect effect on loyalty through personalisation. In other words, trust has a stronger effect on recommendations when customers have a personalised shopping experience, given that perceived personalisation affects customers' cognitive and emotional beliefs about the shopping mall (Komiak & Benbasat, 2006). Furthermore, consumer-peer interaction has an indirect effect on loyalty through the mediating effects of personalisation. Loyalty can be increased by creating more personalised content on social media, through recommendations and endorsements and by building personal relationships (Shadkam & O'Hara, 2013). In addition, relationship commitment has an indirect effect on loyalty through personalisation, since commitment makes customers more engaged with shopping malls and are more likely to form long-term bonds with them (Lin, Swarna & Bruning, 2017). Thus, we propose:

H7. Personalisation mediates the relationships between interface design, trust, consumer-peer interaction and relationship commitment, and smart shopping mall loyalty.

4. Methods

4.1 Measurement scales

The measurement items (see Appendix A) for all constructs were adopted from previous studies. The items for trust (TR), consumer-peer interaction (CPI) and relationship commitment (RC) were derived from Wang et al.'s (2019) study, and interface design (ID) was adopted from Ariff et al. (2013). The statements for personalisation (PE) were adapted from Chellappa and Sin (2005). Items from Chellappa and Sin's (2005) study were used to capture privacy concerns (PR). Finally, shopping mall loyalty was measured using scale items adapted from the works of Chebat et al. (2009) and El-Adly and Eid (2016). To minimise any potential common method variance (CMV) bias, the survey design and administration followed Podsakoff et al.'s (2003) recommendations. In addition, the Harman's single factor test was used to test CMV. Exploratory factor analysis reveal that the first factor accounted for only 16% of the variance in Sample 1 (UAE) and 17% in Sample 2 (UK). In addition, the inner variance inflation factor (VIF) values were lower than the threshold value of 3.3 (Petter, Straub & Rai, 2007). Hence, initial analysis showed that CMV was not a persistent issue.

4.2 Study setting, sampling and data collection

Data were collected from customers patronising two malls in the UK (London) and UAE (Dubai). Similar to previous studies (e.g. Malhotra & Galletta, 1999), purposive sampling was employed to collect data from young shoppers (millennials) patronising the two malls. Participants had to be aged 23–38 in order to be eligible to take part in the study. This age range was chosen for three reasons. First, it is predicted that by 2020 millennials will account for nearly $1.4 trillion in spending power (The Store Front, 2015). Millennials' spending patterns are different from those of older generations, as they seek experiences such as travel, entertainment and technology (The Store Front, 2015). Second, this segment presents challenges for shopping malls, as they are more interested in using technology to complement their shopping experience (Skeldon, 2018). Third, for millennials, the process of making a buying decision is different from that of previous generations; they require a unique, exciting and personalised shopping experience, which also makes them a challenging segment for retailers in shopping malls (Oracle, 2015). Full ethical approval was obtained from a UK-based higher education institution. Respondents were provided with an information sheet and had to complete a consent form prior to taking part in the study. The questionnaire includes an introductory text explaining the purpose of the research and examples of smart technologies in shopping malls. All participants were aged 18 or over and no sensitive data were collected at any point of time. A pilot test took place with 25 respondents and changes were made to the final questionnaire. A total of 1,400 questionnaires were administered face to face in London and Dubai. After identifying missing data, unengaged responses and outliers (Hair et al., 2017), 586 for Sample 1 (UAE) and 553 questionnaires for Sample 2 (UK) were retained for the analysis. The response rate was 79% in the UK and 84% in the UAE.

4.3 Profile of respondents

For Sample 1, 33% were 23–30 years old and 67% were 31–38 years old. Males made up 52% and females 48%. Furthermore, 84% of the respondents in the UK were tourists, while 16% were residents in the country (Table 1). Three per cent patronised shopping malls every day, 88% every week and 9% every month. In terms of technology used while shopping at the mall, 55% used smartphones and mobile applications, 17% used virtual reality, 8% used biometrics and 20% used AI-enabled store services.

Table 1.
Descriptive statistics for the UAE (Sample 1) and UK (Sample 2)

	Sample 1: UAE (%)	Sample 2: UK (%)
Age		
23-30	33	43
31-38	67	57
Gender		
Male		
Female	52	49
	48	51
Tourist shopper		
Yes	84	95
No	16	5
Use of smartphones		
Yes	100	100
No	0	0
Frequency of shopping in shopping malls		
Daily	3	9
Weekly	88	81
Monthly	9	10
Annually	0	0
Use of technology while shopping at the mall		
Yes	100	100
No	0	0
Type of technology used while shopping		
Smartphones and mobile applications	56	58
Augmented reality	0	4
Virtual reality	17	14
Biometrics	8	8
Artificial intelligence (AI)-enabled store services	20	16

For Sample 2, 43% of the respondents were 23–30 years old and 57% were 31–38 years old. Males made up 49%, and females 51%. In addition, 95% of the respondents in the UAE were tourists, while 5% were residents in the country. Nine percent of the UK sample patronised shopping malls every day, 81% every week and 10% every month. In terms of technology used while shopping in the mall, 58% used smartphones and mobile applications, 4% used augmented reality, 14% used virtual reality, 8% used biometrics and 16% used AI-enabled store services.

5. Results

Data were analysed using partial least squares-structural equation modelling (PLS-SEM) (Hair et al., 2017). The hypothesised model was estimated using SmartPLS3 software with a bootstrap re-sampling procedure (5,000 sub-samples were randomly generated) (Hair et al., 2017). Sarstedt, Ringle and Hair (2017) explained that researchers should run bootstrapping, a procedure that draws a large number of subsamples (typically 5,000). In bootstrapping, subsamples are randomly drawn (with replacement) from the original set of data. Each subsample is then used to estimate the model. This process is repeated until a large number of random subsamples have been created, typically about 5,000 (Hair et al. (2017). The variation across these many (e.g., 5,000) estimations from the bootstrap subsamples is used to obtain standard errors for the PLS-SEM results. To test for mediating effects, we follow Preacher and Hayes's (2008) bootstrapping method.

5.1 Assessment of the measurement model

The first stage was assessing the reliability, convergent validity and discriminant validity of the constructs in our proposed model (Hair et al., 2017). Table 2 shows the assessment of AVE, Cronbach's alpha and composite reliability for both samples. In terms of convergent validity, the average variance extracted (AVE) values were all above the threshold value of .5 as suggested by

Fornell and Larcker (1981) for both the UK and UAE samples. Furthermore, composite reliability was above the recommended threshold value of .7 (Urbach & Ahlemann, 2010).

Table 2. Assessment of reliability and convergent validity

Construct	Sample 1: UAE			Sample 2: UK		
	Cronbach's alpha	CR	AVE	Cronbach's alpha	CR	AVE
Consumer peer interaction	0.70	0.85	0.74	0.79	0.85	0.74
Interface design	0.75	0.86	0.66	0.76	0.86	0.67
Loyalty	0.83	0.92	0.86	0.87	0.92	0.79
Personalisation	0.88	0.93	0.61	0.88	0.91	0.72
Privacy concerns	0.89	0.93	0.82	0.91	0.95	0.85
Relationship commitment	0.72	0.84	0.64	0.73	0.85	0.75
Trust	0.76	0.81	0.59	0.70	0.82	0.60

Factor loadings were also used to assess convergent validity of the factors in the model. The items with loadings of .7 and above were retained. However, the items with loadings lower than .7 were removed. Furthermore, discriminant validity was examined by comparing the square root of AVE for each construct with correlations among the latent variables (Fornell & Larcker, 1981). Discriminant validity was further checked using Fornell-Larcker criterion and the heterotrait-monotrait (HTMT). As shown in Table 3, the maximum HTMT ratios across both samples is 0.66, below the threshold of 0.85 (Henseler, Ringle, & Sarstedt, 2015). Together, the analysis indicates good discriminant validity.

Table 3. Assessment of heterotrait-monotrait (HTMT): Sample 1 (UAE) and Sample 2 (UK)

	Sample 1: UAE						Sample 2: UK					
	Consumer peer interaction	Interface design	Loyalty	Personalisation	Privacy concerns	Relationship commitment	Consumer peer interaction	Interface design	Loyalty	Personalisation	Privacy concerns	Relationship commitment
Interface design	0.24						0.21					
Loyalty	0.27	0.64					0.25	0.64				
Personalisation	0.15	0.44	0.69				0.15	0.41	0.71			
Privacy concerns	0.14	0.65	0.60	0.52			0.12	0.66	0.35	0.63		
Relationship commitment	0.09	0.28	0.35	0.42	0.35		0.10	0.24	0.35	0.35	0.31	
Trust	0.11	0.09	0.25	0.43	0.07	0.45	0.08	0.10	0.29	0.47	0.31	0.43

5.2 Structural model and hypothesis testing

The structural model was assessed using standardised path coefficients (β-value), significance level (*t* statistic) and R^2 estimates. The path loadings suggest the strength of the relationships between independent and dependent factors (Hair et al., 2017).

Table 4. Results for the hypothesised model- Direct effects

	Hypotheses	Sample 1: UAE			Sample 2: UK		
		Beta	t-value	Results	Beta	t-value	Results
H1	Interface design -> Personalisation	0.31	5.64 ***	Supported	0.27	5.16 ***	Supported
H2	Trust -> Personalisation	0.27	5.44 ***	Supported	0.31	4.49 ***	Supported
H3	Consumer peer interaction -> Personalisation	0.08	1.60	Not supported	0.10	2.41 **	Supported
H4	Relationship commitment -> Personalisation	0.19	3.19 *	Supported	0.15	2.26 **	Supported
H5	Personalisation -> Loyalty	0.60	15.21 ***	Supported	0.62	10.89***	Supported

The bootstrapping procedure was used to calculate the path loadings, *t*-values and standard errors for the hypothesised relationships (Hair et al., 2017). Table 4 show the results of the assessment of each hypothesised direct relationship in the proposed model in the UAE and in the UK. According to these results, all the hypothesised direct relationships (H1 to H5) are significant in both samples, with the exception of H3 (consumer peer interaction to personalisation: (β=-0.08; 1.60) in Sample 1 (UAE). In addition, the results show that the proposed model has an acceptable predictive power of loyalty across both samples. In Sample 1 (UAE), the R^2 value is .48; in Sample 2 (UK), the R^2 value is .41.

5.3 Cross-national differences-multi-group analysis of direct effects

To further confirm the results of the structural model assessment, a partial least squares-multigroup analysis (PLS-MGA) was performed. In this analysis, we compare the path coefficients (direct relationships) between the two groups (i.e., UK sample vs UAE sample). Prior to running multi-group analysis, measurement invariance of composite models (MICOM) was used to assess the configural compositional and scalar invariance (equality of means and varinaces) using the permutation option in SmartPLS 3(Hensele r et al., 2015). The results of the MICOM procedure supported full measurement invariance, and we then compare the path coefficients between the two samples.

Table 5. Multi-group comparison of direct relationships- Cross country comparison

		UAE Sample		**UK Sample**		
	Hypothesis	Path coefficient	*t* value	Path coefficient	*t* value	Group differences *p* value
H1	Interface design -> personalisation	0.31	6.16***	0.28	4.83***	0.66
H2	Trust -> personalisation	0.28	4.93***	0.31	5.07***	0.35
H3	Consumer peer interaction -> personalisation	0.08	1.56	0.10	2.73**	0.33
H4	Relationship commitment -> personalisation	0.19	2.85**	0.15	2.24*	0.69
H5	Personalisation -> loyalty	0.62	15.86***	0.62	14.23***	0.46

***p < 0.001; **p<0.01; *p<0.05

A *p* value that is less than 0.05 or more than 0.95 indicates a significant difference at the 5% level between specific path coefficients across two groups (Hair et al., 2017; Henseler, Ringle & Sinkovics, 2009; Sarstedt, Henseler & Ringle, 2011). Similar threshold values were adopted in previous studies on human-computer interaction using PLS-MGA (e.g. Widjaja et al., 2019; Valaei & Baroto, 2017; Ameen, Willis & Shah, 2018). The results of the MGA (Table 5) reveal no significant differences between the two samples (UK and UAE) in terms of the path coefficients for the hypotheses H1 to H5.

5.4 The moderating effects of privacy concerns

We assessed the moderating effects of privacy concerns in both samples using the same procedure we followed in assessing the country-level differences (i.e. using PLS-MGA). First, the variable ‘privacy concerns’ was split into two groups. For the UAE sample: low level of privacy concerns (below mean); N=205 vs. high level of privacy concerns (above mean); N=381; for the UK sample: low level of privacy concerns (below mean); N=187 vs. high level of privacy concern (above mean); N=366.

Table 6. Multi-group comparison-moderating effects of privacy concerns- Sample 1-UAE

Hypothesis		Low level of privacy concerns (N=205)		High level of privacy concerns (N=381)		Group differences *p* value	Supported?
		Path coefficient	*t* values	Path coefficient	*t* values		
H6a	Interface design -> personalisation	0.23	2.47**	0.16	3.41***	0.21	No
H6b	Trust -> personalisation	0.34	4.60***	0.20	2.96***	0.04	Yes
H6c	Consumer peer interaction -> personalisation	0.12	1.20	0.01	0.12	0.13	No
H6d	Relationship commitment -> personalisation	0.11	0.67	0.57	6.76***	0.98	Partially supported
H6e	Personalisation -> loyalty	0.40	5.84***	0.70	13.25***	0.99	Partially supported

Table 7. Multi-group comparison-moderating effects of privacy concerns- Sample 2-UK

Hypothesis		Low level of privacy concerns (N=187)		High level of privacy concerns (N=366)		Group differences *p* value	Supported?
		Path coefficient	*t* values	Path coefficient	*t* values		
H6a	Interface design -> personalisation	0.37	4.18***	0.21	3.17**	0.04	Yes
H6b	Trust -> personalisation	0.19	2.46**	0.39	5.08***	0.97	Partially supported
H6c	Consumer peer interaction -> personalisation	0.15	1.52	0.05	0.84	0.18	No
H6d	Relationship commitment -> personalisation	0.09	0.89	0.21	2.33*	0.81	No
H6e	Personalisation -> loyalty	0.69	11.88***	0.56	10.18***	0.08	No

***p < 0.001; **p<0.01; *p<0.05

The results of PLS-MGA show that privacy concerns did not moderate most of relationships in the two samples. In sample 1 (UAE; see table 6)), only H6b (H6b trust -> personalisation) was supported (*p* value= 0.04), and H6d (Relationship commitment -> personalisation) (*p* value = 0.98), H6e (personalisation -> loyalty) (p value = 0.99) were partially supported. Hypotheses H6a and H6c were not supported. In sample 2 (UK; see table 7) only H6a (interface design -> personalisation) was supported (p value= 0.04), while H6b (trust -> personalisation) was partially supported (p value= 0.97). Hypotheses H6c, H6d and H6e were not supported.

5.5 The mediating effects of personalisation

Mediation analysis establishes whether a relationship between independent variables (predictors) and a dependent variable is direct or indirect (Iacobucci et al., 2007). This study hypothesises that personalisation mediates the effects of interface design, trust, consumer-peer interaction and relationship commitment on loyalty. The mediation effects were assessed using Preacher and Hayes's (2008) bootstrapping method with bias-corrected, 95% confidence intervals. We also used 5,000 iterations to assess the significance of the indirect effects in the model. If the indirect effect is significant and the confidence interval is not zero, the mediation effects are supported (Zhao, Lynch & Chen, 2010).

Table 8. Assessment of mediating effects using the bootstrapping method in Sample 1 (UAE)

Hypothesis	Direct effects without mediator	Direct effect with mediator (CI)	Indirect effect (CI)	Supported?
H7 Interface design -> personalisation -> loyalty	0.51***	0.33*** (0.210 to 0.409)	0.31*** (0.24 to 0.42)	Yes
H7 Trust -> personalisation -> loyalty	0.19***	-0.02 (-0.09 to 0.04)	0.31*** (0.22 to 0.42)	Yes
H7 Consumer peer interaction -> personalisation -> loyalty	0.20***	0.12*** (-0.02 to 0.21)	0.07** (0.01 to 0.13)	Yes
H7 Relationship commitment -> personalisation -> loyalty	0.28***	0.07 (-0.06 to 0.19)	0.29*** (0.18 to 0.40)	Yes

***p <0 .001; **p<0.01; *p<0.05; bootstrap confidence in parentheses, CI = confidence interval.

Table 9. Assessment of mediating effects using the bootstrapping method in Sample 2 (UK)

Hypothesis	Direct effects without mediator	Direct effect with mediator (CI)	Indirect effect (CI)	Supported?
H7 Interface design -> personalisation -> loyalty	0.53**	0.42*** (0.32 to 0.53)	0.22*** (0.15 to 0.30)	Yes
H7 Trust -> personalisation -> loyalty	0.22***	0.07 (-0.18 to 0.03)	0.35*** (0.25 to 0.47)	Yes

H7 Consumer peer interaction -> personalisation -> loyalty	0.19***	0.14** (0.04 to 0.24)	0.10* (0.01 to 0.20)	Yes
H7 Relationship commitment -> personalisation -> loyalty	0.30***	0.12* (-0.01 to 0.23)	0.23*** (0.13 to 0.35)	Yes

***p < 0.001;**p<0.01; *p<0.05; bootstrap confidence in parentheses, CI = confidence interval.

From Table 8, for Sample 1 (UAE), personalisation mediates all of the hypothesised relationships as per the conditions for mediating effects (Baron & Kenny, 1986) providing support for H7. Similarly, for Sample 2 (UK), the results (Table 9) further confirm personalisation as a mediator. .

6. Discussions and implications

This study addresses an important gap in understanding how shoppers interact with smart technologies in a broader context (i.e., smart shopping malls) and the personalisation-privacy paradox in explaining shopping mall loyalty. The proposed model draws on the trust-commitment theory (Morgan & Hunt, 1994), the privacy calculus theory (Culnan & Armstrong, 1999) and interface design literature (e.g., Miles et al., 2000; Cheng et al., 2019). Overall, in terms of the direct effects, our findings show that most of the hypothesised relationships are supported across both samples. As an exception, the relationship between consumer peer interaction and personalisation was significant in the UAE sample but not in the UK sample. The other hypothesised direct relationships were significant across both countries, despite the national, economic, cultural and IT infrastructure differences. In addition, personalisation mediates the set of relationships in both samples but we identified differences in the moderating effects of privacy concerns.

Our findings extend the existing theorisations and show the merits of including personalisation as a mediator. Previous studies have found support for the importance of personalisation associated with shopping experiences (Foroudi et al., 2018; Carrozzi et al., 2019; Theodosiou et al., 2019). However, these studies only consider the direct effects of personalisation in the online shopping environment. Our findings show that personalisation mediates all the hypothesised relationships in the context of smart shopping mall loyalty. In particular, personalisation mediates the relationship between interface design, trust, consumer-peer interaction and relationship commitment on loyalty across both samples. This extends findings of previous studies highlighting the role of personalisation in virtual shopping environments (e.g. Koch & Benlian, 2015; Carrozzi et al., 2019; Theodosiou et al., 2019). A high-quality interface design for technology, whether it is mobile, online, AI-enabled service, VR, AR or smartboards, enhances shoppers' perception of personalisation, which in turn positively influence their loyalty to smart shopping malls.

In addition, when customers trust the malls, the retail stores and the technologies that they use as part of their shopping experience, they are motivated to reveal personal information to enjoy a personalised shopping experience (Briggs et al., 2004; Aguirre et al., 2015). Furthermore, the social relationships between consumers on various social platforms and their exchange of information about products and services are important for enabling personalisation, as they allow malls and brands to obtain rich data about consumers' opinions and preferences (Lee, 2017, Malthouse & Li, 2017). This stronger sense of personalisation then leads to loyalty to smart shopping malls, demonstrated by revisiting the malls and providing positive recommendations. Customers' desire to maintain a strong relationship with malls and brands (i.e. their relationship commitment) enhances their sense of personalisation and ultimately loyalty.

Surprisingly, while the existing studies support the personalisation-privacy paradox in online shopping environments (e.g., Martin & Murphy, 2017; Riegger et al., 2021), our results show that personalisation mediates the relationship between consumer interactions with smart technologies in shopping malls and loyalty. However, privacy concerns did not moderate most of our hypothesised relationships. In both samples, findings reveal that a high level of privacy concerns may not necessarily affect consumer preferences for personalisation and consumers are still willing to develop loyalty to smart shopping malls. In addition, in both samples, we found that privacy concerns moderated the effects of trust on shopping mall loyalty but in the opposite direction. In the UAE sample, consumers with a low level of privacy concerns towards how their information is used when they interact with smart technologies in shopping malls have a higher level of trust and prefer a more personalised shopping experience. This extends existing knowledge on privacy concerns, trust and personalisation (e.g., Lee & Cranage, 2011; Riegger et al., 2021). In the UK sample, respondents with high level of privacy concerns find trust to significant influence shopping mall loyalty. Our findings also reveal that consumers' high level of privacy concerns may not necessarily prohibit them from developing a preference for personalised shopping experiences and developing shopping mall loyalty.

Furthermore, contrary to our predictions, respondents in both samples with a high level of privacy concerns find relationship commitment an important determinant of personalisation. Specifically, the differences between consumers with a low and high level of privacy concerns were more prominent in the UAE sample. This contradicts with the findings of earlier studies on consumer-brand relationship, personalisation and privacy concerns (Hayes et al., 2021). Our findings further reveal that privacy concerns do not determine how consumers perceive the interface design of smart technologies in the UAE sample but have an influence in the UK sample. In addition, unlike prior research (e.g. Wang et al., 2019) , peer interaction on social media does not significantly influence consumer perceptions of personalisation whether consumers are in the low or high levels of privacy concerns groups across the two countries.

Our results somehow diverge from previous studies in the context of online shopping (McCole et al., 2010; Li et al., 2017), and reveal that consumer privacy concerns do not necessarily shape how consumers interact with smart technologies in shopping malls. A plausible explanation could be the specific context of this research, focussing on the interactions with smart technologies in physical environments (i.e. shopping malls). Consumers may be less aware of privacy issues associated with their use of smart technologies than when they are shopping online. In addition, younger consumers tend to be more tech savvy and possess relatively high technological innovativeness compared to other generations (Hur, Lee & Choo, 2017) and our sample consisted of millennial shoppers who are possibly less concerned about privacy issues associated with interactions with smart technologies.

6.1 Theoretical contributions

This study offers a number of theoretical contributions. It advances research by proposing and testing a novel model on consumer interaction with smart technologies in shopping malls and loyalty. The model combines the trust-commitment theory (Morgan & Hunt, 1994), the privacy calculus theory (Culnan & Armstrong, 1999) and interface design literature (e.g., Miles et al., 2000; Cheng et al., 2019). Our model integrates the mediating effects of personalisation and the moderating effects of privacy concerns to better understand the personalisation-privacy paradox in the context of consumer interaction with smart technologies in shopping malls. Hence, our research earlier studies on the roles of personalisation and privacy concerns (e.g., Volchek et al., 2021; Carrozzi et al., 2019; Theodosiou et al., 2019). Our findings reveal that while personalisation is a mediator, consumer privacy concerns is not a moderator in the context of young consumers' interactions with smart technologies in shopping malls.

Moreover, our research extends the work of Komiak and Benbasat (2006), Carrozzi et al. (2019) and Theodosiou et al. (2019) by proposing and assessing the mediating role of personalisation on the relationships between customer interaction with smart technologies and shopping mall loyalty. In particular, findings establish the mediating role played by personalisation on the relationships between interface design, trust, consumer-peer interaction and relationship commitment and shopping mall loyalty. Furthermore, the proposed model was empirically tested using data collected from customers patronising smart shopping malls in two different countries, the UK and UAE. Our results found support for the proposed model using data from both countries.

6.2 Managerial implications

Our research assists shopping mall management teams and retailers to achieve a better understanding of customer interaction with smart technologies in smart shopping malls. Shopping malls are increasingly leveraging advanced technologies such as AI, biometrics, VR and AR in a seamless manner to provide a pleasing experience for customers. With changes in customers' needs and preferences, the future of retailing around the world rests of delivering memorable experiences via the integration of smart technologies. Findings show that consumer interaction with smart technologies can strengthen shoppers' sense of a personalised shopping experience, enhancing loyalty to the mall. Hence, smart shopping mall managers should aim to deliver personalised shopping experiences. Personalised services can be achieved by using various in-store and in-mall technologies.

Notwithstanding the significance of providing customers with a personalised shopping experience through different technologies, smart shopping mall management teams and retailers should be transparent with customers about how their data is used and build customer trust by using reliable technologies. Our findings also indicate that customers' interactions with each other using technologies and their commitment to smart malls and retailers, are important in influencing customer loyalty through personalisation. Hence, shopping mall managers are encouraged to collaborate with retailers, and actively interact with customers on social commerce platforms and providing personalised content. While personalised smart shopping experiences in shopping malls proved to be important for consumers, privacy concerns did not have a moderating role on the proposed relationships. However, the role of data privacy should not be underestimated, and smart shopping malls should ensure that procedures are in place to safeguard customers personal data during and after interaction with smart technologies.

7. Conclusions, limitations and future research

Our study investigates consumer interaction with smart technologies in shopping malls using data collected from young consumers patronising two smart shopping malls in the UK and UAE. The study offers interesting and important insights. However, there are some limitations that can be addressed in future research. First, data were collected from shoppers in smart shopping malls in the UK and UAE. Future research can extend the study to other advanced shopping malls that integrate smart technologies into the customer shopping experience. Second, we focus on millennial shoppers aged 23–38. An area for future research would be to collect data from older shoppers, who may not be as active and engaged in using advanced technologies. Other studies can also focus on Generation Z (Gen Z) consumers who have distinct shopping preferences from earlier generations and perceive privacy concerns as an important factor affecting their interaction with smart technologies (Ameen & Anand, 2020). Third, this study is cross-sectional in nature, as data were collected at one point in time. With technology expected to gradually play an even larger part in the customer experience, additional research can collect data at different points in time adopting a longitudinal design.

Another line of enquiry is to study of differences between male and female shoppers in smart shopping malls, as this will help to provide more effective strategies for targeting customers according to their needs and preferences. In addition, we recommend additional research to focus on customers' experience enabled by advanced technologies such as AI, VR, AR and biometrics. Future studies can conduct a comparison between shoppers' experiences when interacting with each of these technologies. Researchers can also examine the role of consumer emotions (positive and negative) when interacting with smart technologies with different levels of personalisation (low to extreme). Finally, future research can study how consumers react when personalisation goes wrong and what are the remedies and coping mechanisms in place to addresses these situations.

Appendix A

Measurement items for all the constructs and their sources

	Sample 1: UAE			Sample 2: UK		
Statements	Mean	Standard deviation	Factor loadings	Mean	Standard deviation	Factor loadings
Interface design (Adapted from Ariff et al., 2013)						
ID1: The interface designs of the technologies used in the shopping mall have good selection	6.13	1.24	0.85	6.08	1.31	0.85
ID2: The interface designs of the technologies used in the shopping mall understand my needs	4.75	2.07	0.78	4.49	2.14	0.78
ID3: I feel comfortable in surfing the interface designs of the technologies used in the shopping mall	5.77	1.34	0.81	5.66	1.39	0.82
ID4: The interface designs of the technologies used in the shopping mall don't waste my time	6.19	1.01	0.70	6.16	1.09	0.61
Trust (Adapted from Wang et al., 2019)						
TR1: The performance of the technologies at the shopping mall always meets my expectations	6.49	1.03	0.77	6.49	1.073	0.76
TR2: The technologies at the shopping mall can be counted as good features	6.54	0.88	0.70	6.53	0.91	0.74
TR3: The technologies at the shopping mall are reliable	6.51	0.95	0.84	6.47	1.05	0.82
Consumer peer interaction (Adapted from Wang et al., 2019)						
CPI1: I maintain close social relationships with other shoppers online and on social media	6.14	1.33	0.78	6.09	1.39	0.76
CPI2: I spend a lot of time interacting with other shoppers online and on social media	6.12	1.29	0.94	6.10	1.33	0.95
CPI3: I know other shoppers on a personal level	6.23	1.09	0.51	6.24	1.13	0.70
CPI4: I have frequent communication with other shoppers	6.25	1.05	0.51	6.24	1.07	0.68
Relationship commitment (Adapted from Wang et al., 2019)						
RC1: I have an emotional attachment to the technologies used as part of my shopping experience at the mall	6.39	1.10	0.76	6.41	1.12	0.77
RC2: I feel a sense of belonging to my favourite retailers' at the shopping mall social media platform(s)	6.44	0.92	0.80	6.43	0.94	0.80
RC3: I feel a strong connection to my favourite retailers' at the shopping mall social media platform (s)	6.40	1.08	0.84	6.39	1.10	0.85

RC4: I feel a part of the group in my favourite retailer's social media platform (s)	6.59	0.88	0.73	6.58	0.89	0.68
Personalisation (Adapted from Chellappa and Sin, 2005)						
PE1: I value technologies at the shopping mall that are personalised for my usage experience preferences	6.00	1.61	0.89	5.85	1.69	0.59
PE2: I value technologies at the shopping mall that acquire my personal preferences and personalise the services and products themselves	6.08	1.41	0.91	5.98	1.45	0.58
PE3: I value goods and services at the shopping mall that are personalised based on information that is collected automatically (such as IP address, pages viewed, access time) but cannot identify me as an individual.	6.08	1.44	0.91	5.94	1.51	0.89
PE4: I value goods and services at the shopping mall that are personalised on information that I have voluntarily given out (such as age range, salary range, Zip Code) but cannot identify me as an individual.	6.03	1.58	0.73	5.89	1.67	0.90
PE5: I value goods and services that are personalised on information I have voluntarily given out to retailers and shopping malls	6.07	1.39	0.59	5.98	1.44	0.90
Loyalty (Adapted from Chebat et al., 2009, El-Adly and Eid, 2016)						
LO1: I have a strong desire to visit or shop at this shopping mall	5.31	1.78	0.93	5.19	1.83	0.89
LO2: I would recommend this shopping mall to friends	5.50	1.65	0.92	5.43	1.68	0.90
LO3: I will come back to this shopping mall	5.41	1.65	0.63	5.29	1.70	0.87
LO4: I will continue to visit this shopping mall	6.59	0.78	0.70	6.57	0.79	0.58
Privacy concerns (adapted from Chellappa and Sin, 2005)						
PR1: I am sensitive about giving out information regarding my preferences	6.12	1.55	0.91	6.43	1.65	0.95
PR2: I am concerned about anonymous information that is collected about me via different technologies while shopping in the mall.	6.11	1.72	0.71	4.24	1.69	0.96
PR3: I am concerned about how my personally un-identifiable information will be used by the shopping mall and retailers.	6.01	1.58	0.88	5.14	0.85	0.86
PR4: I am concerned about how my personally identifiable information will be used by the shopping mall and retailers.	5.27	1.59	0.94	6.57	0.79	0.59

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