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Customer experiences in the age of artificial intelligence

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ABSTRACT

Artificial intelligence (AI) is revolutionising the way customers interact with brands. There is a lack of empirical research into AI-enabled customer experiences. Hence, this study aims to analyse how the integration of AI in shopping can lead to an improved AI-enabled customer experience. We propose a theoretical model drawing on the trust-commitment theory and service quality model. An online survey was distributed to customers who have used an AI- enabled service offered by a beauty brand. A total of 434 responses were analysed using partial least squares-structural equation modelling. The findings indicate the significant role of trust and perceived sacrifice as factors mediating the effects of perceived convenience, personalisation and AI-enabled service quality. The findings also reveal the significant effect of relationship commitment on AI-enabled customer experience. This study contributes to the existing literature by revealing the mediating effects of trust and perceived sacrifice and the direct effect of relationship commitment on AI-enabled customer experience. In addition, the study has practical implications for retailers deploying AI in services offered to their customers.

1. Introduction

The introduction of artificial intelligence (AI) has the potential to revolutionise the way businesses interact with their customers (McLean & Osei-Frimpong, 2019). AI differs from human intelligence in that it is based on the rapid processing of data. In AI, intelligence may be generally defined as the ability to process and transform data into information to inform goal-directed behaviour (Paschen, Kietzmann, & Kietzmann, 2019). More specifically, AI refers to "computational agents that act intelligently" (Poole and Mackworth, 2010, p. 3), designed to imitate the capability of human power while exceeding their ability for accuracy (Dwivedi et al., 2019). This is accomplished through the modelling of biological and natural intelligence using a set of algorithmic models (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2019).

AI technologies supported by data analytics are increasingly embraced by companies as a response to sustained margin pressures, shorter strategy cycles, and increased expectations from customers. This alters the way firms interact with their customers with the potential to achieve better customer-brand relationships (Evans, 2019). Specifically, advances in AI have the potential to improve the customer experience by increasing companies' knowledge about those customers' preferences and patterns of shopping (Evans, 2019). Deploying AI technologies strategically at different key customer touch points may therefore bring significant benefits to companies and a possible increase in customer satisfaction.

Retailers are using AI in various ways, such as through AI-powered chatbots, content generation, and customer insights. Previous reports show that, within the retail sector, the deployment of AI can reach the top 1% of customers, who are worth 18 times more than average customers to retailers. This is achieved through extreme personalisation and increased engagement based on contextual and behavioural data (Solis, 2017). Juniper Research predicts that retailers will spend $7.3 billion on AIby 2022, compared with the approximately $2 billion spent in 2018 (Adair, 2019). In addition, spending in the global retail sector on AI services will reach $12 billion by 2023, up from an estimated $3.6 billion in 2019 (Juniper Research, 2020). Over the same period, it is expected that over 325,000 retailers will adopt AI technology (Martin, 2019).

AI technology can personalise services and product recommendations by processing customer's past purchases and preferences. This has implications for a wide variety of sectors, such as beauty brands to effectively generate personalised styles and product recommendations based on their demands and preferences (Maras, 2020). Expected

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benefits are increased levels of automation, cost reduction, increased flexibility and streamlined customer interactions. For these benefits to be fully realised, it is necessary to analyse and understand this complex phenomenon more deeply. For example, the dependence on AI technology and the need for increasing amounts of customer data may raise trust issues among customers (Dwivedi et al., 2019). Furthermore, the absence of human interaction or additional efforts potentially required from customers may constitute sacrifices affecting their overall experience. The impact of these and other potential issues related to AI-powered customer experiences need to be better understood (Malle, Scheutz, Arnold, Voiklis, & Cusimano, 2015; Shank, Graves, Gott, Gamez, & Rodriguez, 2019).

The conceptualisation of service quality in different contexts is well understood (e.g. Parasuraman, Zeithaml, & Berry, 1994; Collier & Bienstock, 2006; Scheidt & Chung, 2019; Suhartanto, Helmi Ali, Tan, Sjahroeddin, & Kusdibyo, 2019). What is less understood is the potential for AI-based shopping experiences to provoke shifts in how consumers (a) perceive service quality, (b) adjust their commitment to the relationship, and (c) evaluate their overall AI- enabled experience. Despite the significant role these issues can play, previous studies have mainly focused on the use of AI from a technical and organisational perspective (Jarrahi, 2018). As a result, there is a lack of research on how customers perceive AI technology as part of their shopping experience, and how this leads to a more pleasant experience and stronger relationships with brands (Shank et al., 2019; Wang, Molina & Sunder, 2020).

Hence, this research aims to analyse how the integration of AI in shopping can lead to an improved AI-enabled customer experience. To achieve this, we propose a new model drawing on trust commitment theory (Morgan & Hunt, 1994) and the service quality model (Parasuraman et al., 1994). Our model integrates trust and perceived sacrifice as factors mediating the relationships between the AI-enabled service quality, convenience and the customer experience. In addition, the model integrates relationship commitment as a factor affecting the customer experience of AI-enabled shopping.

The research provides theoretical contributions and practical implications. In a broad sense, it responds to recent calls for research in the area of consumer interaction with cutting-edge technologies including AI (Ameen, Tarhini, Shah, & Hosany, 2020). In terms of the theoretical contributions, the research is one of the pioneering studies to advance knowledge on customers' views of AI-enabled customer experiences, our research contributes to a better understanding of human interaction with AI-enabled services. By highlighting the role of trust and perceived sacrifice, our proposed conceptual model contributes to a better understanding of AI-enabled customer experiences. The findings of this study provide guidance for retailers aiming to provide AI-enabled customer experiences.

2. Theoretical background

2.1. AI-enabled customer experience

Customer experience refers to the overall experience a customer has with a retailer, based on their interactions with and thoughts about the brand (Oh, Teo, & Sambamurthy, 2012; Verhoef et al., 2009). Previous studies distinguish four elements of a customer experience: (a) cognitive.

(b) Emotional, (c) physical and sensorial, and (d) social elements (Ladhari, Souiden, & Dufour, 2017). *Cognitive* elements refer to "higher mental processes, such as perception, memory, language, problem solving, and abstract thinking" (American Psychological Association, 2016). According to Keiningham et al. (2017), cognitive elements of a customer experience refer to the functionality, speed, and availability of a service. In addition, previous studies highlighted the *emotional* elements of the customer service which tend to be complex in nature.

(Ladhari et al., 2017). These feelings can be positive or negative, for example delight, regret, anger, outrage, joy or surprise (Keiningham et al., 2017).

In contrast, *physical and sensorial elements* of a customer experience are often differentiated between those in an offline and online context. Offline experiences encompass features like artefacts, lighting, layout, and signage (Lam, 2001), while online experiences encompass technology-related features, such as a friendly-user interface and a clear design (Keiningham et al., 2017). Finally, *social elements* of the customer experience refer to the influence of other people, such as family, friends, and a customer's wider social network (Verhoef et al., 2009). *Social elements* also include a customer's social identity or the mental identity of how they view themselves (Keiningham et al., 2017).

According to a study by Gartner "[t]he use of AI technologies such as machine learning, natural-language understandingand natural-language processing can help analyse customer sentiment and customer feedback at scale, precision and speed not achievable through humans." (Gartner, 2020). This suggests that AI has the potential to become one of the main tools for retailers to continuously improve the customer experience and thus to remain competitive (Newman, 2019). In retail, AI technology is often used in conjunction with other technologies, such as augmented reality, computer vision-driven image recognition, and predictive inventory (Saponaro, Le Gal, Gao, Guisiano, & Maniere, 2018). For these technologies to successfully enhance customer experiences, there is a requirement for a sound understanding of the customer, including their preferences and past experiences. Leveraging AI can help accelerate this understanding as AI tools use data and customer profiles to learn how to best communicate with customers (Omale, 2019).

2.2. Service quality in AI-enabled services

Service quality is traditionally defined as the difference between expected and perceived service and assessed by how customers perceive a brand's service offerings (Parasuraman et al., 1994). This conceptualisation of service quality has its roots in the expectancy dis--confirmation theory (Collier & Bienstock, 2006), where the evaluation of service quality is the result of a comparison between the perception of service received with prior expectations of what that service should provide (Choi, Lee, Lee, & Subramani, 2004). The existing body of research is rich with studies on the quality of interpersonal services (e.g. Prentice & Kadan, 2019; Scheidt & Chung, 2019; Suhartanto et al., 2019), with a lack of research on customer responses to automated services, specifically AI-enabled services (Prentice, Dominique Lopes, & Wang, 2020). As AI- enabled services tend to be built around self-service technologies, service quality in the context of AI-enabled services is likely to differ significantly from interpersonal services.

2.3. Trust-commitment theory

Trust-commitment theory highlights the roles of trust and commitment to a relationship play in the process of developing relationships between buyers and sellers (Morgan & Hunt, 1994). Over the years, the theory has been studied in a wide variety of contexts, including online retailing (Elbeltagi & Agag 2016), group buying websites (Wang, Wang, & Liu, 2016), brand relationships in online communities (Zhang, Bilgihan, Kandampull & Lu 2018), fan pages on social media (Akrout & Nagy, 2018), online shipping behaviour (Rehman, Bhatti, Mohamed, & Ayoup, 2019), and how trust helps to increase relationship commitment between customers and retailers in online settings and on social media (Wang, Tajvidi, Lin, & Hajli, 2019). Each study highlights the significant role that trust and relationship commitment play in technology-mediated interactions between customers and retailers.

Trust is one of fundamental factors present in the trust-commitment theory (Morgan & Hunt, 1994). It is also a fundamental element for the success of automated services as it describes the relationship between humans and automation (Hengstler, Enkel, & Duelli, 2016). Wang et al. (2019) highlight privacy as a key component of trust, given that consumers aim to maintain a degree of control over the use of their data by retailers. In addition, previous studies have shown that trust can alter the relations between different factors in the context of AI use such as service quality and convenience (Siau & Wang, 2018; Ferrario, Loi, & &Viganò, 2019).

3. Proposed model and hypothesis development

Drawing on trust-commitment theory (Morgan & Hunt, 1994) and the service quality model (Parasuraman et al., 1994), the model proposed in this study offers a novel approach to the understanding of how the integration of AI-enabled services can improve the customer experience. The model integrates factors that are relevant to the phenomenon of customer interaction with AI-enabled services. In addition, trust and perceived sacrifice are integrated as mediators in the model, mediating the effects of the exogenous factors: convenience, personalisation and AI-enabled customer service, and the endogenous factor: AI-enabled customer experience.

The proposed model takes into account that customers are motivated by hedonism and a need for autonomy. This has profound implications for marketing, as it implies that customers may be willing to sacrifice hedonic utility for stronger self-relevant values. The decision to accept sacrifices is situation dependent. For example, when a customer thinks that a technology uses their stated preferences for an accurate prediction of their choices, they may select less-preferred alternatives as a counter measure. On the contrary, when a customer is informed that a technology can determine how consistent their choices are with their preferences, they may not deviate from their most-preferred alternatives. Research suggests that customers are willing to sacrifice what they can control, power over choices, and privacy as they have no control over these processes (Anderson & Rainie, 2018; Anderson, Rainie, & Luchsinger, 2018), an effect that is likely to deepen as automated systems become more prevalent and complex. The willingness of consumers to sacrifice in terms of what they are unable to control has led André

et al. (2018, p.33) to propose the question "when do consumers sacrifice preferred choice options to assert their autonomy, and when does the quest for pleasure, comfort, and convenience dominate their choices?". In the context of AI, perceived sacrifice can alter relationships between different factors convenience, personalisation and service quality. As a result, trust and perceived sacrifice can explain *how* and *why* relationships between convenience, personalisation, and AI-enabled customer service and experience exist. This basis of our proposed model is illustrated in Fig. 1 below.

The proposed model integrates AI-enabled customer experience as an endogenous factor. Previous studies have shown that experiences of smart technology (e.g. AI, smart mobile phones, tablets, wearables etc)-enabled services differ from those in traditional shopping (Foroudi, Gupta, Sivarajah, & Broderick, 2018). AI-enabled customer experiences consist of *hedonic* and *recognition* aspects. The *hedonic* aspect refers to memorable, entertaining, exciting, comforting, educational, and novel experiences (Oh et al., 2012; Verhoef et al., 2009; Foroudi et al., 2018). The *recognition* aspect refers to feeling of importance, respect, being welcome, safety, relation, and a sense of beauty (Foroudi et al., 2018; Oh et al., 2012; Otto & Ritchie, 1996; Rose, Clark, Samouel, & Hair, 2012). In AI-enabled services, both hedonic and recognition aspects of the customer experience can be improved in terms of time, efficiency, enjoyment, and personalisation (Saponaro et al., 2018).

From trust-commitment theory (Morgan & Hunt, 1994), the proposed model integrates relationship commitment to analyse its effect on AI-enabled customer experience. Previous studies highlight a knowledge gap with regards to the relationship between the a customer's commitment towards a brand and their overall experience (Keiningham et al., 2017). While some previous studies suggest that customer experience has a significant effect on brand commitment (e.g. Lariviere, Keiningham, Cooil, Aksoy, & Malthouse, 2014; Lemon & Verhoef, 2016), another stream of research argue that, once the brand commitment is initiated, it starts to have a significant effect on subsequent experiences (Keiningham et al., 2017). Customers' commitment to a brand affects their perceptions of their overall experience through dynamics such as cognitive dissonance, self-perception and biased scanning (Keiningham et al., 2017). The next subsections provide an overview of the hypotheses developed in this research.

3.1. Trust

A classic definition of trust is an attitude of confident expectation that one's vulnerabilities in a risky situation will not be exploited (Corritore, Kracher, & Wiedenbeck, 2003). In the context of online commerce, this includes trusting the brand as well as the technology (Corritore et al., 2003). In the context of AI, recent studies show that trust is key in ensuring the acceptance, continuing progress, and development of this technology (Siau & Wang, 2018). Two streams of research have emerged on trusting technology-mediated services: trust in the technology (Ghazizadeh, Lee, & Boyle, 2012), and trust in the innovating firm, including their communication and processes (Chiesa & Frattini, 2011; Nienaber & Schewe, 2014). The concept of trust is more complex in the context of AI-enabled customer service, where trust is not limited to the *technology* and *brand,* but also the *purpose* and *process* of using AI (Hengstler et al., 2016; Siau & Wang, 2018). While purpose

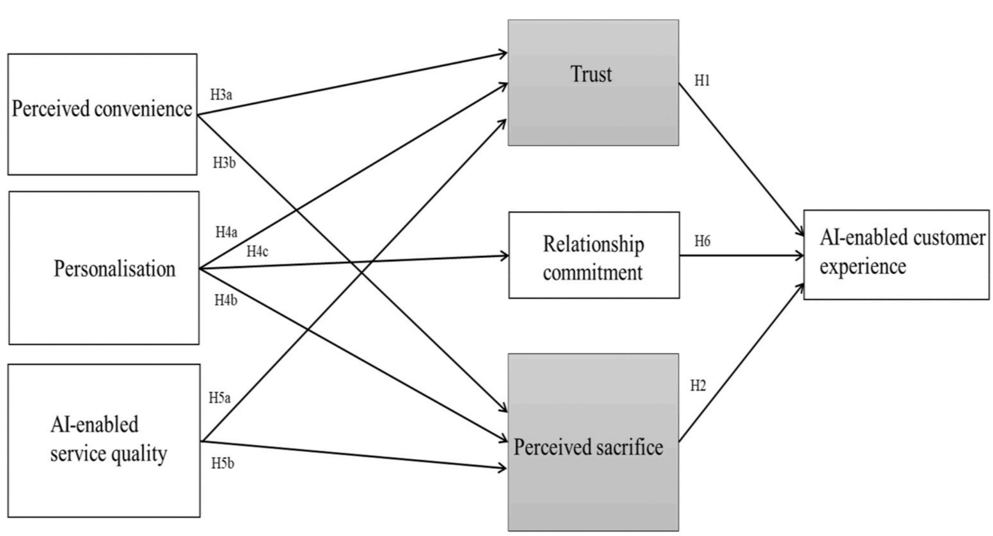

Fig. 1. The proposed model.

reflects faith in intentions (Hengstler et al., 2016), the process dimension refers to the understandability of the technology. When algorithms and functional logic are transparent, trust is likely to be reinforced (Lee & See, 2004).

Establishing trust in an innovative brand and how their innovative technologies are communicated to customers is a complex process. Brands often assume that the use of advanced technologies is sufficient to please customers, yet a wide variety of studies show that the reasons that some innovative technologies fail go beyond technical issues (Heidenreich & Spieth, 2013), and highlight the importance of trust in the way brands communicate the use of innovative technologies. Hengstler et al. (2016) suggest that the introduction of AI technology into the service process should be communicated proactively, beginning at the early stages of diffusion. Their rationale is that when knowledge levels are low, communication by the brand has a higher chance of influencing societal acceptance towards new technologies.

Previous studies also show that the more confident customers feel about a brand they purchase from, the more they are willing to engage in a long-term relationship with that brand (Keiningham et al., 2017). Applied to the context of retail marketing, this suggests that a higher level of trust in a brand and their technology increases the customer experience. While previous studies demonstrate a positive relationship between customer experience and brand trust once customer go through the initial experience and gain this trust, this positive relationship extends to subsequent experiences (Njamfa, 2018). Due to the sensitivity of handling customer data, we suggest that the relationship between brand trust and customer experience is particularly prevalent in the context of digital experiences. Hence, we propose the following hypothesis:

H1. Trust has a positive direct effect on AI-enabled customer experience.

3.2. Perceived sacrifice

Perceived sacrifice pertains to “what is given up or sacrificed to obtain a product [or service]” (Zeithaml, 1988, p. 10) and encompasses monetary and non-monetary costs including time, effort, cognitive engagement, or feelings such as irritation and annoyance (Zeithaml, 1988). Recent studies emphasise the need to study the sacrifice customers make when using automated services, especially when there is a limited number of options available for them to choose from (André et al., 2018).

While monetary and non-monetary sacrifices may be necessary to obtain a service, the potential implications of many non-monetary sacrifices can be difficult to assess. Examples of such sacrifices are *loss of control, loss of privacy, the potential loss of money,* required *time* and *effort,* and *negative emotions* (De Kerviler, Demoulin, & Zidda, 2016; Merisavo et al., 2007; Shin & Lin, 2016). In the context of AI-enabled services, two further non-monetary sacrifices have to be considered: A *lack of human interaction* and the potential for *social isolation* (Davenport, Guha, Grewal, & Bressgott, 2020), both of which can have a negative impact on the customer experience.

The existing service literature is rich with studies emphasising the significance of human interaction and providing a friendly service to customers (e.g. Pham & Ahammad, 2017; Pinto, Dell’Era, Verganti, & Bellini, 2017). AI-enabled services, however, bring a very modern kind of social interaction, requiring high levels of cooperation and social coordination from a human perspective (Christakis, 2019). Customers may perceive this as a sacrifice, especially those first time users (Davenport et al., 2020). Moreover, AI-enabled services can be associated with a loss of human control (Murphy, 2017), due to the structured nature of the customer journey and the need for personal data. AI-enabled services tend to be highly structured with the sequence of steps a customer has to go through often determined by the requirements of the technology rather than the needs of the user. AI-enabled services also require personal data from consumers in order to operate efficiently, which can be perceived as a further loss of control (Cheatham, Javanmardian, & Samandari, 2019). Finally, the lack of human assistance (human agency) in AI-enabled services may create obstacles for customers, especially those without prior experience or those who may take longer to use these services comfortably. Recent studies show that customers prefer a balance between automation and human agents (Gauvrit, 2019). Reducing human interaction could therefore negatively impact the overall customer experience. Hence.

H2. Perceived sacrifice has a negative direct effect on AI-enabled customer experience.

3.3. Perceived convenience

Morganosky (1986, p. 37) defines service convenience as “the ability to accomplish a task in the shortest amount of time with the least expenditure of human energy”. Convenience leads to higher engagement (Roy, Balaji, Sadeque, Nguyen, & Melewar, 2017; Van Doorn et al., 2010). A convenient service is characterised by saving time and effort and allowing mobility which can be important to encourage customers to be interested in a service (Chang, Chen, Hsu & Kuo, 2010). Following the coronavirus health crisis (COVID 19), location convenience may be viewed as an even more significant factor than before as the world had to experience self-isolation and social distancing (Meyer, 2020). The location and time-saving parts of convenience have been studied widely, particularly in terms of the impact perceived waiting times have on customer experience (Roy et al., 2017). The time-saving part of convenience has been studied widely, particularly in terms of the impact of perceived waiting time on customer experience (Roy et al., 2017). The convenience of AI-enabled services can be classified into three main dimensions. First, the availability of these services, since the AI-enabled self service is available 24/7 and the ability to access the service anywhere (Walch, 2019). Second, customers are provided with real-time information and support through their journey (Thiel, 2019).

Third, AI-powered bots can proactively start discussions with clients, provide related information and assist with each touch point throughout the customer lifecycle. This helps customers to obtain the answers that they need when they want them, without having to wait on hold for an employee to become available, which can improve time to resolution and customer satisfaction (Walch, 2019). Convenience motivates customers’ engagement with the brand experience (Roy et al., 2017; Van Doorn et al., 2010).

By reducing or even removing barriers for shoppers (Reimers & Clulow, 2009), convenience increases the trust customers feel toward the brand and the technology used to deliver a service (Ong, Khong, Faziharudean, & Dai, 2012). In addition, the perception of convenience influences customers’ overall assessment of service utility (Pham, Tran, Misra, Maskeliūnas, & Damaševičius, 2018). Finally, convenience is used by retailers to reduce customer’s perceived sacrifices (Kim, Lee, & Park, 2014). An increase in convenience thus leads to a decrease in perceived sacrifice, which means that convenience is negatively correlated with perceived sacrifice. With AI-enabled services, it can be assumed that customer convenience would increase as they can be used anytime and anywhere. Hence.

H3a. Perceived convenience has a positive direct effect on trust.

H3b. Perceived convenience has a negative direct effect on perceived sacrifice.

3.4. Personalisation

Personalisation refers to the degree to which information is tailored to the needs of a single user and thus constitutes an important determinant of positive experiences (Bilgihan, Kandampully, & Zhang, 2016, p. 110). Information is tailored to the needs and preferences of an individual customer through data mining techniques, which can result in a higher level of interest in shopping (Zhang, Edwards, & Harding, 2007). Personalisation is one of the key elements often associated with

AI-enabled services (Zanker, Rook, & Jannach, 2019). The fields of AI and machine learning (ML) primarily focus on the optimisation of personalisation applications and on creating ever more accurate algorithmic decision and prediction models (Zanker et al., 2019).

Zanker et al. (2019) distinguish three dimensions of personalisation in online services (a) the user interface, (b) content, and (c) interaction processes. Personalisation of the *user interface* refers to the adaptability of the screen layout and overall presentation, e.g., for varying screen sizes (Findlater & McGrenere, 2010). Personalisation of *content* refers to the differentiation of information based on an individual user's profile, including product or service offerings, and prices (Zanker et al., 2019). Personalisation of the *interaction process* refers to the autonomy of AI algorithms to decide when and how to approach users (Chen, Chiang, & Storey, 2012; Zanker et al., 2019). AI and ML make it possible for brands to use predictive personalisation, which means that content is adapted in real-time using profiling tools and data analysis (O'Riordan, 2019). The challenge is to access the right data on which the personalisation is based without negatively affecting customers' privacy. The recent introduction of the European Union's General Data Protection Regulation (GDPR) has renewed the discussion on ethical considerations surrounding the transparency of algorithmic decision making. Compliance with regulatory requirements therefore represents a further challenge for brands using all three dimensions of personalising experiences. This suggests the need to study personalisation of AI-enabled services across all three dimensions rather than studying them in distinct silos.

Previous studies have highlighted that customers associated a high level of personalisation with the brand's competence (Komiak & Benbasat, 2006). Moreover, the availability of relevant choices and a perception that their preferences are important to a brand increases customer's perception that a brand and the advice it provides to the customer are unbiased (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015). In the context of AI-enabled customer experiences, customers who enjoy their personalised experience may feel less sensitive to what they are giving up (sacrificing) (Knight, 2018), which indicates a negative relationship between a high degree of personalisation and perceived sacrifice. Finally, personalisation strategies that generate high positive attributions and low negative attributions and are likely to strengthen the commitment of customers towards a brand (Shen & Ball, 2009). Hence.

H4a. Personalisation has a positive direct effect on trust.

H4b. Personalisation has a negative direct effect on perceived sacrifice.

H4c. Personalisation has a positive direct effect on relationship commitment.

3.5. AI-enabled service quality

Previous studies on self-service technologies indicate that customers assess service quality along four distinct dimensions: (a) *security, (b) reliability, (c) customer service,* and (d) *interface design* (McKecnie, Ganguli, & Roy, 2011; Wolfinbarger & Gilly, 2003).

The quality of AI-enabled services depends to a large extend on the amount and quality of personal information a brand is able to collect about customers. While much of this data is typically not sensitive, the combination of seemingly non-sensitive personal information (such as marketing choices and preferences) can result in extensive user profile that, with insufficient security precautions, would enable fraudsters to create false identities from (Cheatham et al., 2019).

Assuming an ability for 'unbiased' customer interactions, Saratchandran (2019) claims that AI enhances the reliability of customer services. While it is much more likely that AI-enabled services exchange past biases for new ones, they are much more scalable than traditional services and have the potential to serve a high number of customers simultaneously. Chatbots and other AI-assisted customer service tools are increasingly used as an automated and potentially efficient way of improving the customer journey (Treasure Data, 2019).

Since many AI-enabled services are based on the self-service model, a carefully designed user interface is often described as a critical success factor of such services. In fact, AI can transform the user interface as it can control all content of the interface design including visual elements, typography, animations and graphical information (Irfan, 2020).

Previous studies acknowledge that technical and functional service quality affect the way customers evaluate brands (Chiou & Droge, 2006; Eisingerich & Bell, 2008). In the absence of other information, the type of technology and the way it is implemented by a service provider may act as a proxy into their character from a consumer perspective and help consumers establish an initial level of trust.

An AI-enabled service perceived by consumers as courteous, caring, and responsive has the potential to inspire confidence in the brand (Wang & Lin, 2017). Moreover, from a consumer perspective, the experience of a high quality service decreases their perception of sacrifice (in terms of loss of control, loss of privacy, loss of money, effort, time consumption, or negative feeling, such as annoyance or irritation). Previous studies also acknowledge the effect of service quality on perceived value, which refers to the trade-off between benefits and sacrifices customers have to makein return for receiving a service (Gallarza, Arteaga, Chiappa, Gil-Saura, & Holbrook, 2017; Li & Shang, 2019). Some studies position perceived sacrifice as a distinct factor from perceived service value (de Medeiros, Ribeiro, & Cortimiglia, 2016). As AI-enabled services often do not involve human interaction, customers perception as a high-quality service is critical for reducing the effect of perceived sacrifices, particularly those related to a loss of human support and control. Hence.

H5a. AI-enabled service quality has a positive direct effect on trust.

H5b. AI-enabled service quality has a negative direct effect on perceived sacrifice.

3.6. Relationship commitment

Relationship commitment refers to an enduring desire to maintain a valued relationship with a brand (Moorman, Zaltman, & Deshpande, 1992). Morgan and Hunt (1994) explain that consumers can become more interested in interacting with brands if they experience positive interactions and build strong relationships with them, which can lead them to be more committed towards these brands. Relationship commitment is an outcome of long-term satisfactory interactions between customers and retailers (Wang et al., 2016, 2019). It directs customers to believe that there are no other alternative brands that would provide similar benefits, making them less likely to shop from alternative brands.

When communicating with brands, customers develop (a) *affective*, (b) *normative* and, (c) *calculative* commitments (Gustafsson, Johnson, & Roos, 2005; Keiningham et al., 2017; Verhoef et al., 2009). *Affective* or emotional commitment refers to the emotional and personal involvement of customers that results in a higher level of trust and commitment (Gustafsson et al., 2005). *Normative* or social commitment is based on subjective norms established over time, where customers feel that they *ought* to stay with a brand (Shukla, Banerjee, & Singh, 2016). Normative commitment is linked to the social environment. *Calculative* or functional commitment takes into account possible costs customers accrue by switching to another brand (Shukla et al., 2016), which may be the result of a less attractive alternative brand or the absence of alternative brands (Shukla et al., 2016).

Although previous studies highlight the significance of positive customer experiences on commitment (Iglesias, Singh, & Batista-Foguet, 2011; Lemon & Verhoef, 2016), more recent studies argue that once customers have gone through the initial experience of building brand commitment, this commitment can, in turn, influence subsequent experiences (Keiningham et al., 2017). As each commitment dimension (affective, normative, and calculative) can be influenced with a particular firm strategy, managers have to recognise the impact each dimension has on how customers evaluate their experience. All three dimensions can thus act as important factors determining how customers evaluate their overall experience. Hence.

H6. Relationship commitment has a positive direct effect on AI-enabled customer experience.

3.7. *Mediating effects of trust and perceived sacrifice*

In the model proposed in this study, three factors affect AI-enabled customer experience: (a) convenience, (b) personalisation, and (c) AI-enabled service quality (Fig. 1). We propose that their effects are mediated by two factors: (d) trust and (e) perceived sacrifice.

Previous studies have investigated the relationship between trust and customer experience, either by considering trust as a mediator (e.g. Martin, Mortimer, & Andrews, 2015; Rose et al., 2012) or as a factor that has a direct effect on experience (Ling, Chai, & Piew, 2010). In the model proposed in this study, the effects of convenience, personalisation and AI-enabled service quality on AI-enabled customer experience are mediated by the presence of trust. More specifically, we propose that the effects of convenience, personalisation and AI-enabled service quality on AI-enabled customer experience are strengthened by the presence of trust. Customers start having positive expectations and feel more comfortable when using a technology-enabled service that they trust, in terms of trusting the brand, process and technology (Alsajjan & Dennis, 2006). As a result, the presence of trust strengthens the effect convenience has on the customer experience.

In addition, AI-enabled services offer a significantly higher level of personalisation to their users. Since personalisation is based on the collection and constant analysis of customers' data. However, trust has often also been associated with the success of this factor (Searby, 2003). In other words, trust in a brand and the AI technology it employs influences the way customers perceive personalisation (Sheridan, 2017). As a consequence, trust can influence the relationship between personalisation and AI-enabled service experience.

Previous studies also indicate that trust mediates the relationship between service quality and loyalty (Chou, 2014). The more consumers know about a service, the more they are willing to trust it (Eisingerich & Bell, 2008). As a result, an AI-enabled customer experience is likely to be more positive if customers trust the brand, technology, and process of the AI-enabled service. Hence.

H7a. Trust mediates the effects of convenience, personalisation, and AI-enabled service quality on AI-enabled customer experience.

In addition to trust, perceived sacrifice is hypothesised as a mediating factor. In the proposed model, the effects of convenience, personalisation and AI-enabled service quality on AI- enabled customer experience are mediated by perceived sacrifice. More specifically, we propose that the effects of convenience, personalisation and AI-enabled service quality on AI- enabled customer experience are strengthened when customers' perceived sacrifice is decreased while using the service. The convenience concept shows the time and effort that customers spend on buying and using a product or service (Pham et al., 2018). Convenience is considered to be one of the main benefits customers can gain when using AI-enabled bots (Payne, Peltier, & Barger, 2018). The decrease in perceived sacrifice elicits the effect of convenience on AI-enabled shopping experiences.

In addition, previous studies have highlighted the significance of personalisation (Bilgihan et al., 2016). Personalisation decreases customers' perception of the sacrifices they are making, since the AI-enabled service is tailored towards their needs. This elicits the effect of personalisation on AI-enabled customer experience. For example, if the service is personalised, customers may be less concerned about some level of loss of privacy (Li & Unger, 2012) which can lead to an improved perception of their AI-enabled experience. Furthermore, perceived sacrifice can underly the relationship between AI-enabled service quality and AI-enabled

Experience. Previous studies indicate that the use a high-quality service decreases the perception of sacrifice (Stamenkov & Dika, 2019). Hence.

H7b. Perceived sacrifice mediates the effects of convenience, personalisation, and AI-enabled service quality on AI-enabled customer experience.

4. Methods

4.1. *Measurement scales*

The measurement items (Appendix A) for all constructs were adopted from previous studies: AI- enabled customer experience (Foroudi et al., 2018; Oh et al., 2012; Otto & Ritchie, 1996), AI- enabled service quality (Wolfinbarger & Gilly, 2003; Chang & Wang, 2011), relationship commitment (Fullerton, 2005), trust (Wang et al., 2019; Paparoidamis, Tran, & Leonidou, 2019), perceived convenience (Collier & &Sherrell, 2010), personalisation (Chellappa & Sin, 2005) and perceived sacrifice (Merisavo et al., 2007; Shin & Lin, 2016). We used multiple items to measure each factor. For each item we used a seven-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree".

4.2. *Sampling and data collection*

AI-enabled virtual artist applications are used by a number of beauty brands to enhance customer experiences. Fig. 2 provides three examples from different brands. The target participants for this study were customers of a well-known European brand specialised in personal care and beauty products retail brand. Participants were recruited online via social media platforms using purposive sampling. Data was collected using an online questionnaire distributed via social media platforms. The case used for this study offers an AI-enabled customer experience by integrating a colour matching tool and a chatbot service.

Shade-matching technology (AI-colour matching technology) helps shoppers to identify the most suitable foundation based on their skin tones (Koltun, 2017). Virtual artist apps, including the one used by respondents, include a colour matching tool that analyses an image of the user's face to estimate the shade of any product shown in the picture (Koltun, 2017; Multivu, 2017; Prnewswire, 2017).

The case advertises and promotes the use of their AI-enabled service mainly via a virtual artist app platform enabled by AI. As the virtual artist app platform shows a reasonable level of interaction by customers, using this platform provided a higher level of access to the target participants. Following Malhotra and Galletta (1999, pp. 1–14), we used purposive (judgment) sampling based on two criteria: Individuals (1) must be at least 18 years old; and (2) have used an AI-enabled service offered by the brand. A pilot study was conducted by collecting 50 responses to the questionnaire and a few minor changes were made in terms of language and clarity accordingly. A total of 434 unique responses were collected between February and April 2020.

4.3. *Profile of respondents*

The respondents were from different age groups: 26% of the respondents were 18–23 years old, 62% were 24–30 years old and 12% were 31–40 years old. In terms of gender, the majority of the participants were females (97%), while only 3% were males. Table 1 shows the descriptive statistics of the sample.

In terms of the length of time participants had shopped at the brand, 54% had shopped there for one to five years, 45% had shopped there for six to ten years and only 1% had shopped there for more than ten years. All participants in the sample had used the brand's mobile app, the virtual artist and the colour match feature and they also had all used the virtual artist app for between one and five years. In addition, 95% of the participants used the brand's chatbot (Kik bot) service, while 5% had not used it. In terms of the number of times participants had used

the virtual artist app, 51% of the participants had used it between one and five times, 29% had used it between six and ten times, and 20%

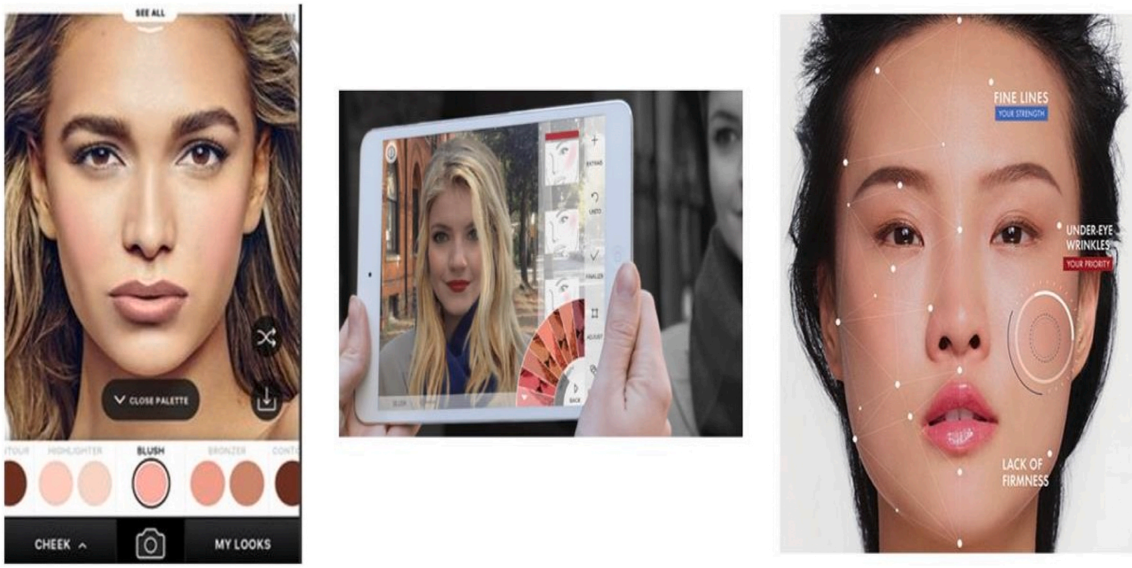

Fig. 2. Examples of three different AI-powered virtual artist applications (Multivu, 2017; de Jesus, 2020; L'Oréal, 2019).

Table 1
Descriptive statistics. Six to ten years 45 *Number of times of virtual artist app use*.

Profile	Percentage	Profile	Percentage
Age		*Use of the brand's virtual artist*	
18–23	26	Yes	100
24–30	62	No	0
31–40	12	*Length of time of using the virtual artist*	
40 and above	0	One to five years	100
Gender		Six to ten years	0
Male	3	More than ten years	0
Female	97	*Use of chatbot service*	
Length of time of shopping at [brand]		Yes	95
One to five years	54	No	5
Six to ten years	45	*Number of times of virtual artist app use*	
More than ten years	1	One to five times	51
Use of the brand's mobile application		Six to ten times	29
Yes	100	More than ten times	20
No	0		
Use of the virtual artist colour match			
Yes	100		
No	0		

had used it more than ten times.

5. Results

The collected data were analysed using partial least squares-structural equation modelling (PLS-SEM) (Hair, Hult, Ringle, & Sarstedt, 2017). PLS-SEM allows the analysis of data that are not normally distributed, and it is suitable for theory-testing and handling small sample sizes (Hair et al., 2017). The hypothesised model was estimated using SmartPLS3 with a bootstrap re-sampling procedure (5000 sub-samples were randomly generated) (Hair et al., 2017). To test for mediating effects, Preacher and Hayes's (2008) bootstrapping method was followed.

Common method variance (CMV) bias exaggerates relationships in the theoretical model. To minimise any potential CMV bias, the survey design and administration adhered to Podsakoff, MacKenzoe, Lee and Podsakoff's (2003) guidelines. Harman's single factor test was employed to assess CMV. Exploratory factor analysis (EFA) revealed the existence of a multi-factor structure, with the first factor accounting for 12% of the variance in the sample. CMV was further examined in Smart PLS using the inner collinearity assessment function. The analysis showed that the inner variance inflation factor (VIF) values were lower than the threshold value of 3.3 (Petter, Straub, & Rai, 2007). Together, these results suggest that CMV is not a pervasive issue in the data.

5.1. Assessment of the measurement model

We first assess the reliability, convergent validity and discriminant validity of the study's main constructs (Hair et al., 2017). Some of the factor loadings were lower than the threshold value of 0.7 (Hair et al., 2017), so they were removed from the analysis. Appendix A shows the factor loadings of all measurement items, including the items which were deleted due to low loadings.

Table 2 shows the mean, standard deviation and assessment of AVE, Cronbach's alpha, composite reliability and discriminant validity. In terms of convergent validity, the average variance extracted (AVE) values were above the threshold value of 0.5 (Fornell & Larcker, 1981). In addition, composite reliability and Cronbach Alpha values were above the threshold value of 0.7 (Urbach & Ahlemann, 2010). Discriminant validity was examined by comparing the square root of AVE for each construct with correlations among the latent variables (Fornell & Larcker, 1981). From Table 2, the results suggest strong evidence of discriminant validity.

Discriminant validity was assessed using heterotrait-monotrait (HTMT) values. To satisfy the heterotrait-monotrait criterion, each value must be equal to or less than 0.85 (Henseler, Ringle, & Sarstedt, 2015). Based on the results shown in Table 3, it can be concluded that discriminant validity was met.

5.2. Structural model and hypothesis testing

The structural model was evaluated using standardised path coefficients (β-value), significance level (*t* statistic) and R^2 estimates. The path loadings (interpreted as standardised regression coefficients) indicate the strength of the relationship between independent and dependent variables (Hair et al., 2017). As shown in Fig. 3, all hypothesised relationships are supported (H1 to H6), except H3b (perceived convenience - > perceived sacrifice: β-value = 0.09 and *t* value = 1.26) and H4a (personalisation - > trust: β-value = 0.02 and *t* value = 1.59).

In addition, the results show that the proposed model has an acceptable predictive power in respect to AI-enabled customer experience. With a R^2 value of 0.59, the proposed model has an acceptable

Table 2
Descriptive statistics, reliability and validity assessment.

	Mean	Standard deviation	Cronbach's Alpha	Composite reliability	Average variance extracted	AI-enabled service experience	AI-enabled service quality	Perceived convenience	Perceived sacrifice	Personalisation	Relationship commitment	Trust
AI-enabled service experience	5.25	1.24	0.89	0.91	0.64	0.80						
AI-enabled service	5.67	1.22	0.75	0.87	0.78	0.06	0.88					
Perceived convenience	4.89	1.45	0.72	0.84	0.72	0.21	0.06	0.85				
Perceived sacrifice	3.56	1.02	0.81	0.87	0.64	−0.15	0.30	0.23	0.80			
Personalisation	6.02	1.67	0.74	0.87	0.77	0.16	0.20	0.17	0.33	0.88		
Relationship commitment	5.87	1.35	0.84	0.90	0.76	0.12	0.23	0.05	0.21	0.16	0.87	
Trust	5.37	1.11	0.89	0.92	0.70	0.25	−0.09	0.31	−0.11	0.24	0.05	0.83

predictive power and explains 59% of the AI-enabled customer experience.

5.3. Mediating effects of convenience and perceived sacrifice

Mediation analysis establishes whether a relationship between independent variables (predictors) and a dependent variable is direct or indirect (Iacobucci, Saldanha, & Deng, 2007). This study hypothesises that trust and perceived sacrifice mediate the effects in respect to AI-enabled customer experience of each of perceived convenience, AI-enabled service quality and personalisation. The mediation effects were assessed using Preacher and Hayes's (2008) bootstrapping method with bias-corrected, 95% confidence intervals. 5000 iterations were used to test the significance of the indirect effects. If the indirect effect is significant and the confidence interval is not zero, mediation is supported (Zhao, Lynch, & Chen, 2010). Table 4 shows the results of the mediation analysis.

The results show that H7a is supported because trust mediates the relationship between AI-enabled service quality and AI-enabled customer experience as the direct effect without mediator is insignificant (t value = 2.52, CI = −0.17 to 0.15) (Baron & Kenny, 1986). Trust also mediates the relationship between perceived convenience and AI-enabled customers experience (t value = 4.19, CI = 0.08 to 0.22) and it mediates the relationship between personalisation and AI-enabled customers experience (t value = 4.21, CI = 0.09 to 0.24). The results also show that H7b is partially supported, because perceived sacrifice mediates the relationship between AI-enabled service quality and AI-enabled customer experience (t value = 3.52, CI = −0.10 to 0.12) and it mediates the relationship between personalisation and AI-enabled customer experience (t value = 2.66, CI = −0.13 to 0.25). However, it does not mediate the relationship between perceived convenience and AI-enabled customer experience (t value = 1.19, CI = −0.07 to 0.13).

6. Discussion

This study aims to analyse the role of AI in the shopping experience, specifically how the integration of AI improves customer experience. In response, a model was proposed drawing on trust-commitment theory (Morgan & Hunt, 1994) and the service quality model (Parasuraman et al., 1994). The proposed model integrates trust and perceived sacrifice as mediating factors between an AI-enabled customer experience and four factors: (a) personalisation, (b) convenience.

(c) AI-enabled service quality, and (d) relationship commitment. Previous studies also highlight the importance of trust and the sacrifices users may have to make when using AI-enabled services (e.g. Davenport et al., 2020), although both factors have to the best of our knowledge yet to be empirically tested as part of a holistic theoretical model. In response, this study proposes a novel theoretical model that integrates trust and perceived sacrifice as factors mediating the effects of

(a) personalisation, (b) convenience, and (c) AI-enabled service quality on AI-enabled customer experience. Our study focuses on the AI-enabled customer experience offered by a beauty brand and findings provide new insights into the view of customers on trust and perceived sacrifice. Furthermore, the findings highlight the significant role that commitment towards the relationship with the brand plays in evaluating an AI-enabled customer experience when customers have had an initial experience with the brand.

The findings reveal that two types of AI-enabled customer experiences exist, which we have classified as hedonic and recognition, which extends the findings of recent studies on the influence of digital experiences on reputation and loyalty (Foroudi et al., 2018), customer experience with the integration of digital technologies (Parise, Guinan,

Table 3
Heterotrait-monotrait ratio.

	AI-enabled service experience	AI-enabled service quality	Perceived convenience	Perceived sacrifice	Personalisation	Relationship commitment	Trust
AI-enabled service experience							
AI-enabled service quality	0.12						
Perceived convenience	0.28	0.11					
Perceived sacrifice	0.17	0.39	0.34				
Personalisation	0.20	0.28	0.32	0.43			
Relationship commitment	0.13	0.29	0.09	0.25	0.21		
Trust	0.51	0.11	0.41	0.13	0.31	0.07	

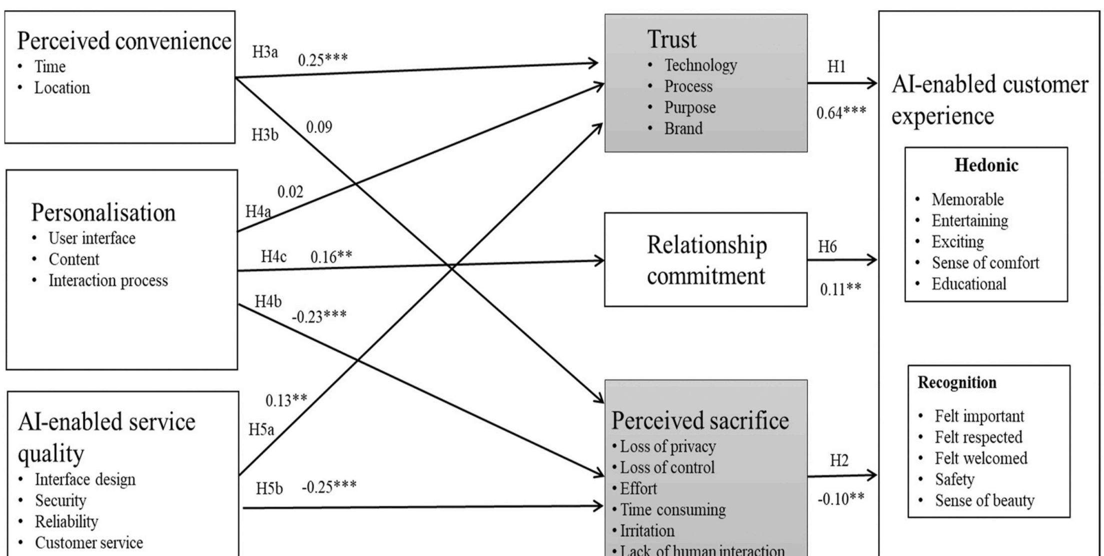

Fig. 3. Structural model.

& Kafka, 2016), and customer experiences in retailing as an antecedent of other factors (Roy et al., 2017). Previous studies also highlight the complex nature of AI use (Dwivedi et al., 2019) and the ambiguity around use areas, such as security, reliability, and ethics.

The findings of our study identify major sacrifices consumers may face in AI-enabled services, such as a lack of human interaction, loss of privacy, loss of control, time consumption, and possible negative feelings of irritation, all of which can have a negative effect on AI-enabled service experiences. Our findings also highlight the central role the concept of trust plays in AI-enabled customer experience. Our study demonstrates how trust mediates the relationship between an AI-enabled customer experience and (a) personalisation, (b) perceived sacrifice, and (c) AI-enabled service quality. Customers begin to trust a brand and the technology it employs when AI-enabled services are (a) personalised, (b) convenient, and (c) of high quality. A high level of trust, in turn, has a positive impact on the overall service experience. Together, these findings provide empirical support for findings from previous studies that highlight the significance of trust in AI technology (e.g. Wang, Molina, & Sundar, 2020).

By examining the mediating effect of perceived sacrifice, our study extends findings from previous studies on service experience (e.g. De Kerviler et al., 2016; Merisavo et al., 2007; Shin & Lin, 2016). Our findings show that perceived sacrifice mediates the paths between AI-enabled customer experience and (a) personalisation and (b) AI-service quality. Specifically, customers perceive sacrifices they have to make for using an AI-enabled service as less problematic when that service is personalised in terms of the user interface, content, and the interaction process. The same is true when the AI-enabled service is perceived as secure and reliable, and when additional support is provided when needed. These findings extend the work conducted in previous studies that highlight issues associated with the use of AI in services (e.g. Shank et al., 2019; Wang et al., 2020). Our findings reveal that customers are willing to sacrifice important elements of conventional services if AI-enabled services are personalised and offer a high-quality service. It is also worth noting that while service quality in conventional contexts (human-to-human) has been studied extensively (e.g. Prentice & Kadan, 2019; Scheidt & Chung, 2019; Suhartanto et al., 2019), our study reveals four distinct quality dimensions of AI-enabled services: (a) Interface design, (b) security, (c) reliability, and (d) additional customer support.

Surprisingly, while perceived sacrifice mediates the effects of personalisation and AI-enabled service quality, it does not mediate the relationship between perceived convenience and AI- enabled customer experience. Even though AI-enabled services are associated with convenience (Thiel, 2019; Walch, 2019), and despite a potentially increase in importance during the COVID-19 health crisis, our findings show that convenience (i.e. flexibility in time and location) does not necessarily affect the perception of sacrifices consumers feel they have to make in order to use these services.

7. Theoretical contributions

Our study contributes to existing knowledge in three main ways. First, we have developed a theoretical model that integrates factors

Table 4
Results of mediation analysis.

Relationships	Direct effects without mediator	Direct effect with mediator (CI)	Indirect effect (CI)	Supported?
H7a. AI-enabled service quality -> Trust -> AI-enabled service experience	2.19** (−0.08 to 0.14)	2.43 ** (−0.24 to0.20)	2.52** (−0.17 to 0.15)	Yes
H7a. Perceived convenience - > Trust - > AI-enabled service experience	2.85*** (0.06–0.26)	4.27*** (0.13 to 0.33)	4.19*** (0.08 to	Yes
H7a. Personalisation -> Trust - > AI-enabled service experience	2.49** (0.03–0.25)	4.50*** (0.13–0.34)	4.21*** (0.09–0.24)	Yes
H7b. AI-enabled service quality_ -> Perceived sacrifice - > AI-enabled service experience	2.46** (−0.07 to 0.14)	5.05 *** (0.15–0.34)	3.52*** (−0.10 to 0.12)	Yes
H7b. Perceived convenience - > Perceived sacrifice - > AI-enabled service experience	2.81** (0.05–0.26)	1.33 (−0.03 to 0.22)	1.19 (−0.07	No
H7b. Personalisation -> Perceived sacrifice - > AI-enabled service experience	2.44*** (0.03–0.25)	4.02*** (0.13–0.38)	2.66** (−0.13 to 0.25)	Yes

***p < 0 0.001; **p < 0.01; *p < 0.05; bootstrap confidence in parentheses, CI = confidence interval.

influencing AI-enabled customer experience. Results of our analysis show an acceptable fit for our model. Furthermore, our model integrates trust and perceived sacrifice as mediators. Despite the existence of studies explaining the significance of trust and sacrifice (e.g. Dwivedi et al., 2019), our study pioneers the integration and empirical test of these factors as mediators in a theoretical model on AI-customer experience.

Second, our study conceptualises AI-enabled customer experience in retail environments based on two dimensions: Hedonic and recognition. Despite the absence of human interaction in AI-enabled services, our results reveal that human emotions and a feeling of recognition remain important aspects. While the influence of technology on customer experience has been studied in different contexts (Ameen, Willis, & Shah, 2018; Foroudi et al., 2018), our research offers insights into one of the more complex technologies (AI) to automate service provision. Our findings reveal how the integration of AI causes a shift in how consumers perceive their experiences, and the factors they consider to be important for the success of these experiences. Moreover, when studying AI-enabled services, the context and dimensions of established constructs such as service quality may have to be adjusted in response to the unique nature of AI technology.

Third, our study reveals the significant effect of relationship commitment on AI-enabled customer experiences. Once customers gain an initial experience with a brand, their commitment to maintain an ongoing relationship has a significant positive effect on AI-enabled customer experience. Our findings also reveal that customers develop three distinct processes with brands (affective, normative, and calculative) that can result in a more positive AI-enabled experience. In summary, by examining the effect of relationship commitment on AI-enabled customer experiences, our study responds to recent calls to examine this effect in smart digital environments (Foroudi et al., 2018).

8. Managerial implications

Although AI is not a new concept, the technology is far from being ubiquitous in retaining. Given the importance of pleasant shopping experiences, the deployment of AI remains a challenge for retailers. While it is important for retailers to implement innovative technologies, for those affecting the customer experience, it is essential to first understand how consumers perceive their effect and specifically the potential benefit they may associate with them. In other words, a better understanding of the customer perspective is a critical first step towards an effective retail strategy to implement innovative technologies. The findings of our research highlight important areas for retailers to consider, such as perceived convenience and perceived sacrifices.

While convenience has been identified as a key advantage of AI-enabled services, it is important for retailers to understand that convenience alone is not sufficient to overcome the significance of sacrifices customers feel they have to make in order to use a service, such as loss of control, loss of privacy, or a lack of human interaction. It is important to acknowledge that perceived sacrifices remain important concerns for customer, even after several interactions with AI-enabled services.

Retailers should respond by maintaining collaborations with AI systems designers to address these concerns. For example, as one feature of AI-enabled services that retailers can benefit from, automation has the potential to offer flexibility and cost savings, yet, the lack of human interaction remains an issue for customers, which does not decrease in importance for consumers even when AI-enabled services increase their convenience. Accordingly, retails should aim for a balanced approach in terms of human interaction, for example, through carefully personalised experiences that are accompanied by a well-trained customer support team. This can increase relationship commitment, which our study has shown has a significant effect on how consumers perceive their AI-enabled experiences.

Consumer trust is an important factor for retailers to consider when introducing technologies, but it may be even more important when deploying AI. Findings from our study show that trust plays a central role in AI-enabled experiences. Given the complexity and potential ambiguity of AI technology from the perspective of consumers, gaining their trust is a major challenge in AI- enabled services. Results from our research indicate a positive relationship between trust and (a) convenience and (b) service quality. Trust in a brand, the technology and, process they employ, and the purpose for which they collect and analyse customer data increases when a service is (a) more convenient in terms of time and location, and (b) offers better service quality in terms of security, interface design, reliability, and customer support. It is important that retailers communicate their performance in these areas clearly to customers.

9. Limitations and future research

Our study is among the first to focus on customers' experience in the context of AI-enabled services. We encourage marketing and IS researchers to conduct further interdisciplinary studies to examine additional factors that have the potential to provide an even more nuanced perspective on the success factors of AI-enabled services among different consumer segments and in a cross-national context. In addition, we collected data based on 434 responses which were included in the analysis. However, future research can collect and analyse data using a larger sample size to increase the opportunity of generalising the findings. Furthermore, this study focuses on customers using the AI-enabled services of one pioneering brand in the beauty industry, future studies could investigate different retailers and industries. While our research identifies critical success factors of AI-enabled customer experiences from the perspective of consumers (such as trust, sacrifice, convenience, personalisation, and service quality), future studies should consider how each of these success factors can and should be implemented within a retail organisation. Finally, investigating ethics and security of AI technology from a consumer perspective provide additional opportunities for future research.

10. Conclusion

This study contributes to a better understanding of AI-enabled customer experiences. By highlighting the hedonic and recognition aspects of AI-enabled customer experiences, our study offers a pioneering effort to analyse how a cutting-edge technology, artificial intelligence, can improve the shopping experience for consumers. Our study further highlights the positive role of relationship commitment, and the significant mediating effects of trust and perceived sacrifice in AI-enabled customer experience.

Credit author statement

Nisreen Ameen, Designed the study, conducting the literature review, data collection and analysis, Ali Tarhini, Designed the study, editing, refining drafts, final checking, Alexander Reppel, Designed the study, final checking, Amitabh Anand, Designed the study, final checking.

Declaration of competing interest

None.

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Appendix A. Measurement items and factor loadings

Factors/items	Factors Loading	Factors/items	Factors Loading
AI-enabled customer experience		4. It would be very hard for me to switch away from [brand] right now even if I wanted to	0.89
Hedonic		5. My life will be disrupted if I switch away from [brand]	0.82
1. Memorable	0.86	6. It would be too costly for me to switch from [brand] right now	0.71
2. Entertaining	0.77	Trust	
3. Exciting	0.77	1. The performance of Virtual Artist app always meets my expectations	0.77
4. Sense of comfort	0.75	2. The Virtual Artist app has good Features	
			0.73
5. Educational	0.52 [dropped]	3. The Virtual Artist app introduced is reliable	0.84
		4. [brand] IS honest	0.87
Recognition		5.1 trust [brand]	0.86
1. Important	0.55 [dropped]	6. [brand] shows interest in me as a Customer	0.87
2. Respected	0.74	Perceived convenience	
3. Welcomed	0.75	1. This Virtual Artist app allows me to use the service whenever I choose	0.88
4. Safety	0.77	2. This Virtual Artist app allows me to use the service at a convenient time	0.72
5. Sense of beauty	0.85	3. I value the ability to use the virtual Artist app from the comfort of home	0.82
AI-enabled service quality		Personalisation	
1. The [brand] virtual Artist app is well designed	0.89	1. I value the Virtual Artist app as it is personalised for my usage experience preferences	0.88
2. The [brand] Virtual Artist app is reliable	0.88	2. I value Virtual Artist app that acquire my personal preferences and personalise the services and products themselves.	0.77
3. The [brand] Virtual Artist app is secure	0.81	Perceived sacrifice	
4. The [brand] customer service team ¿5 helpful	0.75	1. I am concerned about the loss of control when using [brand] virtual Artist app	0.61 [dropped]
Relationship commitment		3. [brand] Virtual Artist app IS tune consuming	
1. I have an emotional attachment to [brand]		4. I get annoyed when using [brand] Virtual Artist app	0.75
2. [brand] has a great deal of personal meaning for me	0.74	5.1 a.m. concerned about the loss of privacy when using the [brand] virtual Artist app	0.77
3. I feel a strong sense of identification with [brand]	0.77	6. Using [brand] virtual Artist app requires additional effort	0.79
		7. I am concerned about the lack of human interaction when using [brand] Virtual artist app	0.71
			0.81

References

Adair, M. (2019). *Why retail is one of the leading sectors investing in AI*. https://www.forbes.com/sites/forbestechcouncil/2019/03/29/why-retail-is-one-of-the-leading-sectors-investing-in-ai/#5d3dca0d1b4b. (Accessed 1 May 2020).

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing, 91*(1), 34–49.

Akrout, H., & Nagy, G. (2018). Trust and commitment within a virtual brand community: The mediating role of brand relationship quality. *Information and Management, 55*(8), 939–955.

Alsajjan, B., & Dennis, C. (2006). The Impact of trust on acceptance of online banking. In *European association of education and research in commercial distribution, 27–30 june 2006*. West London, United Kingdom: Brunel University.

Ameen, N., Tarhini, A., Shah, M., & Hosany, S. (2020). *Consumer interaction with cutting-edge technologies*. https://www.journals.elsevier.com/computers-in-human-behavior/call-for- papers/consumer-interaction-with-cutting-edge-technologies. (Accessed 1 May 2020).

Ameen, N., Willis, R., & Shah, M. H. (2018). An examination of the gender gap in smartphone adoption and use in arab countries: A cross-national study. *Computers in Human Behavior, 89*, 148–162.

American Psychological Association. (2016). *Glossary of psychological terms*. March 2020 www.apa.org/research/action/glossary.aspx.

Anderson, J., & Rainie, L. (2018). *Artificial intelligence and the future of humans*. https://www.pewresearch.org/internet/2018/12/10/artificial-intelligence-and-the-future-of-humans/. (Accessed 24 April 2020).

Anderson, J., Rainie, L., & Luchsinger, A. (2018). *Artificial intelligence and the future of humans*. https://www.elon.edu/docs/e- web/imagining/surveys/2018_survey/AI_and_the_Future_of_Humans_12_10_18.pdf. (Accessed 23 February 2020).

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., et al. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer Needs and Solutions, 5*(1–2), 28–37.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Bilgihan, A., Kandampully, J., & Zhang, T. (2016). Towards a unified customer experience in online shopping environments: Antecedents and outcomes. *International Journal of Quality and Service Sciences, 8*(1), 102–119.

Cheatham, B., Javanmardian, K., & Samandari, H. (2019). *Confronting the risks of artificial intelligence*. https://www.mckinsey.com/business-functions/mckinsey-analytics/our- insights/confronting-the-risks-of-artificial-intelligence. (Accessed 22 February 2020).

Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology Management, 6*(2–3), 181–202.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 1165–1188.

Chiesa, V., & Frattini, F. (2011). Commercializing technological innovation: Learning from failures in high-tech markets. *Journal of Product Innovation Management, 28*(4), 437–454.

Chiou, J., & Droge, C. (2006). Service quality, trust, specific asset investment, and expertise: Direct and indirect effects in a satisfaction-loyalty framework. *Journal of the Academy of Marketing Science, 34*(4), 613–627.

Choi, B., Lee, C., Lee, H., & Subramani, M. (2004). January). Effects of web retail service quality and product categories on consumer behavior: A research model and empirical exploration. In *37th annual Hawaii international conference on system sciences, 2004. Proceedings of the* (p. 10). IEEE.

Chou, P. F. (2014). An evaluation of service quality, trust, and customer loyalty in home-delivery services. *International Journal of Research in Social Sciences, 3*(8), 99–108.

Christakis, N. (2019). *How AI Will Rewire Us. For better and for worse, robots will alter humans' capacity for altruism, love, and friendship*. https://www.theatlantic.com/magazine/archive/2019/04/robots-human-relationships/583204/. (Accessed 22 February 2020).

Collier, J. E., & Sherrell, D. L. (2010). Examining the influence of control and convenience in a self-service setting. *Journal of the Academy of Marketing Science, 38*(4), 490–509.

Collier, J. E., & Bienstock, C. C. (2006). Measuring service quality in E-retailing. *Journal of Service Research, 8*(3), 260–275.

Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. *International Journal of Human-Computer Studies, 58*(6), 737–758.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.

De Kerviler, G., Demoulin, N. T., & Zidda, P. (2016). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? *Journal of Retailing and Consumer Services, 31*, 334–344.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., & Crick, T. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

Eisingerich, A. B., & Bell, S. J. (2008). Perceived service quality and customer trust: Does enhancing customers' service knowledge matter? *Journal of Service Research, 10*(3), 256–268.

Evans, M. (2019). *Build A 5-star customer experience with artificial intelligence*. https://www.forbes.com/sites/allbusiness/2019/02/17/customer-experience-artificial-intelligence/#1a30ebd415bd. (Accessed 30 April 2020).

Ferrario, A., Loi, M., & Viganò, E. (2019). In *AI we trust incrementally: A multi-layer model of trust to analyze human-artificial intelligence interactions* (pp. 1–17). Philosophy & Technology.

Findlater, L., & McGrenere, J. (2010). Beyond performance: Feature awareness in personalized interfaces. *International Journal of Human-Computer Studies, 68*(3), 121–137.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior, 80*, 271–282.

Fullerton, G. (2005). The impact of brand commitment on loyalty to retail service brands. *Canadian Journal of Administrative Sciences - Revue Canadienne des Sciences de l Administration, 22*(2), 97–110.

Gallarza, M. G., Arteaga, F., Chiappa, G. D., Gil-Saura, I., & Holbrook, M. B. (2017). A multidimensional service-value scale based on holbrook's typology of customer value: Bridging the gap between the concept and its measurement. *Journal of Service Management, 28*(4), 724–762.

Gartner. (2020). *Drive growth in times of disruption*. https://www.gartner.com/en. (Accessed 3 March 2020).

Gauvrit, P. (2019). *Why the future of customer service is AI and humans together*. https://www.eptica.com/blog/why-future-customer-service-ai-and-humans-together. (Accessed 23 February 2020).

Ghazizadeh, M., Lee, J. D., & Boyle, L. N. (2012). Extending the technology acceptance model to assess automation. *Cognition, Technology & Work, 14*(1), 39–49.

Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2019). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*. https://doi.org/10.1016/j.indmarman.2019.11.009.

Gustafsson, A., Johnson, M. D., & Roos, I. (2005). The effects of customer satisfaction, relationship commitment dimensions, and triggers on customer retention. *Journal of Marketing, 69*(4), 210–218.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling* (2nd ed.). Thousand Oaks, CA: Sage.

Heidenreich, S., & Spieth, P. (2013). Why innovations fail—the case of passive and active innovation resistance. *International Journal of Innovation Management, 17*(5), 1–42.

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—the case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change, 105*, 105–120.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Iacobucci, D., Saldanha, N., & Deng, X. (2007). A meditation on mediation: Evidence that structural equations models perform better than regressions. *Journal of Consumer Psychology, 17*(2), 139–153.

Iglesias, O., Singh, J. J., & Batista-Foguet, J. M. (2011). The role of brand experience and affective commitment in determining brand loyalty. *Journal of Brand Management, 18*(8), 570–582.

Irfan, M. (2020). *Artificial intelligence and the future of web design*, 22 February 2020 https://usabilitygeek.com/artificial-intelligence-and-the-future-of-web-design/.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586.

de Jesus, A. (2020). *Artificial intelligence for beauty and cosmetics – current applications*. https://emerj.com/ai-sector-overviews/artificial-intelligence-for-beauty-and-cosmetics- current-applications/. (Accessed 26 May 2020).

Juniper Research. (2020). *AI spending by retailers to reach $12 billion by 2023, driven by the promise of improved margins*. https://www.juniperresearch.com/press/press-releases/ai- spending-by-retailers-reach-12-billion-2023. (Accessed 1 May 2020).

Keiningham, T., Ball, J., Benoit, S., Bruce, H. L., Buoye, A., Dzenkovska, J., et al. (2017). The interplay of customer experience and commitment. *Journal of Services Marketing, 31*(2), 148–160.

Kim, Y. K., Lee, M. Y., & Park, S. H. (2014). Shopping value orientation: Conceptualization and measurement. *Journal of Business Research, 67*(1), 2884–2890.

Knight, W. (2018). *How artificial intelligence enhances personalized communication*. https://www.business2community.com/communications/artificial-intelligence-enhances- personalized-communication-02041997. (Accessed 4 March 2020).

Koltun, N. (2017). *Sephora's Virtual Artist app now includes AI-powered color matching*. https://www.mobilemarketer.com/news/sephoras-virtual-artist-app-now-includes-ai-powered-color-matching/444484/. (Accessed 4 March 2020).

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 941–960.

Ladhari, R., Souiden, N., & Dufour, B. (2017). The role of emotions in utilitarian service settings: The effects of emotional satisfaction on product perception and behavioral intentions. *Journal of Retailing and Consumer Services, 34*, 10–18.

Lam, S. Y. (2001). The effects of store environment on shopping behaviors: A critical review. In M. C. Gilly, & J. Meyers-Levy (Eds.), *Advances in consumer research* (Vol. 28, pp. 190–197). Valdosta, GA: Association for Consumer Research.

Lariviere, B., Keiningham, T. L., Cooil, B., Aksoy, L., & Malthouse, E. C. (2014). A longitudinal examination of customer commitment and loyalty. *Journal of Service Management, 25*(1), 75–100.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Hum.Factors, 46*(1), 50–80.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing, 80*(6), 69–96.

Ling, K. C., Chai, L. T., & Piew, T. H. (2010). The effects of shopping orientations, online trust and prior online purchase experience toward customers' online purchase intention. *International Business Research, 3*(3), 63.

Li, Y., & Shang, H. (2019). *Service quality, perceived value, and citizens' continuous-use intention regarding e-government: Empirical evidence from China* (p. 103197). Information & Management. https://doi.org/10.1016/j.im.2019.103197.

Li, T., & Unger, T. (2012). Willing to pay for quality personalization? Trade-off between quality and privacy. *European Journal of Information Systems, 21*(6), 621–642.

L'Oréal. (2019). *L'oréal and modiface: An artificial intelligence-powered skin diagnostic*. https://www.loreal.com/media/news/2019/february/2019-modifacexloreal. (Accessed 26 May 2020).

Malhotra, Y., & Galletta, D. F. (1999). Extending the technology acceptance model to account for social influence: Theoretical bases and empirical validation. *Proceedings of the 32nd annual Hawaii international conference on systems sciences*.

Malle, B. F., Scheutz, M., Arnold, T., Voiklis, J., & Cusimano, C. (2015). March. Sacrifice one for the good of many? People apply different moral norms to human and robot agents. In *2015 10th ACM/IEEE international conference on human-robot interaction (HRI)* (pp. 117–124). IEEE.

Maras, E. (2020). *Beauty retailers embrace AR, AI*. https://www.digitalsignagetoday.com/articles/beauty-retailers-embrace-ar-ai/. (Accessed 22 April 2020).

Martin, C. (2019). *Retail AI spending projected to hit $12 billion*. https://www.mediapost.com/publications/article/334349/retail-ai-spending-projected-to-hit- 12-billion.html. (Accessed 23 April 2020).

Martin, J., Mortimer, G., & Andrews, L. (2015). Re-examining online customer experience to include purchase frequency and perceived risk. *Journal of Retailing and Consumer Services, 25*, 81–95.

McKecnie, S., Ganguli, S., & Roy, S. K. (2011). Generic technology- based service quality dimensions in banking. *International Journal of Bank Marketing, 29*(2), 168–189.

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa… examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior, 99*, 28–37, 2019.

de Medeiros, J. F., Ribeiro, J. L. D., & Cortimiglia, M. N. (2016). Influence of perceived value on purchasing decisions of green products in Brazil. *Journal of Cleaner Production, 110*, 158–169.

Merisavo, M., Kajalo, S., Karjaluoto, H., Virtanen, V., Salmenkivi, S., Raulas, M., et al. (2007). An empirical study of the drivers of consumer acceptance of mobile advertising. *Journal of Interactive Advertising, 7*(2), 41–50.

Meyer, S. (2020). *Understanding the COVID-19 effect on online shopping behavior*. https://www.bigcommerce.co.uk/blog/covid-19-ecommerce/. (Accessed 1 May 2020).

Moorman, C., Zaltman, G., & Deshpande, R. (1992). Relationships between providers and users of market research: The dynamics of trust within and between organizations. *Journal of Marketing Research, 29*(3), 314–328.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing, 58*(3), 20–38.

Morganosky, M. A. (1986). Cost- versus convenience- oriented consumers: Demographic, lifestyle, and value perspectives. *Psychology and Marketing, 3*(1), 35–46.

Multivu. (2017). *Sephora virtual artist debuts new cheek product try on, expanded looks, and ai- powered color match technology in latest update*. https://www.multivu.com/players/English/7926154-sephora-virtual-artist-cheek-try-on- color-match/. (Accessed 2 May 2020).

Murphy, M. (2017). *A mind of its own Humanity is already losing control of artificial intelligence and it could spell disaster for our species, warn experts*. https://www.thesun.co.uk/tech/3306890/humanity-is-already-losing-control-of-artificial- intelligence-and-it-could-spell-disaster-for-our-species/. (Accessed 23 February 2020).

Newman, D. (2019). *5 ways AI is transforming the customer experience*. https://www.forbes.com/sites/danielnewman/2019/04/16/5-ways-ai-is-transforming-the- customer-experience/#49e17a31465a. (Accessed 1 March 2020).

Nienaber, A.-M., & Schewe, G. (2014). Enhancing trust or reducing perceived risk, what matters more when launching a new product? *International Journal of Innovation Management, 18*(1), 1–24.

Njamfa, O. (2018). *The importance of trust to customer experience in. 2019* https://www.eptica.com/blog/importance-trust-customer-experience-2019. (Accessed 22 February 2020).

O'Riordan, P. (2019). *Using AI and personalization to provide a complete brand experience*. https://www.aithority.com/guest-authors/using-ai-and-personalization-to-provide-a- complete-brand-experience/. (Accessed 22 February 2020).

Oh, L. B., Teo, H. H., & Sambamurthy, V. (2012). The effects of retail channel integration through the use of information technologies on firm performance. *Journal of Operations Management, 30*(5), 368e381.

Omale, G. (2019). *Improve customer experience with artificial intelligence*. https://www.gartner.com/smarterwithgartner/improve-customer-experience-with-artificial- intelligence/. (Accessed 2 March 2020).

Ong, F. S., Khong, K. W., Faziharudean, T. M., & Dai, X. (2012). Path analysis of atmospherics and convenience on flow: The mediation effects of brand affect and brand trust. *International Review of Retail Distribution & Consumer Research, 22*(3), 277–291.

Otto, J. E., & Ritchie, J. B. (1996). The service experience in tourism. *Tourism Management, 17*(3), 165e174.

Paparoidamis, N. G., Tran, H. T. T., & Leonidou, C. N. (2019). Building customer loyalty in intercultural service encounters: The role of service employees' cultural intelligence. *Journal of International Marketing, 27*(2), 56–75.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: Implications for further research. *Journal of Marketing, 58*(1), 111–124.

Parise, S., Guinan, P. J., & Kafka, R. (2016). Solving the crisis of immediacy: How digital technology can transform the customer experience. *Business Horizons, 59*(4), 411–420.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing, 34*(7), 1410–1419.

Payne, E. M., Peltier, J. W., & Barger, V. A. (2018). Mobile banking and AI-enabled mobile banking. *Journal of Research in Interactive Marketing, 12*(3), 328–346.

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly, 31*(4), 623–656.

Pham, T. S. H., & Ahammad, M. F. (2017). Antecedents and consequences of online customer satisfaction: A holistic process perspective. *Technological Forecasting and Social Change, 124*, 332–342.

Pham, Q. T., Tran, X. P., Misra, S., Maskeliūnas, R., & Damaševičius, R. (2018). Relationship between convenience, perceived value, and repurchase intention in online shopping in Vietnam. *Sustainability, 10*(1), 1–4.

Pinto, G. L., Dell'Era, C., Verganti, R., & Bellini, E. (2017). Innovation strategies in retail services: Solutions, experiences and meanings. *European Journal of Innovation Management, 20*(2), 190–209.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Poole, D. L., & Mackworth, A. K. (2010). *Artificial intelligence: Foundations of computational agents*. Cambridge: Cambridge University Press.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891.

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing & Management*, 1–18. https://doi.org/10.1080/19368623.2020.1722304.

Prentice, C., & Kadan, M. (2019). The role of airport service quality in airport and destination choice. *Journal of Retailing and Consumer Services, 47*(2019), 40–48.

Prnewswire. (2017). *Sephora Virtual Artist debuts new cheek product try on, expanded looks, and ai-powered color match technology in latest update*. https://www.prnewswire.com/news- releases/sephora-virtual-artist-debuts-new-cheek-product-try-on-expanded-looks-and-ai- powered-color-match-technology-in-latest-update-300470427.html. (Accessed 2 May 2020).

Rehman, S. U., Bhatti, A., Mohamed, R., & Ayoup, H. (2019). The moderating role of trust and commitment between consumer purchase intention and online shopping behavior in the context of Pakistan. *Journal of Global Entrepreneurship Research, 9*(1), 43.

Reimers, V., & Clulow, V. (2009). Retail centers: it's time to make them convenient. *International Journal of Retail & Distribution Management, 37*(7), 541–562.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. *Journal of Retailing, 88*(2), 08-322.

Roy, S. K., Balaji, M. S., Sadeque, S., Nguyen, B., & Melewar, T. C. (2017). Constituents and consequences of smart customer experience in retailing. *Technological Forecasting and Social Change, 124*, 257–270.

Saponaro, M., Le Gal, D., Gao, M., Guisiano, M., & Maniere, I. C. (2018). December. Challenges and opportunities of artificial intelligence in the fashion world. In *2018 international conference on intelligent and innovative computing applications (ICONIC)* (pp. 1–5). IEEE.

Saratchandran, V. (2019). *Artificial intelligence (AI) : Ways AI is redefining the future of customer service*. https://becominghuman.ai/artificial-intelligence-ai-ways-ai-is-redefining-the-future-of-customer-service-4dc667bfa59. (Accessed 22 February 2020).

Scheidt, S., & Chung, Q. B. (2019). Making a case for speech analytics to improve customer service quality: Vision, implementation, and evaluation. *International Journal of Information Management, 45*, 223–232, 2019.

Searby, S. (2003). Personalisation—an overview of its use and potential. *BT Technology Journal, 21*(1), 13–19.

Shank, D. B., Graves, C., Gott, A., Gamez, P., & Rodriguez, S. (2019). Feeling our way to machine minds: people's emotions when perceiving mind in artificial intelligence. *Computers in Human Behavior, 98*, 256–266, 2019.

Shen, A., & Ball, A. D. (2009). Is personalization of services always a good thing? Exploring the role of technology- mediated personalization (TMP) in service relationships. *Journal of Services Marketing, 23*(2), 80–92.

Sheridan, J. (2017). *An exploration into the potential impact in adopting a personalisation strategy and how it could affect the customer's experience on a company's own website*. Doctoral dissertation. Dublin: National College of Ireland.

Shin, W., & Lin, T. T. C. (2016). Who avoids location-based advertising and why? Investigating the relationship between user perceptions and advertising avoidance. *Computers in Human Behavior, 63*, 444–452.

Shukla, P., Banerjee, M., & Singh, J. (2016). Customer commitment to luxury brands: Antecedents and consequences. *Journal of Business Research, 69*(1), 323–331.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal, 31*(2), 47–53.

Solis, B. (2017). *Extreme personalization is the new personalization: How to use AI to personalize consumer engagement*. https://www.forbes.com/sites/briansolis/2017/11/30/extreme-personalization-is-the-new-personalization-how-to-use-ai-to-personalize-consumer-engagement/#ef3c32e829ad. (Accessed 22 April 2020).

Stamenkov, G., & Dika, Z. (2019). Quo vadis,(e-) service quality? Towards a sustainability paradigm. *Total Quality Management and Business Excellence, 30*(7–8), 792–807.

Suhartanto, D., Helmi Ali, M., Tan, K. H., Sjahroeddin, F., & Kusdibyo, L. (2019). Loyalty toward online food delivery service: The role of e-service quality and food quality. *Journal of Foodservice Business Research, 22*(1), 81–97.

Thiel, W. (2019). *The role of AI in customer experience*. https://www.pointillist.com/blog/role-of- ai-in-customer-experience/. (Accessed 22 February 2020).

Treasure Data. (2019). *AI vs. Human customer service: Survey data shows when consumers prefer a bot the current state of electronic systems & human interactions*. https://app.hushly.com/runtime/content/hweB8PE1UYgB6oQR. (Accessed 22 February 2020).

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application, 11*(2), 5–40.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., et al. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of Service Research, 13*(3), 253–266.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing, 85*(1), 31e41.

Walch, K. (2019). *AI's increasing role in customer service*. https://www.forbes.com/sites/cognitiveworld/2019/07/02/ais-increasing-role-in-customer-service/#4ffaba4c73fc. (Accessed 22 February 2020).

Wang, E. S. T., & Lin, R. L. (2017). Perceived quality factors of location-based apps on trust, perceived privacy risk, and continuous usage intention. *Behaviour & Information Technology, 36*(1), 2–10.

Wang, J., Molina, M. D., & Sundar, S. S. (2020). When expert recommendation contradicts peer opinion: Relative social influence of valence, group identity and artificial intelligence. *Computers in Human Behavior, 107*, 106278.

Wang, X., Tajvidi, M., Lin, X., & Hajli, N. (2019). Towards an ethical and trustworthy social commerce community for brand value co-creation: A trust-commitment perspective. *Journal of Business Ethics*, 1–16. https://doi.org/10.1007/s10551-019-04182-z.

Wang, W. T., Wang, Y. S., & Liu, E. R. (2016). The stickiness intention of group-buying websites: The integration of the commitment–trust theory and e-commerce success model. *Information and Management, 53*(5), 625–642.

Wolfinbarger, M., & Gilly, M. C. (2003). eTailQ: dimensionalizing, measuring and predicting etail quality. *Journal of Retailing, 79*(3), 183–198.

Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies, 131*, 160–168, 2019.

Zeithaml, V. (1988). A consumer's perceptions of price, quality, and value: A means–end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2–22.

Zhang, T., Bilgihan, A., Kandampully, J., & Lu, C. (2018). Building stronger hospitality brands through online communities. *Journal of Hospitality and Tourism Technology, 9*(2), 158–171.

Zhang, X., Edwards, J., & Harding, J. (2007). Personalised online sales using web usage data mining. *Computers in Industry, 58*(8–9), 772–782.

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206.