Technological Forecasting & Social Change 168 (2021) 120763

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

# The effects of anthropomorphism presence and the marketing mix have on retail app continuance use intention

Xin-Jean Lim [a], Jun-Hwa Cheah [a,*], Siew Imm Ng [a], Norazlyn Kamal Basha [a], Geoff Soutar [b]

[a] School of Business and Economics, Universiti Putra Malaysia, Selangor, Malaysia
[b] Department of Marketing, UWA Business School, The University of Western Australia (M263), 35 Stirling Highway, Crawley, Perth 6009, Australia

ARTICLE INFO

*Keywords:*
Anthropomorphism presence
Marketing mix
Consumer engagement
Prevention focus
Promotion focus
Continuance use intention of retail app

ABSTRACT

Retail applications (or retail apps) have emerged as a game-changer to complement and enhance the consumer purchase experience. Responding to calls of prior research, this study used the Two-factor Theory to understand how hygiene (i.e., anthropomorphism presence-AP) and motivation factors (i.e., marketing mix- MM) influence consumers' retail app continuance use intention. Consumer engagement (CE) was investigated as a mediator, while prevention focus and promotion focus were suggested as moderators. Data were collected from 456 Millennial mobile shoppers and analyzed using PLS-SEM. Result from the study's structural model suggested that continuance use intention was dependent on retailers' effectiveness on engaging with consumers and establishing attractive marketing elements. CE was found to mediate the path between AP and MM on continuance use intention. In addition, Millennial consumers with a high prevention focus was found to emphasize MM components in the engagement process. Some implications and suggestions for further research were discussed.

## 1. Introduction

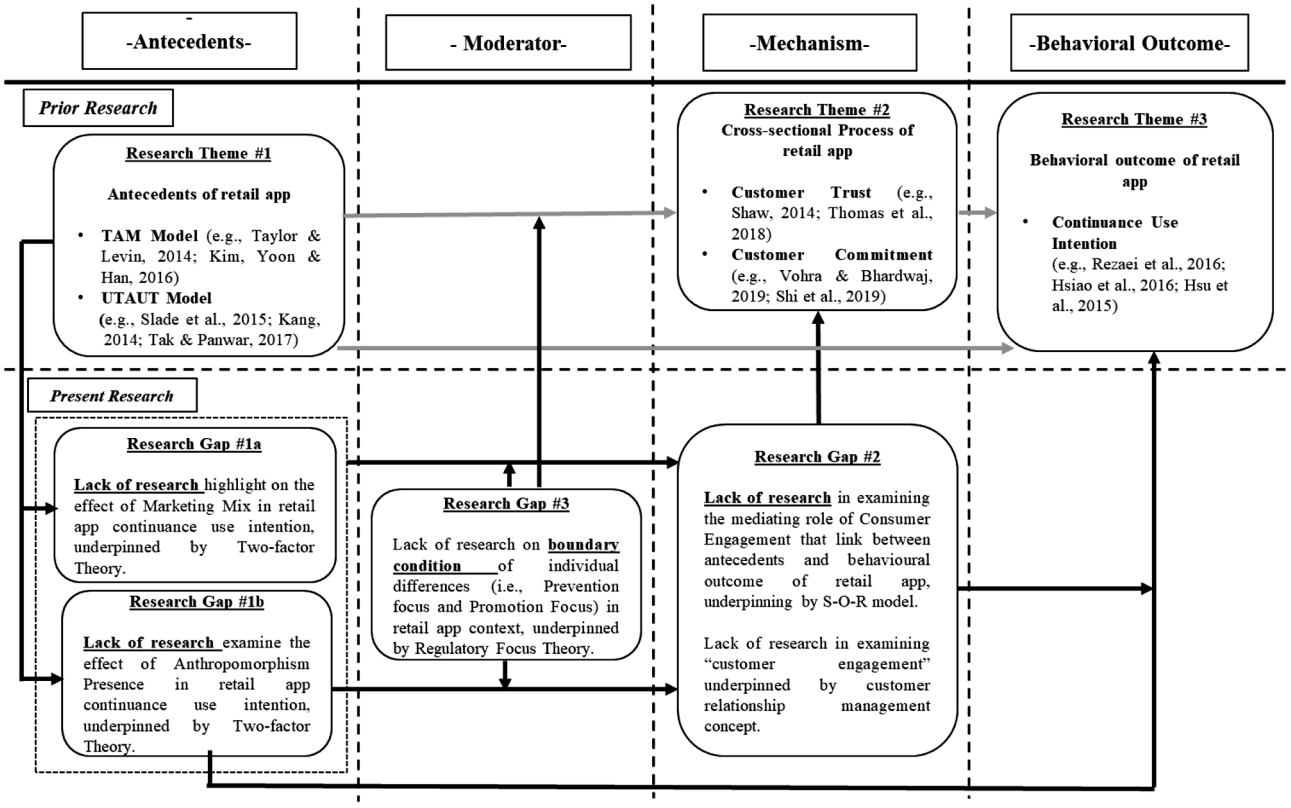
Gone are the days when marketers announce special offers and discounts on billboards or in catalogues, mailers and printed materials. The rise of the "always-on, constantly connected" shopper (Lamberton and Stephen, 2016), coupled with the rapid increase in the global smartphone adoption, has facilitated the growth of a mobile-dominated marketing world (Newman et al., 2018). Such development has prompted retailers to utilize retail applications (or retail apps) as one of the main technological tools to expand online marketing and establish a long-term advantage in brand building (van Heerde et al., 2019; Wang et al., 2018). This was increasingly evidence by the dominance of retail app usage, in where the volume of retail apps increasing 174% year-over-year (Khalaf, 2015). Indeed, the App Annie report (2018, p.1) have suggested 2017 was "a monumental year for the App Economy".

Despite retail app being touted as a magic marketing bullet, many companies are struggling to implement effective strategies to stimulate consumers' continued usage of the retail app. A recent survey found that approximately 25% of apps downloaded by users were only accessed once (Statista, 2020), and almost 50% of retail apps were deleted within a week (The Manifest, 2018). The Criteo survey (2020) revealed that retail app retention rate was an abysmal with only 4% in the Asia-Pacific region. In this vein, to obtain and sustain consumer loyalty in retail apps is a complicated task, especially since users often encounter phone storage restrictions and continuous change in preferences (Newman et al., 2018; Robertson et al., 2016).

At this point, it is worth acknowledging that existing literature offers retailers little direction as how to implement effective strategies in identifying factors that drive retail app continuance use intention. As evidenced by Groß's (2015, p. 222) this field of mobile commerce research is still in the stages of infancy. Wang et al.'s (2019) recently noted that marketing and technology attributes should be integrated to achieve optimal success in online marketing. In scholarly literature, studies on the retail app mainly centres around using the Technology Acceptance Model (TAM) (e.g., Taylor and Levin, 2014; Kim et al., 2016), or the Unified Theory of Acceptance and Use of Technology (UTAUT) (e.g., Slade et al., 2015; Kang, 2014; Tak and Panwar, 2017) in studying consumers' initial adoption intentions. Despite their popularity, these theoretical bases (i.e., TAM and UTAUT) have been criticized for only being applicable when examining users' intention to use or adopt during the development stage of a technology (Park and Lee, 2019; Fang, 2017). Taking into account retail app has reached the stage

* Corresponding author.
*E-mail addresses:* lim.xinjean@yahoo.com (X.-J. Lim), jackycheahjh@gmail.com (J.-H. Cheah), imm_ns@upm.edu.my (S.I. Ng), norazlyn@upm.edu.my (N.K. Basha), geoff.soutar@uwa.edu.au (G. Soutar).

https://doi.org/10.1016/j.techfore.2021.120763
Received 31 July 2020; Received in revised form 16 March 2021; Accepted 17 March 2021
Available online 31 March 2021
0040-1625/© 2021 Elsevier Inc. All rights reserved.




Notes:

(i) The top panel reviews three themes in past literature. The lower panel identifies three research gaps that are the foci of this study.
(ii) TAM (Technology Acceptance Model); UTAUT (Unified Theory of Acceptance and Use of Technology)

**Fig. 1. Gaps in extant literature.** Notes: The top panel reviews three themes in past literature. The lower panel identifies three research gaps that are the foci of this study. TAM (Technology Acceptance Model); UTAUT (Unified Theory of Acceptance and Use of Technology).

of maturity, there is a need for scholars to employ a different theoretical approach to further understand technology post-adoption. Similarly, Taylor and Strutton's (2010) study highlighted that a unifying framework consisting interdisciplinary concept is warranted when exploring technology continuance usage. This study, therefore, responds to these calls by exploring the determinants that might promote post-adoption behavior (i.e., retail app continuance use intention) from Two-factor Theory (Herzberg, 1987; 1965).

In alignment with the complexity of users' behavior, Two-factor Theory is deemed to exhibit high explaining power in conceptual clarity (Lee et al., 2009; Bassett-Jones and Lloyd, 2005). Specifically, this theory articulates how hygiene (i.e., the basic component or general function) and motivation factors (additional factor) influence users' intention to adopt a technology device (Cenfetelli and Schwarz, 2011; Park and Ryoo, 2013). On this account, we argue that marketing mix (MM) is the hygiene factor, which should be well-designed in to avoid non-adoption of the retail app. As evidence in literature, MM has been effectively used to improve consumers' attitudes and satisfaction while allowing the company to build competitive advantage over time (Buil et al., 2013; Kushwaha and Agrawal, 2015; Melis et al., 2015).

Meanwhile, the lack of human and social elements, as well as the components of trust-building was reported as main drawbacks hindering the growth of online marketing (Keeling et al., 2010; Schultze and Brooks, 2019; Shin and Choo, 2011). To address this issue, retailers are suggested to build on motivation factors in addition to the abovementioned hygiene factors by anthropomorphizing virtual platforms with a myriad of interactive technology-based features (Petit et al., 2019; van Esch et al., 2019; Scholz and Smith, 2016). As defined by Guthrie (1993), anthropomorphism presence (AP) is the psychological process of assigning human qualities or features to non-human entities. An online selling platform that rich with AP (i.e., incorporating humanlike chatbots/virtual agents or designing a message via first-person narration) were found to effective in evoking users' commitment and emotional attachment ((Tuškej and Podnar, 2018); Shin, 2019). Putting all these together, it would appear that integrating AP and MM within retail app strategies could reshape practical and emotional needs, which, in turn, stimulate continuance use intention.

In the current digital era, (apart from providing amazing features in their marketing tools), it is imperative for retailers to use relationship marketing as a "secret strategy" to manage and sustain relationships with consumers. Unlike transactional marketing, which focuses on a "hit-and-run" approach, relationship marketing stresses on how companies develop long-term value by emphasizing a consumer-centric relationship (Islam et al., 2019; Ndubisi and Nataraajan, 2018). Consumer engagement (CE) is regarded as an approach to mediate the relationship with users throughout post-purchase consumption journeys (Osei-Frimpong and McLean, 2018; Beckers et al., 2018). Individuals who engaged typically display higher involvement, satisfaction as well as loyalty (Harrigan et al., 2018; Thakur, 2019; Islam and Rahman, 2016). While the applicability of CE has been widely recognized in

various studies, little remains known whether CE is able to mediate the links between AP and MM on continuance use intention in the context of retail app, hence this becomes the study's second objective.

Despite the study's significance, the effectiveness of AP, as well as MM on CE, is may be ambiguous as impact may vary between consumers due to differences in personality. As a matter of fact, past marketing scholars have highlighted the need to integrate consumer differences in designing appropriate strategies to evoke positive engagement responses (Cal and Adams, 2014). A similar concern was highlighted in the context of information systems (IS), where researchers were advised to incorporate consumer differences in exploring technology acceptance and use (e.g., Rauschnabel et al., 2016; Wu and Ke, 2015). In accordance with the Regulatory Focus Theory (RFT), there are two individual differences that may influence consumer consumption decisions that warrant the use of diverse strategies (Higgins, 1998, 2012). These are; (1) prevention focus (i.e., consumers who tend to emphasize on avoidance and loss) and (2) promotion focus (i.e., consumers who most likely alter by presence or absence of gaining) were found to employ diverse strategies during their consumption decisions (Higgins, 1998, 2012). Likewise, both of these factors were seen as potential consumer traits that may moderate the paths between the antecedents (i.e., the MM and AP) on CE, exhibiting the third aim of this study. Therefore, all the above-mentioned study gaps lead to the model in Fig. 1 that reflects our three research objectives, namely:

*(i) To evaluate the degree to which AP and MM effect retail app continuance use intention.*

*(ii) To examine the mediating effect of CE,*

*(iii) To estimate the moderating effect of prevention focus and promotion focus have on these relationships.*

Taken together, the present study exhibits three novel aspects. First, it used the Two-factor theory to understand the consequences of an AP and the MM in app usage behavior. Second, it examined the indirect connection between CE, and last, the model is integrated with RFT to explore the moderating role of prevention focus and promotion focus. The study's theoretical background and hypotheses are presented in the next section.

## 2. Theoretical background

### 2.1. Two-factor theory

The Two-factor Theory (Herzberg, 1987,1965) is a well-established theoretical lens that is used to understand underlying factors that may increase an individual's motivation. Past literature determines the applicability of this theory in many IS studies to investigate users' motivation to use a technology device (e.g., Park and Ryoo 2013; Sanford and Oh, 2010). At its core, the Two-factor Theory proposes that users' intentions are affected by enablers (motivation factors) and inhibitors (hygiene factors). Specifically, hygiene factors are viewed as basic factors that do not necessarily increase the intention to adopt a technology, but in its absence, may lead to non-adoption (Lo et al., 2016). On the other hand, motivation factors play an essential role in encouraging consumers to adopt a technology device (Cenfetelli, 2004; Park and Ryoo, 2013; Huang et al., 2018). Hence, these two factors tend to co-exist in the adoption of technology.

One of the earliest studies in website development (Zhang and von Dran, 2000) revealed that hygiene factors are crucial to ensure the website's functionality, while motivation factors act a significant role in a website's added value. This view is supported by Wu et al. (2008), who found that hygiene factors offer general and functional operations of search engine design. In contrast, motivation factors contribute to search engine design, particularly in increasing user satisfaction. Besides that, the Two-factor Theory provided further insight in the context of cloud computing (Park and Ryoo, 2013), website design (Sambhanthan and Good, 2013; Zhang and Von Dran, 2000), online software services (Huang et al., 2012; Lee et al., 2013), and mobile services (Zhou, 2013). However, there is insufficient evidence regarding the effect of hygiene and motivation factors in the retail app context.

Therefore, we have accordingly invoked the Two-Factor Theory as theoretical foundation in the current study and simultaneously examining both hygiene and motivator factors is expected to provide a better understanding of retail app continue use intention. First, MM is highlighted as the hygiene factor that each app should contain to meet the basic needs of consumers so that they will continuously use a retail app. Indeed, MM is the most promising tool used to raise users' awareness (i.e., download the app) (Kushwaha and Agrawal, 2015; Melis et al., 2015). When hygiene factors and thus consumers' basic needs are met, there would be fewer reasons to switch to other alternatives. Second, as contended by Shin (2013), creating the perception of "presence" in the technology-mediated environment significantly conveyed a sense of human contact, and subsequently stimulating a positive response from consumers. Hence, AP is emphasized as the motivation factor that humanizes online interactions and increases sense of connectedness, which in turn encourages continued use of retail apps. We'd expect the study of hygiene and motivation factors to bring underexplored outcomes to surface.

### 2.2. Regulatory focus theory (RFT)

The cognitive psychology literature advocates Regulatory Focus Theory (RFT) as an emotional and cognitive state that elucidates how people implement different strategies in pursuing goals to meet their distinct needs (Higgins et al., 1997). Higgins's RFT classified individuals based on two independent self-regulation models: promotion focus and prevention focus (Higgins, 1998; 2012). Theoretically, prevention-focused consumers are typically sensitive to the occurrence of negative consequence as they are more vigilant and meticulous when making decisions. Meanwhile, promotion-focused consumers are more attuned to the occurrence of positive consequences and aspire to gain achievements (Chang et al., 2019). Additionally, Zou and Chan (2019) further explained this domain based on the notion of perceived risk whereby promotion-focused consumers are typically risk-takers, and conversely, prevention-focused consumers tend to generally be more risk-averse.

RFT has been employed in various past research to explain consumers' differences in decision making. For instance, in the context of technology adoption, Zhang et al. (2018) claimed that promotion-focused consumers have a preference to obtain as much gratifications as they can by using various different apps. In contrast, prevention-focused consumers tend to practice a minimalist approach in managing his/her needs by avoiding the undesirable consequences of downloading unnecessary apps. Within the domain of marketing, promotion-oriented consumers are found more attracted to promotion-framed ads (i.e., Ads that highlight potential benefits that can be obtained from the use of a particular product) and prevention-oriented consumers are prone to prevention-framed ads (i.e., Ads that highlight possible losses if not using a particular product) (Avent and Higgins, 2003). Moreover, Roy and Ng's (2012) research revealed that prevention-focused consumers exhibit a more favourable attitude towards a product with highlighted utilitarian features, while promotion-focused consumers tend to favor those with hedonic features.

Despite the potential theoretical interplay, empirical evidence that captures the impact of RFT in retail app context remains scant. Therefore, building upon RFT, this study will take into account prevention focus and promotion focus as potential moderators for observing consumer characteristics that might impact the relationships between (i) AP and CE as well as (ii) MM and CE. A detailed argument on these relationships is elaborated in the upcoming sections.

## 3. Hypotheses development

### 3.1. Drivers of continuance use intention

Following Ou et al. (2014), we operationalize AP as two-dimensions: telepresence and social presence. In particular, telepresence is the extent to which a buyer perceives immediacy or physical distance when dealing with a seller (Steuer, 1992; Ou et al., 2014). The higher the degree of telepresence a consumer feels in an online store, the more they perceive to being close to a seller. Meanwhile, the concept of social presence refers to the extent a virtual environment can convey a sense of human contact, sensitivity, and human warmth (; Ou et al., 2014). In a computer-mediated environment, social presence is perceived to create a feeling of "being together with another", which reduces the psychological distance between others (Shin, 2013).

In recent times, the infusion of AP in online shopping websites, advertising, and product design has gained traction from both academicians and practitioners (Gursoy et al., 2019; Laksmidewi et al., 2017). For instance, deployment of mascots, online chat agents, and text-based personification (e.g., using of first-personal pronouns like "he or she" rather than "it") has been seen as the best approach to infuse AP in the online selling platform (Go and Sundar, 2019; Letheren et al., 2017). Apart from that, the integration of human-like virtual agents in retail websites has been suggested to enhance the perceptions of credibility and trust (Etemad-Sajadi, 2016), attitude (Han et al., 2019) as well as patronage intention (Chattaraman et al., 2014). From consumers' perspectives, virtual agents act as actual salespeople that provide them with purchase information, such as product recommendation, special offer notification and payment process guidance (Liew et al., 2017).

Correspondingly, it is expected that when a retail app is highly anthropomorphic with human-like features, the tendency to influence consumer usage will be higher. That is, an app with a high degree of telepresence would lead to consumers' perception that they are well-informed; thus, they feel more secure when dealing with the online vendor (Pelet et al., 2017; Han et al., 2020). As for social presence, it is perceived to arouse consumers' belief and sense of belonging, which in turn, increases intimacy with a particular retailer ( Shin, 2019). Based on the Two-factor Theory, we therefore argue that AP emerges as a complementary tool (motivating factor) that drive consumers to continue using a retail app. The following is proposed:

***H1: An AP is positively related to retail app continuance use intention***

The concept of MM (McCarthy, 1960) is acknowledged as the most trusted and appropriate operative tool to facilitate managers and academics in achieving marketing goals, as well as in handling various marketing practices (Festa et al., 2016; Resnick et al., 2016; Fan et al., 2015). In an online marketplace where products are not physically accessible, consumers often undertake MM as a proxy to assist them in making purchase decisions, interpreting the sellers' image (Krishnamurthy and Kumar, 2018) and minimizing their uncertainty (Faryabi et al., 2015). As suggested by Talpau (2014), to achieve ongoing success, online sellers should emphasize offering goods and services anticipated by consumers, both in terms of tangible (e.g., price and packaging) and intangible features (e.g., delivery arrangement and after-sales service). Moreover, existing literature has presented price, promotion and product guarantee as the determinant factors that enhance online user' satisfaction, trust and repurchase intention (Jiang and Rosenbloom, 2005; Wu and Li, 2018). Additional research found that marketing factors such as price advantage and after-sales service are important cues used by consumers to judge an online store's image (Melis et al., 2015), while product assortment was found to exhibit a significant impact on favourable attitude towards an online store (Lombart et al., 2018).

By deriving insights from past studies and responding to the call of Gordon (2012), this incorporates product assortment, product guarantee, price advantage, after-sale service, monetary promotion, non-monetary promotion, ease of payment, and channel transparency as the MM in the retail app domain.[1,2] Each of the components is further elaborated below:

*Product Assortment:* a wide array of assortment (or merchandise mix) across the retail app. It consists of two key components: (i) product breath: providing a variety of product line within an app; and (ii) product depth: providing a deep assortment within a particular product category (e.g., variations in size, color, design). It is perceived that assortment planning is invaluable in optimizing retail app's strategy, offering superior selection and greater convenience for consumers.

*Price Advantages:* consumers are able to experience the benefit of purchasing the product at a lower price in retail app compared to physical stores. In fact, price advantage is the leading factor to attract consumers' attention and encourage them to continue using an app as consumers can easily compare the price at a click of button.

*Channel Transparency:* order visibility, and the ability of retail app to track orders from purchase to delivery. This is one of the fundamental prerequisites to diminish transaction risk while empowering consumers to manage their purchase records.

*Product Guarantee:* the assurance given by retailers to reduce consumers' uncertainty regarding product quality. To encourage app usage, it is essential to allow consumers' request for refund if the product received is not in satisfactory condition (e.g., damaged, incomplete, incorrect or defective).

*After-Sales Service:* the provision of services after products or service purchase from a particular retailer. Excellent after-sales service available in retail app, such as the availability of technical support, pricing policies, warranties, and coverage play a pivotal role in cultivating long-term user-seller bond.

*Monetary Promotion:* short-term incentives that are used to stimulate purchase of product or services, which allows consumers to buy at a lower price (price saving) and trigger utilitarian benefits. For example, 11.11 Single Day sales is one such promotion that offers amazing discounts and cashbacks.

*Non-monetary Promotion:* reflects a promotion strategy that does not utilize price reductions to differentiate a brand. This strategy instead emphasizes on consumers' hedonic benefits, such as free sample giveaways and free shipping.

*Ease of Payment*: refers to the extent to which consumers perceived the payment process is efficient and easy to use without sophisticating procedures. For example, many retail apps have introduced their own electronic wallet (e-wallet) to enable install payment for any purchase.

Accordingly, we suggest that MM acts as the basic need (i.e., hygiene factor) that attract consumer to use a particular retail app. That is, a well-designed MM will lead to a higher continuance use intention. Hence, we suggest:

***H2: The MM is positively related to continuance use intention***

In this study, CE is conceptualized as a multi-dimensional construct comprising: conscious attention, enthused participation, and social connection. Corresponding to Vivek et al. (2014, p.410) definition, CE indicates "the intensity of an individual's participation in and connection with an organization's offerings and/or organizational activities,

[1] As pointed by Kalyanam and McIntyre (2002), the marketing mix element does not restrict to traditional 4Ps but sought to include a collection of microelements that clustered together and aims to simplify the managerial tasks. The continued growth mobile commerce, has forced retailers to re-tooling the marketing mix to adapt in the contemporary digitalize era.

[2] Retail app is considered as one of the tools to complement online selling strategies. Hence, the marketing mix factors that is proposed in the present study have similar traits as to those in e-commerce.

which is either initiated by the customer or the organization". The term "engagement" can be viewed as a fusion of psychological state that motivates user's behavioral manifestation (Brodie et al., 2011; Hollebeek et al., 2019; Van Doorn et al., 2010). In the field of marketing, the impact of CE has been recognized as a significant factor by academics and practitioners alike. A marketing survey from McKinsey's Data Matics (2014) found that strategically engaging consumers can hugely pay off in terms of profitability and revenues. Likewise, around 63% of marketers agreed that engagement behavior can result in higher retention and repeat purchase (Marketo, 2019).

From an academic perspective, Pansari and Kumar (2017) posit that online patronage behavior and positive word-of-mouth may serve as consequences of CE. Engaged consumers who identify with the company and hold feelings of attachment are most likely to display positive behaviors, such as providing positive word-of-mouth referrals (De Matos and Rossi, 2008). It has also been found that loyalty can be a direct consequence of consumers highly engaged with a particular brand (Leckie et al., 2018).

Hence, CE indicates an excellent strategy in establishing customer relationship, thereby promoting an uptick in retail app usage. As highlighted by Ryan and Jones (2012), the critical success for a mobile app highly depends on its capability to enhances consumers' level of value or engagement. Against this background, the hypothesis is suggesting as:

***H3: CE is positively related to retail app continuance use intention***

### 3.2. Predictors of CE

Along with the advancement of technology, online presence is becoming a "must-have" tool to create a compelling consumer experience (Lemon and Verhoef, 2016; Pantano and Timmermans, 2014). It is perceived that when consumers gain familiarity with human-like technology, the sense of uncertainty and complexity towards virtual retail environment may be mitigated (Gursoy et al., 2019; Puzakova et al., 2015). Likewise, the research conducted by Gao and Li (2019) demonstrated that compared to seemingly mindless features, anthropomorphized retail technology tends to be more reliable and trusted by users, and consequently influence their willingness to use. A similar outcome was reported in a study by Ou et al. (2014), where users were found to more easily and quickly develop a mutual understanding with sellers in a website with high AP features. As a result, AP is the extreme version of humanization that acts as a precursor to bridge the gap between humans and technology. Drawing on this notion, AP would seem like an essential factor to build CE in the retail app context. We argue that when consumers are able to experience the AP of "being there" (i.e., telepresence) and "being together (i.e., social presence), they are more likely to be enthusiastic in using the retail app. Thus, we suggest:

***H4: AP is positively related to CE***

(Pansari and Kumar, 2017) study demonstrate that retailers can enhance bonding with consumers via implementing different marketing tactics such as on-time delivery, valuable promotion, efficient after-sales service, etc. A considerable number of studies have examined the positive effect of MM effects, and generally, the outcome is consistent over time. For example, Kim et al. (2013) contended that online marketers may effectively engage with users by providing them with unique purchase experiences. Kim et al. (2015) claimed that the provision of systematic selling strategies in retail app results in higher user satisfaction, thereby enhancing company performance. Again, Bellman et al.'s (2011) study concurred with this finding, where the effectiveness of the branded app is significantly explained by user experience in terms of information or experiential.

This suggests that, in the retail app context, superior engagement strategy depends to a large extent, on what retailers are able to offer to consumers. It is expected that high MM is associated with a high level of CE. Therefore, we propose:

***H5: The MM is positively related to CE***

### 3.3. The mediating role of CE

Extant literature has suggested CE as one of the psychological mechanisms that incur consumers' attachment to the company whether directly and indirectly, that eventually stimulate loyalty among new and existing users (Pansari and Kumar, 2017). Generally, consumers who are highly engaged are more likely to experience a sense of empowerment, which will eventually fosters a wide array of positive transactional outcomes such as repurchase intention (Islam and Rahman, 2016).

In a similar vein, engagement was also reported as an essential factor to stimulate technology post-adoption behavior. As cited by Bellman et al. (2011), individuals are not likely to stick with any app activities, unless they are strongly engaged with it. Further, research by Lim et al. (2015) mentioned that users' desire to continue using a commerce site largely depends on their degree of engagement. Based on this rationale, we suggest the continuing exchange behavior in retail app can be further enhanced through consumer engagement process. That is, CE is likely to mediate retail app features (i.e., AP and MM) with continuance use intention. Consequently, we suggest:

***H6: CE mediates the relationship between an AP and continuance use intention***

***H7: CE mediates the relationship between the MM and continuance use intention***

### 3.4. The moderating role of regulatory focus

In this study, we proposed that the interrelationships between app features (i.e., AP and MM) on CE would not be equally pronounced as this linkage may be affected by consumer differences. Given this case, we drew on RFT to examine the boundary conditions of prevention focus and promotion focus. According to Higgins et al. (1997), RFT sheds light on the process consumers use when regulating their thoughts and pursuing their end-states.

By focusing on decision-making behavior, Roy's (2017) study demonstrated that promotion-focused consumers preferred using imagery approach; meanwhile, prevention-focused orientation consumers preferred using analytical attributes approach. Similarly, Ozcelik and Varnali (2019) concluded that customized online advertisement would appeal more to promotion-focused consumers as they are more eager to obtain a timely offer. In contrast, prevention-focused consumers are less likely to respond favourably towards customized advertising, as they are more vigilant against taking potential risks (e.g., the tracking of private data). On top of that, relationship management research framed by RFT has shown that both promotion and prevention-focused individuals form relationship processes differently (Rodrigues et al., 2019). Specifically, promotion-focused consumers prefer to seek personal advancement by connecting with others, while prevention-focused consumers strive for stability in a relationship (Righetti and Kumashiro, 2012). Along with this reasoning, Vaughn's (2017) research has verified that prevention-focused tend to emphasize feelings of basic needs satisfaction as a way to predominantly minimize losses and maximize non-losses.

Following this notion, it can be perceived that promotion-focused consumer usually exhibits a sense of eagerness and look forwards for high social relationship (Fournier and Alvarez, 2013). In contrast, prevention-focused consumers are typically more cautious; as such, they tend to take an "avoidance" approach to prevent mistakes (Kordrostami and Kordrostami, 2019). Therefore, we formulate the following hypotheses:

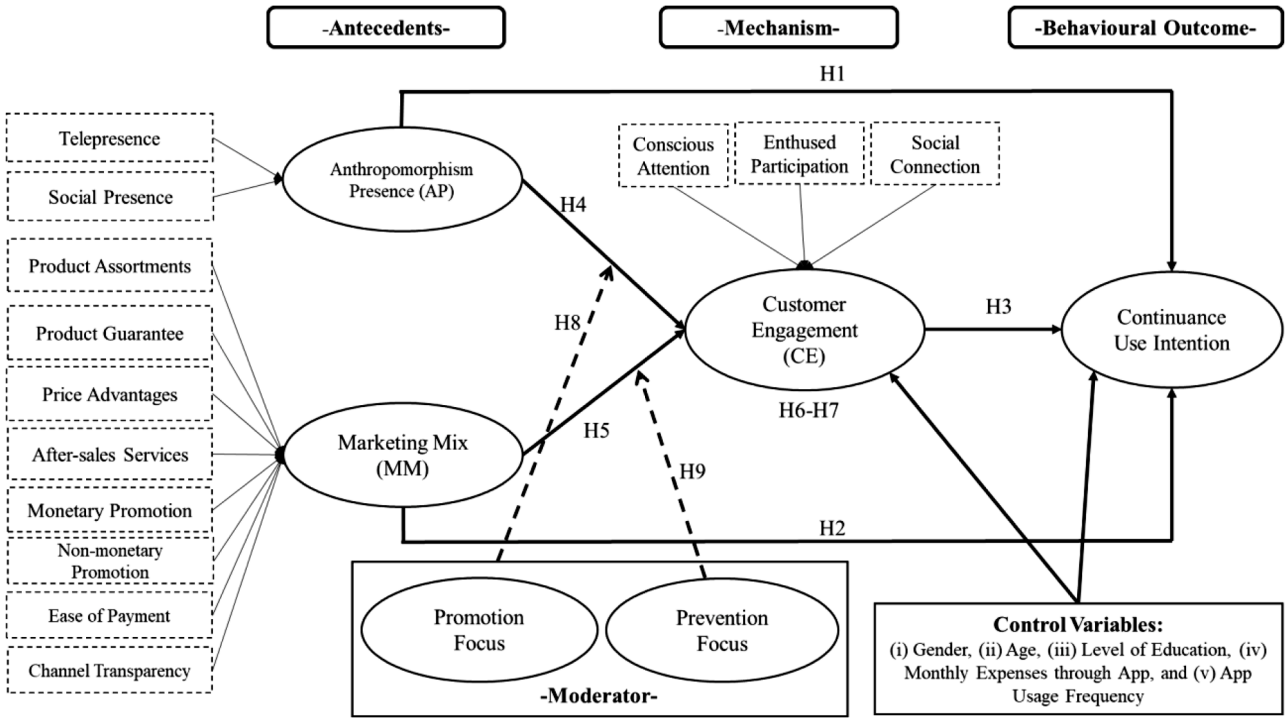



**Fig. 2. Research model**. Note: dashed line box represents lower order constructs.

***H8: Promotion focus moderates the relationship between AP and CE, as the relationship is stronger when the promotion focus is high.***
***H9: Prevention focus moderates the relationship between MM and CE, as the relationship is stronger when the prevention focus is high.***

To avoid confounding variables or faulty results from these proposed hypotheses, control variables such as gender, age, education level, monthly expenses through app, and app usage frequency were included in the model. Generally, most research indicates that users who are female, well- educated, younger, spend more, and frequently using an app are more likely to result in high engagement and intention to continue use (Wottrich et al., 2018). The research model is presented in Fig. 2 and the methodology undertaken to examine these hypotheses is discussed in the following section.

## 4. Methodology

### 4.1. Data collection procedures

Using a face-to-face and self-administered approach, data were obtained from a sample of Millennial mobile shoppers in Malaysia. As Chen et al. (2019) stated, "mobile shoppers" refer to users with experience in buying products or services through mobile devices. To ensure respondents are able to provide valid responses, a purposive sampling method was utilized in recruiting respondents. They must be Malaysian, born between 1981 and 1996[3] (Millennials), and had used a retail app within the past six months (e.g., Shopee, Taobao, Lazada, Uniqlo, H&M, etc.). Data collection was conducted in various major shopping malls in Klang Valley, Malaysia. Klang Valley is known as one of the most progressive areas in Peninsular Malaysia, where businesses flourish and residents are diverse in terms of ethnicity, religion, income level, academic level, and purchasing power (Gindi et al., 2016). Based on these characteristics, this population is a desirable sample and represent the best proxy to examine retail app continuance use intention of Millennial mobile shoppers in Malaysia. Prior to the actual collection of data, the questionnaire was pre-tested with fifty respondents, with acceptable content validity.

A total of 500 responses were obtained, while 44 were eliminated using the case-wise deletion approach, as respondents had given "straight-line" answers (i.e., chosen the same option for all items). Thus, 456 Millennial mobile shoppers were included in the subsequent analysis. As can be seen in Table 1, most respondents were female (74%), aged between 23 and 26 years (26%) and had completed an undergraduate degree (43%). More than a third were students (34%), earned between RM2,001- RM3,000 (or ~US$5,00 - US$7,50) per month (29%). In the same vein, most respondents used their preferred retail app at least once every month (35%) and had spend between RM 501 - RM 700 (or ~US$125 to US$175) (24%) through the app.

### 4.2. Measures

All the scales were adapted from prior research. In this study, most of the constructs (i.e., AP, MM, CE) were measured as higher-order constructs that was formed by lower-order constructs (or dimensions) Specifically, AP comprises of two dimensions: social presence and telepresence (Ou et al., 2014). MM was measured with eight dimensions, namely, product assortment (Ahn et al., 2014), after-sales service (Kim and Hyun, 2011), price advantage (Fassnacht and Unterhuber, 2016), product guarantee (Clemes et al., 2014), monetary promotion (Buil et al., 2013), non-monetary promotion (Buil et al., 2013), ease of payment (Bitner, 1992), and channel transparency (Otim and Grover, 2006). Also, Vivek et al. (2014) three-dimension scale (i.e., conscious attention, enthused participation and social connection) was chosen in measuring CE. Both prevention focus and promotion focus were measured through Haws et al. (2010) scale, while continuance use intention was measured through Bhattacherjee's (2001) scale. The items used in these constructs is shown in Table 2.

[3] According to the previous research, anyone born from 1981 to 1996 (ages ranging from 23 to 38) is considered a Millennial. In Malaysia, nine million consumers use smartphones to purchase online (The Borneo Post, 2018), with approximately 50% of Millennial mobile shoppers purchasing in this way multiple times each month (MCMC, 2018)

**Table 1**
Respondent profile.

| Category | | Frequency ($n$ = 456) | Percent (%) |
|---|---|---|---|
| Gender | Male | 117 | 25.7 |
| | Female | 339 | 74.3 |
| Age | 23–26 years old | 213 | 46.7 |
| | 27–30 years old | 103 | 22.6 |
| | 31–34 years old | 100 | 21.9 |
| | 35–38 years old | 40 | 8.8 |
| Education Level | Secondary or below | 14 | 3.1 |
| | Diploma | 66 | 14.5 |
| | Undergraduate Degree | 198 | 43.4 |
| | Graduate Degree | 123 | 27 |
| | Postgraduate Degree or higher | 55 | 12.1 |
| Monthly Income | Less than RM2,000 (less than ~ US$500) | 42 | 9.2 |
| | RM2,001-RM3,000 (~US $500 - US$750) | 130 | 28.5 |
| | RM3,001-RM4,000 (~US $750 - US$1000) | 107 | 23.5 |
| | RM4,001-RM5,000 (~US $1000 - US$1250) | 50 | 11 |
| | RM5,001-RM6,000 (~US $1250 - US$1500) | 72 | 15.8 |
| | RM6,000 and above (~US $1500 and above) | 55 | 12.1 |
| Occupation | Manager | 45 | 9.9 |
| | Housewife | 10 | 2.2 |
| | Non-Manager | 98 | 21.5 |
| | Student | 155 | 34 |
| | Self-employed | 81 | 17.8 |
| | Others | 67 | 14.7 |
| Monthly Expenses through app | Less than RM 100 (Less than ~US$25) | 68 | 14.62 |
| | RM 100 -RM 300 (~US$25 to US$75) | 85 | 18.28 |
| | RM 301- RM 500 (~US$75 to US$125) | 98 | 21.08 |
| | RM 501 - RM 700 (~US $125 to US$175) | 113 | 24.3 |
| | More than RM 700 (More than ~US$175) | 101 | 21.72 |
| App Usage Frequency | Daily | 85 | 18.6 |
| | Weekly | 124 | 27.2 |
| | Monthly | 169 | 35.1 |
| | Once Every 2–3 months | 87 | 19.1 |

## 5. Data analysis

Partial least squares structural equation modelling (PLS-SEM) was seen as the most appropriate technique to examine the relationships of interest. PLS-SEM uses a causal prediction approach that suits the prediction-oriented objective of the present research (Chin et al., 2020; Hair and Sarstedt, 2019). Also, this approach outperforms when assessing complex models, such as models that have reflective-formative higher-order constructs (HOCs) (Sarstedt et al., 2019a), mediation effects (Hayes, 2009) and moderation effects (Becker et al., 2018). Further, PLS-SEM has some useful supplementary analyses (i.e., examining endogeneity, non-linearity and unobserved heterogeneity) (Sarstedt et al., 2019b). In this study, SmartPLS 3.3.3 software was used to estimate the suggested model (Sarstedt and Cheah, 2019).

### 5.1. Common method variance (CMV)

Significant efforts were made to minimize CMV. First, a procedural remedy was used to reduce CMV, as two different Likert scales (i.e., 5-point and 7-point) were used to measure the exogenous and endogenous constructs. Second, the full collinearity approach recommended by Kock and Lynn (2012) was used to evaluate potential adverse CMV effects statistically. As shown in Table 2, the full collinearity assessment

**Table 2**
Results of measurement model and full collinearity.

| Construct | Loading |
|---|---|
| **Anthropomorphism Presence (AP)** | |
| *(i) Social Presence [α=0.786; rho_A = 0.790; CR=0.862; AVE=0.609; Full Collinearity=1.510]* | |
| SP1: There is a sense of human contact with this retail app. | 0.760 |
| SP2: This retail app has a personal touch as I interface with it. | 0.738 |
| SP3: There is a human-like warmth associated with this retail app. | 0.840 |
| SP4: There is a sense of human sensitivity associated with this retail app. | 0.782 |
| *(ii) Telepresence [α=0.791; rho_A = 0.792; CR=0.865; AVE=0.615; Full Collinearity=1.529]* | |
| TP1: When browsing this retail app, I felt that my mind was inside the world created by this seller. | 0.814 |
| TP2: When browsing this retail app, I felt that I was immersed in the world this seller had created. | 0.813 |
| TP3: This seller-generated world seemed to me to be 'somewhere I visited' rather than 'something I saw.' | 0.755 |
| TP4: I felt I was more in the 'real world' than in the 'computer world' when I was browsing in this retail app. | 0.753 |
| **Marketing Mix (MM)** | |
| *(i)Product Assortment [α=0.628; rho_A = 0.629; CR=0.800; AVE=0.572; Full Collinearity=1.340]* | |
| PA1: This retail app updates with new products. | 0.729 |
| PA2: This retail app sells various assortments. | 0.775 |
| PA3: This retail app offers products with unique characteristics. | 0.763 |
| PA4: This retail app carries a variety of products that cannot easily be found in other app stores. | D |
| *(ii) Price Advantages [α=0.638; rho_A = 0.686; CR=0.804; AVE=0.583; Full Collinearity=1.222]* | |
| ADV1: When selecting this retail app, shipping and handling cost was a major consideration. | 0.604 |
| ADV2: The marked price of the product was the cheapest when utilizing this retail app. | 0.863 |
| ADV3: The total price (product + shipping + handling) was the cheapest when utilizing this retail app. | 0.800 |
| *(iii) Channel Transparency [α=0.882; rho_A = 0.959; CR=0.910; AVE=0.669; Full Collinearity=1.041]* | |
| The expected date of receipt of the product is clear when purchasing through this app. | 0.748 |
| The delivery information is readily available when using this app. | 0.842 |
| I know when my order has been received using this app. | 0.884 |
| I know when my order has been shipped or is being compiled using this app. | 0.806 |
| I know when my order has been delivered or is ready to be picked up in this app. | 0.803 |
| *(iv) Product Guarantee [α=0.722; rho_A = 0.722; CR=0.844; AVE=0.643; Full Collinearity=1.284]* | |
| PG1: The quantity and quality of the products I received from this retail app are exactly the same as in my order. | 0.813 |
| PG2: This retail app honours their product guarantees. | 0.825 |
| PG3: The products I ordered are delivered to me within the time frame promised by this retail app. | 0.767 |
| *(v) After-sales Service [α=0.778; rho_A = 0.782; CR=0.871; AVE=0.692; Full Collinearity=1.284]* | |
| AS1: In this retail app, the process of call for after-sales service is simple. | 0.805 |
| AS2: In this retail app, the restoration of the system is fast. | 0.825 |
| AS3: In this retail app, the result of after-sales service is desirable. | 0.864 |
| *(vi) Monetary Promotion [α=0.783; rho_A = 0.790; CR=0.874; AVE=0.700; Full Collinearity=1.368]* | |
| MP1: This retail app frequently offers price discounts. | 0.847 |
| MP2: This retail app often uses price discounts. | 0.890 |
| MP3: This retail app uses price discounts more frequently than other competing brands. | 0.768 |
| *(vii) Non-monetary Promotion [α=0.898; rho_A = 0.899; CR=0.937; AVE=0.831; Full Collinearity=1.269]* | |
| NMP1: This retail app frequently offers gifts. | 0.910 |
| NMP2: This retail app often uses gifts. | 0.930 |
| NMP3: This retail app uses gifts more frequently than other competing brands. | 0.895 |
| *(viii) Ease of Payment [α=0.578; rho_A = 0.584; CR=0.780; AVE=0.542; Full Collinearity=1.242]* | |
| EOP1: This retail app has efficient payment procedures. | 0.673 |
| EOP2: The payment procedures of this retail app seem to take a long time. | D |
| EOP3: The payment facilities of this retail app are easy to use. | 0.793 |
| EOP4: Paying for goods in this retail app is straightforward. | 0.738 |
| | D |

(*continued on next page*)

**Table 2** (*continued*)

| Construct | Loading |
|---|---|
| EOP5: Paying for goods in this retail app does not involve entering a lot of details. | |
| **Consumer Engagement (CE)** | |
| *(i) Conscious Attention [α=0.827; rho_A = 0.842; CR=0.873; AVE=0.536; Full Collinearity=1.682]* | |
| CA1: I like to know more about this retail app. | 0.643 |
| CA2: I like the events that are related to this retail app. | 0.625 |
| CA3: I like to learn more about this retail app. | 0.738 |
| CA4: I pay a lot of attention to anything about this retail app. | 0.805 |
| CA5: I keep up with things related to this retail app. | 0.789 |
| CA6: Anything related to this retail app grabs my attention. | 0.772 |
| *(ii) Enthused Participation [α=0.877; rho_A = 0.882; CR=0.911; AVE=0.673; Full Collinearity=1.882]* | |
| EP1: I spend a lot of my discretionary time visiting this retail app. | 0.773 |
| EP2: I am heavily into this retail app. | 0.834 |
| EP3: Visiting this retail app is part of my schedule. | 0.883 |
| EP4: I am passionate about this retail app. | 0.848 |
| EP5: My days would not be the same without this retail app. | 0.758 |
| *(iii) Social Connection [α=0.870; rho_A = 0.870; CR=0.920; AVE=0.794; Full Collinearity=1.418]* | |
| SC1: I love talking about this retail app with my friends. | 0.868 |
| SC2: I enjoy visiting this retail app more when I am with my friends. | 0.909 |
| SC3: Visiting this retail app with my friends is fun. | 0.896 |
| **Continuance Use Intention** *[α=0.873; rho_A = 0.874; CR=0.913; AVE=0.724; Full Collinearity=1.560]* | |
| CONT1: I intend to continue using this retail app. | 0.846 |
| CONT2: I plan to keep using this retail app. | 0.864 |
| CONT3: I expect to continue using this retail app. | 0.869 |
| CONT4: If I could, I would like to continue my use of this retail app. | 0.824 |
| **Promotion Focus** *[α=0.640; rho_A = 0.509; CR=0.771; AVE=0.532; Full Collinearity=1.184]* | |
| PRO1: When I see an opportunity for something I like, I get excited right away. | 0.742 |
| PRO2: I frequently imagine how I will achieve my hopes and aspirations. | 0.612 |
| PRO3: I see myself as someone who is primarily striving to reach my "ideal self"—to fulfil my hopes, wishes, and aspirations. | 0.820 |
| **Prevention Focus** *[α=0.611; rho_A = 0.633; CR=0.789; AVE=0.556; Full Collinearity=1.368]* | |
| PRE1: I worry about making mistakes. | 0.800 |
| PRE2: I frequently think about how I can prevent failures in my life. | 0.766 |
| PRE3: I see myself as someone who is primarily striving to become the self I "ought" to be—fulfil my duties, responsibilities, and obligations. | 0.664 |

Note: *D*= Item deleted; CR=Composite Reliability; AVE=Average Variance Extracted.

produced a variance inflation factor (VIF) between 1.041 and 1.882, which is less than 3.33, suggesting CMV was not likely to be an issue (Kock and Lynn, 2012).

### 5.2. Assessing the reflective measurement model

Various approaches were used to evaluate the constructs' reliability and validity. First, the internal consistency of items was evaluated. Table 2 results showed all constructs had Cronbach's alphas (α), rho_A, and composite reliability (CR) values exceeding the minimum rule of thumb of 0.70 (Hair et al., 2019). Second, the convergent validity of the constructs was checked using outer loadings and average variance extracted (AVE) scores. Table 2 showed most items met suggested outer loading criteria (between 0.604 to 0.930) (Bagozzi et al., 1991) and three items (i.e., PA4, EOP2 and EOP5) with low loading were excluded.[4] The AVE scores illustrated all the constructs exceeded the suggested 0.50 minimum (Bagozzi and Yi, 1988; Fornell and Larcker, 1981) (see Table 3). Finally, Heterotrait-Monotrait (HTMT) ratio was used to check for discriminant validity (Henseler et al., 2015). As can be seen in Table 3, the constructs' HTMT values were all below the conservative threshold of 0.85 (Kline, 2011), confirming their discriminant validity.

### 5.3. Assessing the higher-order constructs (HOCs)

Three constructs (AP, MM and CE) were reflective-formative HOCs. The assessment of HOC was undertaken using a disjoint two-stage approach[5] (Sarstedt et al., 2019a). First, the convergent validity of the HOC was measured using a single global item, as suggested by Cheah, Sarstedt, Ringle, Ramayah, and Ting (2018). A redundancy analysis found the global single-item measure of AP, MM and CE had path coefficients of 0.769, 0.720 and 0.705 respectively, suggesting the sub-dimensions explained more than 50% of the criterion construct's variance (Table 4). None of the LOCs was negatively affected by collinearity, as the VIF values were less than 3.33, ranging from 1.012 to 1.669 (Table 4) (Becker, Ringle, Sarstedt, and Völckner, 2015). Therefore, collinearity was not at a critical level for the three HOCs. Finally, the LOCs' outer weights and significance were examined (Sarstedt et al., 2019a). Both LOCs (i.e., social presence = 0.519; telepresence = 0.619) had a pronounced and significant effect ($p<0.05$) on AP, while five out of eight LOCs (i.e., ease of payment = 0.282; monetary promotion = 0.223; price advantage = 0.123; product assortment = 0.455; product guarantee = 0.292) were statistically significant ($p<0.05$) impacted on MM. However, all of the MM sub-dimensions were retained to capture its domain fully. Finally, the sub-dimensions for CE (conscious attention = 0.476; enthused participation = 0.505; social connection = 0.234) all had a significant effect. Thus, consistent with the previous research, the three HOCs were found to be formatively formed by several LOCs.

### 5.4. Estimating the model and hypotheses testing

Table 5 shows the VIF values for all of the exogenous constructs ranged between 1.067 and 1.314, suggesting collinearity is not a problem in this case (Becker et al., 2015) and indicating the path coefficients can be assessed with confidence. The significances of the various path coefficients were assessed using a bootstrapping technique with 5000 sub-samples (Streukens and Leroi-Werelds, 2016) and the result illustrated that the five control variables (i.e., gender, age, level of education, monthly expenses through app, app usage frequency) demonstrated insignificant effects across the model (see Table 5). Contrary to our hypothesis, AP did not positively influence retail app continuance use intention (H1: β=0.001; $p$ = 0.49); therefore, H1 was not supported. However, MM did impact positively on continuance use intention (β=0.260; $p<0.001$), supporting H2. Further, CE had a positive influence on continuance use intention, supporting H3. Indeed, CE was the strongest predictor of continuance use intention (β=0.382; p-value < 0.001). Further, AP (β=0.362; $p<0.001$) and MM (β=0.251; $p<0.001$) affected CE positively, supporting H4 and H5. Hayes's (2009) method was used to assess the mediating role of CE. As can be seen in Table 5, CE significantly mediated the paths between AP ($p<0.001$) and MM ($p<0.001$) on continuance use intention, supporting H6 and H7. Overall, 28% of the variance in continuance use intention was explained by AP, MM and CE, while AP and MM are explained 24% of the variance in CE (Table 5).

Following Cohen's (2003) guidelines, CE ($f^2$ = 0.154), MM ($f^2$ = 0.082), AP ($f^2$ = 0.001) had a medium, small and trivial effect sizes on continuance use intention, respectively. AP ($f^2$ = 0.161) had a medium

[4] The outer loading values for ADV1, EOP1, CA1, CA2, PRO2, and PRE2 were in the range of 0.6 to 0.7, hence those items still remain for content validation (Hair et al., 2017). Besides, Hair et al. (2019) have suggested that item with outer loading >0.40 should not be removed if the construct achieved satisfactory values for convergent validity (> 0.50) and internal consistency (> 0.70).

[5] In the first stage, the LOC's (i.e., lower-order construct) assessment were based on a standard reflective measurement model. In the second stage, the HOC was assessed using formative measurement model criteria including an assessment of convergent validity, an examination of collinearity and an examination of the indicators' outer weights and significance.

**Table 3**
Discriminant validity result using the Heterotrait-Monotrait (HTMT) ratio correlation.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. After-sales service | | | | | | | | | | | | | | | | |
| 2. Channel Transparency | 0.073 | | | | | | | | | | | | | | | |
| 3. Conscious Attention | 0.226 | 0.047 | | | | | | | | | | | | | | |
| 4. Continuance Use Intention | 0.127 | 0.120 | 0.459 | | | | | | | | | | | | | |
| 5. Ease of Payment | 0.144 | 0.148 | 0.274 | 0.405 | | | | | | | | | | | | |
| 6. Enthused Participation | 0.214 | 0.078 | 0.634 | 0.473 | 0.124 | | | | | | | | | | | |
| 7. Monetary Promotion | 0.301 | 0.044 | 0.279 | 0.261 | 0.372 | 0.254 | | | | | | | | | | |
| 8. Non-monetary Promotion | 0.162 | 0.050 | 0.220 | 0.075 | 0.176 | 0.294 | 0.398 | | | | | | | | | |
| 9. Prevention Focus | 0.166 | 0.088 | 0.413 | 0.445 | 0.318 | 0.218 | 0.200 | 0.076 | | | | | | | | |
| 10. Price Advantage | 0.318 | 0.070 | 0.220 | 0.230 | 0.373 | 0.212 | 0.405 | 0.221 | 0.358 | | | | | | | |
| 11. Product Assortment | 0.357 | 0.062 | 0.339 | 0.433 | 0.482 | 0.226 | 0.399 | 0.127 | 0.414 | 0.421 | | | | | | |
| 12. Product Guarantee | 0.463 | 0.045 | 0.243 | 0.253 | 0.293 | 0.234 | 0.394 | 0.290 | 0.092 | 0.279 | 0.255 | | | | | |
| 13. Promotion Focus | 0.067 | 0.078 | 0.174 | 0.174 | 0.250 | 0.078 | 0.056 | 0.098 | 0.592 | 0.147 | 0.231 | 0.103 | | | | |
| 14. Social Connection | 0.107 | 0.047 | 0.414 | 0.368 | 0.098 | 0.542 | 0.151 | 0.262 | 0.219 | 0.114 | 0.067 | 0.195 | 0.084 | | | |
| 15. Social Presence | 0.257 | 0.059 | 0.341 | 0.232 | 0.136 | 0.396 | 0.145 | 0.188 | 0.116 | 0.190 | 0.176 | 0.224 | 0.066 | 0.308 | | |
| 16. Telepresence | 0.228 | 0.058 | 0.362 | 0.246 | 0.156 | 0.418 | 0.161 | 0.257 | 0.103 | 0.171 | 0.155 | 0.204 | 0.094 | 0.313 | 0.685 | |

Note: HTMT<0.85 (Kline, 2015).

**Table 4**
Result of higher-order construct.

| Higher-order Construct | Sub-dimension for LOC | Convergent Validity | Outer VIF | Outer Weight | Std. Error | t-value | p-value |
|---|---|---|---|---|---|---|---|
| Anthropomorphism Presence (AP) | (i) Social Presence | 0.769 | 1.415 | 0.519 | 0.137 | 3.781 | 0.000 |
| | (ii) Telepresence | | 1.415 | 0.619 | 0.131 | 4.730 | 0.000 |
| Marketing Mix (MM) | (i) Product Assortment | | 1.222 | 0.455 | 0.109 | 4.180 | 0.000 |
| | (ii) Price Advantages | 0.720 | 1.195 | 0.123 | 0.106 | 1.164 | 0.245 |
| | (iii) Channel Transparency | | 1.020 | 0.149 | 0.107 | 1.396 | 0.163 |
| | (iv) Product Guarantee | | 1.249 | 0.292 | 0.105 | 2.795 | 0.005 |
| | (iv) After-Sales Service | | 1.233 | 0.046 | 0.100 | 0.455 | 0.649 |
| | (vi) Monetary Promotion | | 1.334 | 0.223 | 0.111 | 2.003 | 0.046 |
| | (vii) Non-monetary Promotion | | 1.157 | 0.192 | 0.129 | 1.485 | 0.138 |
| | (viii) Ease of Payment | | 1.178 | 0.282 | 0.108 | 2.619 | 0.009 |
| Consumer Engagement (CE) | (i) Conscious Attention | 0.705 | 1.489 | 0.476 | 0.077 | 6.186 | 0.000 |
| | (ii) Enthused Participation | | 1.669 | 0.505 | 0.076 | 6.644 | 0.000 |
| | (iii) Social Connection | | 1.314 | 0.234 | 0.082 | 2.875 | 0.004 |

Note: VIF = Variance Inflation Factor.

effect size, and MM ($f^2 = 0.077$) had a small effect size on CE. Predictive relevance was assessed through Stone-Geisser's $Q^2$ statistic (Geisser, 1974; Stone, 1974). The $Q^2$ for continuance use intention was 0.188 and for CE was 0.136, as both are greater than zero, the model had predictive relevance. The PLSpredict technique (see Shmueli et al., 2019) was used to examine the prediction relevance of the endogenous construct. As presented in Table 6, most of the values for continuance use intention items had a lower prediction error (i.e., RMSE and MAE) than the linear model (LM), except for CONT1 and CONT2, suggesting continuance use intention had medium prediction power (Shmueli et al., 2019). Such a result is likely due to Millennials being connected to a number of technologies and digital platforms that impact on their lifestyles, preferences and behavior (Bento et al., 2018); thus, their behaviors are more sophisticated. Indeed, the prediction results show the importance of using Herzberg et al.'s (1987; 1965) Two-factor Theory when examining retail app continuance use intention, as Millennials typically have diverse needs when using a technological device. In this case, we have suggested AP, MM and CE as important antecedents that impact on continuance use intention.

### 5.5. Robustness checks

To check the robustness of the results, a series of supplementary analyses were undertaken, including nonlinearity, endogeneity, and unobserved heterogeneity (Sarstedt et al., 2019b). A two-step process was used to test for potential nonlinearities (Sarstedt et al., 2019b; Pierce and Aguinis, 2013). Initially, Ramsey RESET (1969) approach was used. The results suggested neither the partial path model of AP and MM on CE [F (3487) = 0.30, $p = 0.823$], nor the partial path model of AP, CE and MM on continuance use intention [F (3487) = 0.57, $p = 0.637$] were likely to be non-linear. In addition, we included interaction terms to examine potential quadratic effects. As no significant changes were found, it is unlikely there were nonlinear effects in our study (see Appendix A1).

As this study examined several hypotheses, it is important to consider potential endogeneity problems that could arise if constructs have been omitted (Sarstedt et al., 2019b). Park and Gupta's (2012) Gaussian copula approach was utilized to examine this issue.[6] The results in Appendix A2 show the combinations of Gaussian copulas in the model. As none were significant (p-value > 0.05), we can conclude there are no endogeneity problems, confirming the model's robustness (Hult et al., 2018).

[6] Before initiating the Gaussian copula approach to meet its assumptions, we first ran the Kolmogorov–Smirnov test with Lilliefors correction on the latent variable scores (i.e., AP, CE, and MM), which serve as independent variables in the PLS path model's partial regressions. The results show that none of the constructs were normally distributed scores (see Appendix A2 that all the constructs' p-value were below 0.05), allowing us to proceed with Gaussian copula approach.

**Table 5**
Result of structural model.

| Path Relationship | Direct Effect | Indirect Effect | Std. Error | t-value | CI | VIF | $f^2$ | $R^2$ | $Q^2$ |
|---|---|---|---|---|---|---|---|---|---|
| H1) AP -> Continuance Use Intention | 0.001 | | 0.038 | 0.017 | (−0.058, 0.063) | 1.239 | 0.001(T) | 0.281 | 0.188 |
| H2) MM -> Continuance Use Intention | 0.260 | | 0.05 | 5.283** | (0.178, 0.346) | 1.149 | 0.082 (S) | | |
| H3) CE -> Continuance Use Intention | 0.382 | | 0.046 | 8.449** | (0.302, 0.453) | 1.314 | 0.154 (M) | | |
| H4) AP -> Consumer Engagement | 0.362 | | 0.045 | 7.863** | (0.281, 0.436) | 1.067 | 0.161(M) | 0.236 | 0.136 |
| H5) MM -> Consumer Engagement | 0.251 | | 0.051 | 5.264** | (0.180, 0.346) | 1.067 | 0.077 (S) | | |
| H6) AP -> CE -> Continuance Use Intention | | 0.138 | 0.025 | 5.527** | (0.092, 0.191) | | | | |
| H7) MM -> CE -> Continuance Use Intention | | 0.096 | 0.025 | 3.861** | (0.045, 0.138) | | | | |
| H8) AP*Promotion Focus-> CE | −0.012 | | 0.045 | 0.275 | (−0.083, 0.054) | | | | |
| H9) MM*Prevention Focus -> CE | 0.097 | | 0.038 | 2.523* | (0.045, 0.173) | | | | |
| **Control Variable** | | | | | | | | | |
| Gender -> CE | 0.062 | | 0.053 | 1.167 | (−0.033, 0.096) | | | | |
| Age -> CE | 0.051 | | 0.040 | 1.266 | (−0.013, 0.085) | | | | |
| Education Level -> CE | 0.024 | | 0.060 | 0.407 | (−0.068, 0.127) | | | | |
| Monthly Expenses through App -> CE | 0.042 | | 0.051 | 0.828 | (−0.033, 0.137) | | | | |
| App Usage Frequency -> CE | 0.052 | | 0.063 | 0.826 | (−0.067, 0.141) | | | | |
| Gender -> Continuance Use Intention | 0.018 | | 0.051 | 0.356 | (−0.060, 0.097) | | | | |
| Age -> Continuance Use Intention | 0.027 | | 0.054 | 0.506 | (−0.038, 0.086) | | | | |
| Education Level-> Continuance Use Intention | 0.040 | | 0.054 | 0.745 | (−0.004, 0.152) | | | | |
| Monthly Expenses through App-> Continuance Use Intention | 0.042 | | 0.051 | 0.828 | (−0.033, 0.137) | | | | |
| App Usage Frequency -> Continuance Use Intention | 0.077 | | 0.063 | 1.214 | (−0.048, 0.152) | | | | |

Note: **$p<0.05$, *$p<0.001$; AP (Anthropomorphism Presence); MM (Marketing Mix); CE (Consumer Engagement); CI (Confidence Interval); Effect Size (T: Trivial; S: Small; M: Medium).

**Table 6**
Result of PLSpredict.

| | PLS | | | LM | | | PLS-LM | | | Predict Power |
|---|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAE | $Q^2$_predict | RMSE | MAE | $Q^2$_predict | RMSE | MAE | $Q^2$_predict | |
| CONT1 | 0.896 | 0.722 | 0.141 | 0.887 | 0.717 | 0.158 | 0.009 | 0.005 | −0.017 | Medium |
| CONT2 | 0.902 | 0.709 | 0.086 | 0.888 | 0.705 | 0.114 | 0.014 | 0.004 | −0.028 | |
| CONT3 | 0.911 | 0.709 | 0.103 | 0.912 | 0.713 | 0.101 | −0.001 | −0.004 | 0.002 | |
| CONT4 | 0.956 | 0.761 | 0.083 | 0.961 | 0.767 | 0.073 | −0.005 | −0.006 | 0.01 | |

Note: CONT (Continuance Use Intention).

Finally, potential unobserved heterogeneity was examined using finite mixture PLS (FIMIX-PLS) procedure (Sarstedt et al., 2017).[7] Given the minimum sample size requirement to reliably estimate the model on each segment (Hair et al., 2017), we evaluated two- and three-segment solutions. The $AIC_3$ and CAIC statistics, which work well in FIMIX-PLS contexts (Sarstedt et al., 2011) suggested the two-segment solution was superior. However, the entropy values were well below the commonly suggested 0.50 threshold, suggesting unobserved heterogeneity was not an issue here.

### 5.6. Moderating effect

The bootstrapping technique was used to examine the suggested moderation effect (Table 5). The two-stage latent interaction technique (Becker et al., 2018) suggested having a promotion focus did moderate the proposed relationship (β=−0.012; p-value=0.392). Thus, H8 was not supported. In contrast, having prevention focus significantly impact the relationship between MM and CE (β=0.097; p-value < 0.05), supporting H9. Due to positive moderating effect (β=0.097), the plot illustrates that the slope of high prevention (dotted line) is steeper compare to low prevention focus (solid line) (see Fig. 3). Therefore, it can be concluded that the relationship between MM and CE is stronger with high level of prevention focus, compared to low prevention focus.

## 6. Discussion, theoretical and practical contributions

### 6.1. Discussion of findings

The first objective of our study was to examine the antecedents that encourage retail app continuance use intention. Drawing on the Two-factor Theory (Herzberg et al., 1987, 1965), we suggested AP and MM (i.e., motivation and hygiene factors) as the determinants that can influence continuance use intention. Surprisingly, contradicting with the initial prediction, AP did not significantly predict continuance use

[7] Following Matthews et al. (2016), we initiated the procedure by assuming a one-segment solution, using the default settings for the stop criterion ($10^{-10}$ = 1.0E-10), the maximum number of iterations (5000), and the number of repetitions (10).

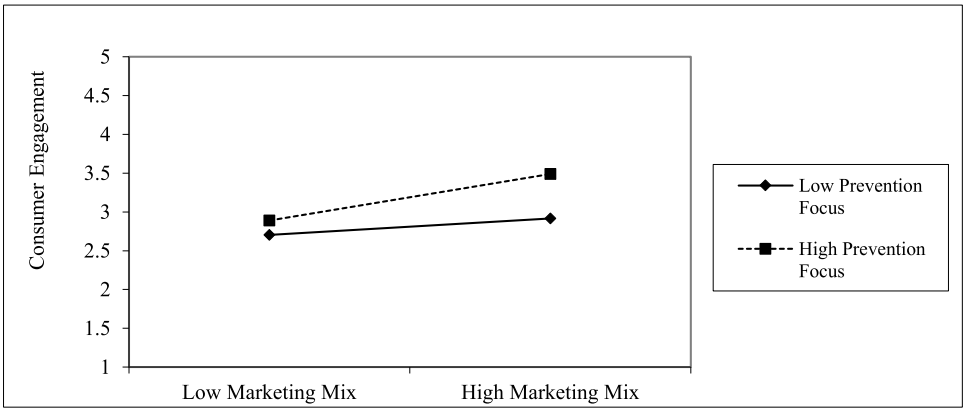



**Fig. 3.** Interaction plot (Marketing Mix*Prevention Focus).

intention directly, although several earlier studies have found a positive link between AP and consumer behavior (Roy and Naidoo, 2021; Moriuchi, 2021). However, it is worth it to note that AP does indirectly influence continuance use intention through CE. This coincided with the notion highlighted by Longoni et al. (2019), that users find humanlike technology less capable in understanding their needs and wishes over time, making the existence of AP a double-edged sword. When technology becomes more "human", consumers may find such features increasingly unnerving (Davenport et al., 2020). In the case of the retail app, the humanized features (i.e., AP) alone is not enough to cause continuance use intention; the features need to also be engaging or appealing to consumers. This would also seem to indicate that human interactions cannot be replaced entirely by technology (Ostrom et al., 2019). Instead, the relationship between consumers and retailers remains the driving force behind a successful retail app acceptance strategy.

Moreover, the result of this study showed that MM exerts a positive influence on retail app continuance use intention. The significant relationship supports the claim that MM (i.e., hygiene factor) is the basic need that must be fulfilled in order to maintain the use of a retail app (Herzberg, 1965, 1987). This once again confirmed (McCatthy's 1960) idea that MM is a crucial predictor of positive behavior, such as purchase intention and patronage intention. When MM is well-established, it is easier for retailers to elicit positive responses from consumers. Besides, MM has been acknowledged as one of the key strategies to maintain relationship, and convert consumers into "patrons" in both online and offline platforms (Liu et al., 2019).

Furthermore, consistent with the assertion regarding the role of CE in shaping consumer behavior (i.e., Flavián et al., 2019; Dwivedi et al., 2020), this study denoted that CE is the strongest predictor in influencing users to continue using a particular retail app. Earlier literature exhibit anecdotal evidence that engagement is particularly important to create a constant connection and seamless experience across online selling platforms ( Gursoy et al., 2019). This implies that it is imperative for retailers to shift away from traditional marketing and to instead adopt a collaborative approach to engage with their target market, (i.e., receiving and responding to their feedback).

Compared to MM, AP may play a more substantial role in enhancing CE (as indicated by higher effect size). As predicted, when AP is high, users can feel and sense warmth, and thus they are likely to engage more with the retail app. This result is in line with previous literature, which also found product and technology with anthropomorphism characteristics have a positive impact on perceived enjoyment (Baker et al., 2019), trust (Peng and Ke, 2015), and willingness to pay (Yuan and Dennis, 2019). The act of "humanizing" online platform is indeed an effective way to increase virtual "presence", as well as to gain visibility and sales (Baker et al., 2019). Therefore, it can be concluded that AP is a key factor in determining users' stickiness and engagement towards a particular retail app. In addition, MM was found to influence CE. Undeniably, MM has consistently reported a positive impact on consumer behavior (i.e., Chatterjee, 2018; Wu and Li, 2018). In the online selling platform, MM remains a set of tactical tools that should be used by the retailers to maintain and sustain retail patronage and performance (Berman and Evans, 2010). This study offers evidence on the role of MM in coordinating and building a long-term relationship with target consumers in the online market (i.e., retail app), adding to the limited literature in this area.

In the second objective, we aim to examine the mediating role of CE. Indeed, our findings have shown that CE is a significant mechanism that links retail app features (i.e., AP and MM) to continuance use intention. Corresponding to Wang et al.'s (2019), retail app with a combination of excellent marketing and technology attributes (i.e., MM and AP) did enhance CE to achieve optimal marketing goals (i.e., continuance app usage). As stated by Dessart et al. (2016), engagement is a necessity to facilitate continuance interaction. The current finding is consistent with those of de Oliveira et al. (2016) and Harrigan et al. (2018), who reported the mediating effect of CE on retail device usage intention. Therefore, contemporary marketing should consider customer-centric strategies by creating emotional bonding (i.e., build and boost relationship with users) through the "engagement" process. In this case, when AP and MM are enhanced, CE becomes the key factor that contribute to retail app continuance usage.

The last objective focuses on investigating the moderating role of consumer differences (i.e., prevention focus and promotion focus) in bringing differential effect on CE. In this study, the moderating results showed that prevention-focused consumers are more likely to use MM as a cue in engagement decision. As predicted, MM to CE path is stronger among consumers who are higher in prevention focus. Such interaction infers that MM is prevalent in heightening engagement among high prevention-focused consumers. As highlighted by Liang et al. (2013), the desired state of prevention-focused is the absence of negative outcomes, which they aimed at minimizing loss. That is, prevention-focused consumers prefer to "play it safe" by focusing on important marketing information to prevent potential loss from over-committing their

engagement level. The significant finding corresponds to the formative characteristics of the target sample in this study (i.e., Millennials) who are more sceptical and pragmatic compared to other generations (Ladhari et al., 2019). As outlined by Millennial Marketing Production (2010), a vast majority of Millennials are labelled as "Gen-Frugal", a generation who are more cost-conscious and vigilant towards promotions and special offers. This segment of consumers will emphasize more on MM features as they want to avoid potential future losses by knowing more about product, price, and promotion information.

On the other hand, the interaction analysis indicated that AP on CE did not differ across the low and high promotion-focused consumers. The insignificant moderating effect specifies that AP to CE relationship is robust across high or low promotion-focused Millennials. That is, AP influence on CE is not conditional on Millennials' differences on being promotion-focused. Parallel with other studies, AP is found as one of the practical tools to stimulate engagement (Tuškej and Podnar, 2018). This phenomenon largely coincides with the characteristics and lifestyle of the Millennials, who live a fast-paced and socially connected lifestyle. As noted by Parment (2013), Millennials are characterized as technological natives, complete with full information, making this generation cohort less loyal and more demanding. As such, the implementation of AP in technology (i.e., retail app) can significantly contribute in enhancing a sense of immersion, presence and confidence (Poushneh, 2018; van Esch et al., 2019), regardless of whether the targeted Millennials are high, or low promotion-focused.

### 6.2. Theoretical contributions

The present study contributes to the literature in three different aspects. First, this study extends the use of the Two-factor Theory (Herzberg, 1965, 1987) to the context of the retail app. Tracing its roots to IS theories, both "hygiene" and "motivation" factors are essential in motivating the continuance use of technology among users. Responding to (Wang et al.'s, 2019) suggestion, both MM (i.e., hygiene factor) and AP (i.e., motivation factor) should be integrated to create an optimal retail app marketing strategy. In particular, the results of this study established that MM represents a vital cue that need to be incorporated in driving retail app continuance use intention. Regardless of offline or online settings, MM acts as a necessary foundation to develop a successful marketing strategy that meets the needs of consumers. Conversely, AP only indirectly impacts continuance use intention through CE. Despite the apparent benefits of anthropomorphic features reported in previous literature, this study's finding suggests that AP should not be used solely to replace humans, thus adding value to existing knowledge. In addition, it is noteworthy that AP is a double-edged sword, where users may find human-like technology less capable of understanding their long-term needs (Longoni et al., 2019). Therefore, it is crucial for IS researchers to consider engagement as one of the more important tactics to influence continuance use through AP.

Second, our findings unveiled a mediation process whereby retail app features (i.e., AP and MM) influence consumers' continuance use intention via CE. Most notably, it demonstrates that relationship management (i.e., engaging with users) is desperately needed, both in physical and online spaces. Such findings echo previous claims that the toolkits of user-retailer relationships have moved beyond mere transactions to become more sophisticated (Steinhoff et al., 2019; ThaiChon et al., 2019). A high level of engagement in the digital world is often referred to as the "flow" (Osei-Frimpong and McLean, 2018), which can lead to positive responses, such as the intention to continue using a particular technology device. Through this, our research complements prior studies by offering a comprehensive understanding of the mechanism that improves continued app usage. Accordingly, the critical role of relationship management, especially in engaging Millennial users, should be given more attention in future IS studies.

Third, most previous studies have implicitly assumed homogenous user behavior across the app feature-engagement link, without considering the boundary condition of consumer differences. This study extends this stream of research by applying Higgins's (1998, 2012) RFT to explicitly test the moderating role of consumer differences in the context of the retail app. The findings discovered that prevention focus moderates the relationship between the MM and CE relationship; nevertheless, promotion focus does not moderate the relationship between AP and CE. This indicates that all promotion-focused consumers, whether high or low, rely on AP for engagement purposes. Moreover, RFT was applicable in explaining how high prevention-focused consumers tend to use MM in deriving engagement. As a result, these empirical findings fill the existing literature gap and offer novel insights into the role of consumer variations in the relationship between app features and CE, particularly in the context of the retail app.

### 6.3. Practical contributions

Apart from advancing literature through theoretical contributions, this study also offers substantial contributions from the managerial aspect. Of the factors examined, CE exhibits the highest effect on continuance use intention. The results of mediation showed that the effectiveness of app features (i.e., AP and MM) on retail app continuance use intention was primarily depended on the retailer's effectiveness in engaging with users. Strategically, retailers are suggested to introduce a compelling MM to the retail app that comprises of rich product assortments, reliable product guarantee, low price deals, excellent after-sales service, attractive monetary and non-monetary promotions, a secure payment system, as well as transparent shipping information as a compelling marketing strategy. This will enable retailers to engage with Millennial mobile shoppers and eventually stimulate their intention to continue using a retail app. Also, they are suggested to boost emotional bonding by anthropomorphize the retail app with more humanizing features, such as using human-like chatbot, 3D image, animation, and first-person language (e.g., "I", "you", etc.) as the best means to create an immersive experience. Without doubt, they should regard the formation of excellent consumer engagement as a long-term asset to uphold the continuance use of a retail app, which in turns drives advantageous business performance.

On the other hand, retailers should consider how different types of users may engage with different kinds of functions. According to the findings, prevention-focused consumers are more likely to appreciate the components of MM in determining their engagement level. Similar to other online selling tools, MM is one of the more important cues that assist in alleviate barriers when using the retail app, especially for prevention-focused consumers. In this case, retailers may be able to engage with prevention-focused consumers if they able to develop an authentic and fair MM that meets the expectations of mitigating loss. For example, consistency communicating to users in terms of delivery efficiency, reliable promotion, detailed purchase information, great after-sales service, etc. These strategies will, in turn, increase users' trust and reduce the perception of loss.

Furthermore, we provide implications for IS managers (i.e., app developer), particularly in improving the development and execution of functional features. Humanizing the retail app by making it look, sound, and feel more human is the secret recipe for attracting users to get engaged with the app. Accordingly, app developers are suggested to embed more humanized features within the retail app using a

conversational interface (chatbot), voice recognition, live streaming video when the products are displayed. These strategies are expected to enhance the feelings of users "being there", giving them the feeling of being physically present in an online store. Furthermore, it is suggested that the app to have built-in featured that can facilitate human warmth, sensitivity, and contact, which can improve the interpersonal relationship between users and retailers. For instance, by implementing artificial intelligence machine that able to analyse their location, past interaction, past buying behavior, demographics, and etc., will provide opportunities for retailers to display/deliver personalize content to each user (Dacko, 2017). Through this personalize interaction, such features may create a feeling of humanity between the retailer with user (transmitting messages tailored to each consumer's special queries and needs), thus stimulate engagement behavior.

## 7. Conclusion and future research directions

We drew on Two-factor theory to develop and examine a model of Millennial mobile shoppers' intentions to continue using a retail app. The results provide answers to the first objective, that is, continuance use intention was positively influenced by MM, but not AP. We also provided evidence that CE is an important mechanism that should not be overlooked in establishing a positive impact between MM and AP towards continuance use intention, which addressed the second objective of this study. With regards to third objective, we found the relationship between MM and CE was stronger for prevention-focused consumers, thus adding to our understanding of consumer characteristic that impact on CE.

Despite these findings, the study has some limitations. First, data were only collected in Malaysia, making it impossible to see whether cultural values play a role. Future IS research can reexamine this issue by collecting cross-country data. The research committee suggested continuance use may be impacted by national culture (Sunny et al., 2019; Wang et al., 2017), hence it would be useful to investigate the similarities and differences between Millennial's behaviors across different countries. Second, the composition of respondents chosen in this study were unequal, for instance, number of female is greater than male. To overcome sample self-selection bias, it is suggested to apply the weighted PLS (WPLS) algorithm as a possible solution to ensure sample representative while avoid imperfections in terms of non-response and non-coverage (Cheah et al., 2020). Third, the insignificant relationship between AP and continuance use intention portrays an interesting direction for future studies. As remarked by Steinhoff et al. (2019), privacy issues have emerged as one of the key concerns in the ever-changing digital landscape. Human-like virtual agents may put forth the notion of the "uncanny valley", where humans tend to perceive humanoid interaction as a threat that evokes a sense of unease (MacDorman and Chattopadhyay, 2016; Gray and Wegner, 2012). A recent study by (ThaiChon et al. 2019) alluded that privacy infringement is one possible reason that leads to value destruction in online marketing. To consolidate existing knowledge, it would be interesting for future IS research to examine how privacy concerns, as a boundary condition, may strengthen or weaken the relationship between technology features and continuance use intention.

## Acknowledgement

We would like to express our gratitude to Yayasan Muhibbah Tan SriFng Ah Seng for financially funding this research (Grant ID: 6300255-10601).

## Appendices

Tables A1, A2 and A3

**Table A1**
Result of the non-linear approach.

| Non-Linear Relationship | Std Beta | Std Error | t-value | p-value | BCa 95% Confidence Interval LB | UB | $f^2$ | Ramsey's reset test |
|---|---|---|---|---|---|---|---|---|
| AP*AP -> CE | 0.027 | 0.038 | 0.720 | 0.471 | −0.045 | 0.103 | 0.002 | F (3487) = 0.30, $p = 0.823$ |
| MM*MM -> CE | −0.022 | 0.036 | 0.606 | 0.545 | −0.097 | 0.044 | 0.001 | |
| AP*AP -> CUI | −0.037 | 0.027 | 1.390 | 0.165 | −0.093 | 0.013 | 0.003 | F (3487) = 0.57, $p = 0.637$ |
| CE*CE -> CUI | 0.015 | 0.029 | 0.533 | 0.594 | −0.038 | 0.074 | 0.001 | |
| MM*MM -> CUI | 0.012 | 0.029 | 0.422 | 0.673 | −0.048 | 0.068 | 0.000 | |

Note: AP (Anthropomorphism Presence); MM (Marketing Mix); CE (Consumer Engagement); CUI (Continuance Use Intention).

**Table A2**
Result of the endogeneity test using the Gaussian Copula approach.

| | Gaussian Copula of Model 1 (Endogenous Variable; AP) | | Gaussian Copula of Model 2 (Endogenous Variable; MM) | | Gaussian Copula of Model 3 (Endogenous Variable; CE) | | Gaussian Copula of Model 4 (Endogenous Variables; AP & MM) | | Gaussian Copula of Model 5 (Endogenous Variables; MM & CE) | | Gaussian Copula of Model 6 (Endogenous Variables; AP & CE) | | Gaussian Copula of Model 7 (Endogenous Variables; AP, CE, & MM) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient | p-value | Coefficient | p-value | Coefficient | p-value | Coefficient | p-value | Coefficient | p-value | Coefficient | p-value | Coefficient | p-value |
| AP | 0.214 | 0.078 | 0.001 | 0.981 | 0.001 | 0.976 | 0.216 | 0.073 | 0.001 | 0.972 | 0.232 | 0.057 | 0.232 | 0.055 |
| CE | 0.383 | 0.000 | 0.382 | 0.000 | 0.258 | 0.206 | 0.383 | 0.000 | 0.278 | 0.176 | 0.215 | 0.307 | 0.235 | 0.262 |
| MM | 0.267 | 0.000 | 0.063 | 0.847 | 0.256 | 0.000 | 0.060 | 0.861 | 0.086 | 0.790 | 0.262 | 0.000 | 0.092 | 0.783 |
| CAP | −0.191 | 0.564 | | | | | −0.196 | 0.542 | | | −0.193 | 0.549 | −0.183 | 0.661 |
| CCE | | | | | 0.126 | 0.496 | | | 0.105 | 0.575 | 0.171 | 0.373 | 0.150 | 0.436 |
| CMM | | | 0.195 | 0.544 | | | 0.205 | 0.547 | 0.170 | 0.594 | | | 0.170 | 0.608 |

*Note: The* Kolmogorov–Smirnov test with Lilliefors correction (Sarstedt and Mooi, 2019) on the latent variable scores [i.e., AP (p-value was < 0.000), CE (p-value was < 0.009), and MM (p-value was <0.036)] were significant, allowing us to proceed with Park and Gupta's (2012) Gaussian copula approach.

**Table A3**
Result of the unobserved heterogeneity using the FIMIX approach.

| Criteria | Number of Segments 2 | 3 |
|---|---|---|
| AIC (Akaike's Information Criterion) | 2499.33 | 2497.22 |
| AIC 3 (Modified AIC with Factor 3) | 2514.33 | 2520.22 |
| AIC 4 (Modified AIC with Factor 4) | 2529.33 | 2543.22 |
| BIC (Bayesian Information Criteria) | 2562.34 | 2593.83 |
| CAIC (Consistent AIC) | 2577.34 | 2616.83 |
| HQ (Hannan Quinn Criterion) | 2524.07 | 2535.15 |
| MDL5 (Minimum Description Length with Factor 5) | 2934.37 | 3164.28 |
| LnL (LogLikelihood) | −1234.67 | −1225.61 |
| EN (Entropy Statistic (Normed)) | 0.233 | 0.496 |
| NFI (Non-Fuzzy Index) | 0.286 | 0.521 |
| NEC (Normalized Entropy Criterion) | 377.995 | 243.648 |

## References


Ahn, H.-.K., Kim, H.J., Aggarwal, P., 2014. Helping fellow beings: anthropomorphized social causes and the role of anticipatory guilt. Psychol. Sci. 25 (1), 224–229.

App Annie (2018). End-of-year retrospective report. Retrieved 21 February 2019 from http://go.appannie.com/1801RetrospectiveENLP_LP01RegisterUpdated.html?utm_source=facebook&utm_medium=paidsocial&utm_campaign=emea-paidsocial-rtg-201801-1801-emearetro-rtg-&-adbridge&utm_content=report-&sfdcid=7016F0000026f0V.

Avnet, T., Higgins, E.T., 2003. Locomotion, assessment, and regulatory fit: value transfer from "how" to "what. J. Exp. Soc. Psychol. 39 (5), 525–530.

Bagozzi, R.P., Yi, Y., 1988. On the evaluation of structural equation models. J. Acad. Mark. Sci. 16 (1), 74–94.

Bagozzi, R.P., Yi, Y., Phillips, L.W., 1991. Assessing construct validity in organizational research. Adm. Sci. Q. 36 (3), 421–458.

Baker, E.W., Hubona, G.S., Srite, M., 2019. Does "being there" matter? The impact of web-based and virtual world's shopping experiences on consumer purchase attitudes. Inf. Manag. 56 (7), 103153.

Bassett-Jones, N., Lloyd, G.C., 2005. Does Herzberg's motivation theory have staying power? J. Manag. Dev. 24 (10), 929–943.

Becker, J.-.M., Ringle, C.M., Sarstedt, M., 2018. Estimating moderating effects in PLS-SEM and PLSc-SEM: interaction term generation* data treatment. J. Appl. Struct. Equ. Model. 2 (2), 1–21.

Becker, J.-.M., Ringle, C.M., Sarstedt, M., et al., 2015. How collinearity affects mixture regression results. Mark. Lett. 26 (4), 643–659.

Beckers, S.F., Van Doorn, J., Verhoef, P.C., 2018. Good, better, engaged? The effect of company-initiated customer engagement behavior on shareholder value. J. Acad. Mark. Sci. 46 (3), 366–383.

Bellman, S., Potter, R.F., Treleaven-Hassard, S., et al., 2011. The effectiveness of branded mobile phone apps. J. Interact. Mark. 25 (4), 191–200.

Bento, M., Martinez, L.M., Martinez, L.F., 2018. Brand engagement and search for brands on social media: comparing Generations X and Y in Portugal. J. Retail. Consum. Serv. 43, 234–241.

Berman, B., Evans, J.L., 2010. Retail Management, A Strategic Approach. Prentice Hall, Upper Saddle River, NJ.

Bhattacherjee, A., 2001. Understanding information systems continuance: an expectation-confirmation model. MIS Q. 25 (3), 351–370.

Bitner, M.J., 1992. Servicescapes: the impact of physical surroundings on customers and employees. J. Mark. 56 (2), 57–71.

Brodie, R.J., Hollebeek, L.D., & Smith, S.D. (2011). Engagement: an important bridging concept for the emerging SD logic lexicon. In Proceedings.

Buil, I., De Chernatony, L., Martínez, E., 2013. Examining the role of advertising and sales promotions in brand equity creation. J. Bus. Res. 66 (1), 115–122.

Cal, Adams, 2014. The effect of hedonistic and utilitarian consumer behavior on brand equity: Turkey–UK comparison on Coca Cola. Procedia-Social and Behavioral Sciences 150, 475–484.

Cenfetelli, R.T., 2004. Inhibitors and enablers as dual factor concepts in technology usage. J. Assoc. Inf. Syst. 5 (11), 16. Article.

Cenfetelli, R.T., Schwarz, A., 2011. Identifying and testing the inhibitors of technology usage intentions. Inf. Syst. Res. 22 (4), 808–823.

Chang, K.C., Hsu, C.L., Hsu, Y.T., Chen, M.C., 2019. How green marketing, perceived motives and incentives influence behavioral intentions. J. Retail. Consum. Serv. 49, 336–345.

Chattaraman, V., Kwon, W.-S., E., Gilbert, J., et al., 2014. Virtual shopping agents: persona effects for older users. J. Res. Interact. Mark. 8 (2), 144–162.

Chatterjee, J., 2018. Role of services marketing mix and customer-company identification in building engaged customers. Amity J. Manag. Res. 3 (1), 112–122.

Cheah, J.H., Roldán, J.L., Ciavolino, E., Ting, H., & Ramayah, T. (2020). Sampling weight adjustments in partial least squares structural equation modeling: guidelines and illustrations. Total quality management & business excellence, Forthcoming.

Chen, J.V., Tran, A., Nguyen, T., 2019. Understanding the discontinuance behavior of mobile shoppers as a consequence of technostress: an application of the stress-coping theory. Comput. Hum. Behav. 95, 83–93.

Chin, W., Cheah, J.H., Liu, Y., Ting, H., Lim, X.J., Cham, T.H., 2020. Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. Ind. Manag. Data Syst. Forthcoming.

Clemes, M.D., Gan, C., Zhang, J., 2014. An empirical analysis of online shopping adoption in Beijing, China. J. Retail. Consum. Serv. 21 (3), 364–375.
Cohen, J., 2003. A power primer. In: Kazdin, A.E. (Ed.), Methodological Issuesand Strategies in Clinical Research (3rd ed.). American Psychological Association, Washington, DC, pp. 339–348.
Criteo (2020). Mobile app engagement: how to keep them coming back. Retrieved 14 January 2021 from https://www.criteo.com/blog/mobile-app-engagement-apac/.
Dacko, S.G., 2017. Enabling smart retail settings via mobile augmented reality shopping apps. Technol. Forecast. Soc. Change 124, 243–256.
Davenport, T., Guha, A., Grewal, D., et al., 2020. How artificial intelligence will change the future of marketing. J. Acad. Mark. Sci. 48 (1), 24–42.
De Matos, C.A., Rossi, C.A.V, 2008. Word-of-mouth communications in marketing: a meta-analytic review of the antecedents and moderators. J. Acad. Mark. Sci. 36 (4), 578–596.
de Oliveira, M.J., Huertas, M.K.Z., Lin, Z, 2016. Factors driving young users' engagement with Facebook: evidence from Brazil. Comput. Hum. Behav. 54, 54–61.
Dessart, L., Veloutsou, C., Morgan-Thomas, A., 2016. Capturing consumer engagement: duality, dimensionality and measurement. J. Mark. Manag. 32 (5–6), 399–426.
Dwivedi, Y.K., Rana, N.P., Slade, E.L., Singh, N., & Kizgin, H. (2020). Editorial introduction: advances in theory and practice of digital marketing. J. Retail. Consum. Serv., (in press).
Etemad-Sajadi, R., 2016. The impact of online real-time interactivity on patronage intention: the use of avatars. Comput. Hum. Behav. 61, 227–232.
Fan, S., Lau, R.Y., Zhao, J.L., 2015. Demystifying big data analytics for business intelligence through the lens of marketing mix. Big Data Res. 2 (1), 28–32.
Fang, Y.H., 2017. Beyond the usefulness of branded applications: insights from consumer–brand engagement and self-construal perspectives. Psychol. Mark. 34 (1), 40–58.
Faryabi, M., Fesaghandis, K.S., Saed, M., 2015. Brand name, sales promotion and consumers' online purchase intention for cell-phone brands. Int. J. Mark. Stud. 7 (1), 167.
Fassnacht, M., Unterhuber, S., 2016. Consumer response to online/offline price differentiation. J. Retail. Consum. Serv. 28, 137–148.
Festa, G., Cuomo, M.T., Metallo, G., Festa, A., 2016. The (r) evolution of wine marketing mix: from the 4Ps to the 4Es. J. Bus. Res. 69 (5), 1550–1555.
Flavián, C., Ibáñez-Sánchez, S., Orús, C., 2019. The impact of virtual, augmented and mixed reality technologies on the customer experience. J. Bus. Res. 100, 547–560.
Fornell, C., Larcker, D.F., 1981. Structural equation models with unobservable variables and measurement error: algebra and statistics. J. Mark. Res. 18 (3), 382–388.
Fournier, S., Alvarez, C., 2013. Relating badly to brands. J. Consum. Psychol. 23 (2), 253–264.
Gao, W., Li, X., 2019. Building presence in an online shopping website: the role of website quality. Behav. Inf. Technol. 38 (1), 28–41.
Geisser, S., 1974. A predictive approach to the random effect model. Biometrika 61 (1), 101–107.
Gindi, A.A., Abdullah, A.M., Ismail, M.M., Nawi, N.M., 2016. Shopping drivers of generational cohorts: a comparison between night market and wet market formats for fresh fruit and vegetable purchase in Malaysia. Australas. Mark. J. 24 (2), 165–170.
Go, E., Sundar, S.S., 2019. Humanizing chatbots: the effects of visual, identity and conversational cues on humanness perceptions. Comput. Hum. Behav. 97, 304–316.
Gordon, R., 2012. Re-thinking and re-tooling the social marketing mix. Australas. Mark. J. 20 (2), 122–126.
Gray, K., Wegner, D.M., 2012. Feeling robots and human zombies: mind perception and the uncanny valley. Cognition 125 (1), 125–130.
Groß, M., 2015. Mobile shopping: a classification framework and literature review. Int. J. Retail Distrib. Manag. 43 (3), 221–241.
Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169.
Guthrie, S., 1993. Faces in the Clouds. Oxford University Press, Oxford, United Kingdom.
Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2019a. Multivariate Data Analysis, 8th ed. Cengage Learning, London.
Hair, J.F., Risher, J.J., Sarstedt, M., et al., 2019b. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24.
Hair, J.F., Sarstedt, M., Ringle, C.M., Gudergan, S.P., 2017. Advanced Issues in Partial Least Squares Structural Equation Modeling. Sage Publications, Los Angeles, CA.
Hair, J.J.F., Sarstedt, M, 2019. Factors versus composites: guidelines for choosing the right structural equation modeling method. Project Manag. J. 50 (6), 619–624.
Han, S.L., An, M., Han, J.J., Lee, J., 2020. Telepresence, time distortion, and consumer traits of virtual reality shopping. J. Bus. Res. 118, 311–320.
Han, N.R., Baek, T.H., Yoon, S., et al., 2019. Is that coffee mug smiling at me? How anthropomorphism impacts the effectiveness of desirability vs. feasibility appeals in sustainability advertising. J. Retail. Consum. Serv. 51, 352–361.
Harrigan, P., Evers, U., Miles, M.P., Daly, T., 2018. Customer engagement and the relationship between involvement, engagement, self-brand connection and brand usage intent. J. Bus. Res. 88, 388–396.
Haws, K.L., Dholakia, U.M., Bearden, W.O., 2010. An assessment of chronic regulatory focus measures. J. Mark. Res. 47 (5), 967–982.
Hayes, A.F., 2009. Beyond Baron and Kenny: statistical mediation analysis in the new millennium. Commun. Monogr. 76 (4), 408–420.
Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43 (1), 115–135.
Herzberg, F., 1965. The motivation to work among Finnish supervisors. Pers. Psychol. 18, 393–402.
Herzberg, F., 1987. One more time: how do you motivate employees? Harv. Bus. Rev. 65 (5), 109–120.
Higgins, E.T., 1998. Promotion and prevention: regulatory focus as a motivational principle. Advances in Experimental Social Psychology. Academic Press, pp. 1–46. Vol. 30.
Higgins, E.T. (2012). Regulatory focus theory.
Higgins, E.T., Shah, J., Friedman, R., 1997. Emotional responses to goal attainment: strength of regulatory focus as moderator. J. Pers. Soc. Psychol. 72 (3), 515.
Hollebeek, L.D., Srivastava, R.K., Chen, T., 2019. SD logic–informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM. J. Acad. Mark. Sci. 47 (1), 161–185.
Huang, E.Y., Lin, S.W., Huang, T.K., 2012. What type of learning style leads to online participation in the mixed-mode e-learning environment? A study of software usage instruction. Comput. Educ. 58 (1), 338–349.
Huang, S.-Y., Yang, M.M., Chen, C.-H., 2018. When do motivational factors lead to negative user experience on social networking applications? Australas. J. Inf. Syst. 22, 1–30.
Hult, G.T.M., Hair, J.F., Proksch, D., et al., 2018. Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. J. Int. Mark. 26 (3), 1–21.
Islam, J.U., Rahman, Z., 2016. Linking customer engagement to trust and word-of-mouth on Facebook brand communities: an empirical study. J. Internet Commerce 15 (1), 40–58.
Islam, J.U., Hollebeek, L.D., Rahman, Z., Khan, I., Rasool, A., 2019. Customer engagement in the service context: an empirical investigation of the construct, its antecedents and consequences. J. Retail. Consum. Serv. 50, 277–285.
Jiang, P., Rosenbloom, B., 2005. Customer intention to return online: price perception, attribute-level performance, and satisfaction unfolding over time. Eur. J. Mark. 39 (1/2), 150–174.
Kang, S., 2014. Factors influencing intention of mobile application use. Int. J. Mobile Commun. 12 (4), 360–379.
Keeling, K., McGoldrick, P., Beatty, S., 2010. Avatars as salespeople: communication style, trust, and intentions. J. Bus. Res. 63 (8), 793–800.
Khalaf, S. (2015). Shopping, productivity and messaging give mobile another stunning growth year. Retrieved 23 March 2019 from.
Kim, E., Lin, J.-S., Sung, Y., 2013. To app or not to app: engaging consumers via branded mobile apps. J. Interact. Advert. 13 (1), 53–65.
Kim, J.-H., Hyun, Y.J., 2011. A model to investigate the influence of marketing-mix efforts and corporate image on brand equity in the IT software sector. Ind. Mark. Manag. 40 (3), 424–438.
Kim, S.C., Yoon, D., Han, E.K., 2016. Antecedents of mobile app usage among smartphone users. J. Mark. Commun. 22 (6), 653–670.
Kim, S.J., Wang, R.J.-H., Malthouse, E.C., 2015. The effects of adopting and using a brand's mobile application on customers' subsequent purchase behavior. J. Interact. Mark. 31, 28–41.
Kline, R.B., 2011. Convergence of structural equation modeling and multilevel modeling. In: Williams, M., Vogt, P. (Eds.), The Sage Handbook of Innovation in Social Research Methods. Sage Publications, Thousand Oaks, CA.
Kock, N., Lynn, G., 2012. Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations. J. Assoc. Inf. Syst. 13 (7), 546–560.
Kordrostami, M., & Kordrostami, E. (2019). Secure or fearful, who will be more resentful? Investigating the interaction between regulatory focus and attachment style. J. Prod. Brand Manag., (in press).
Krishnamurthy, A., Kumar, S.R., 2018. Electronic word-of-mouth and the brand image: exploring the moderating role of involvement through a consumer expectations lens. J. Retail. Consum. Serv. 43, 149–156.
Kushwaha, G.S., Agrawal, S.R., 2015. An Indian customer surrounding 7P's of service marketing. J. Retail. Consum. Serv. 22, 85–95.
Ladhari, R., Gonthier, J., Lajante, M., 2019. Generation Y and online fashion shopping: orientations and profiles. J. Retail. Consum. Serv. 48, 113–121.
Laksmidewi, D., Susianto, H., Afiff, A.Z., 2017. Anthropomorphism in advertising: the effect of anthropomorphic product demonstration on consumer purchase intention. Asian Acad. Manag. J. 22 (1), 1–25.
Lamberton, C., Stephen, A.T., 2016. A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry. J. Mark. 80 (6), 146–172.
Leckie, C., Nyadzayo, M.W., Johnson, L.W., 2018. Promoting brand engagement behaviors and loyalty through perceived service value and innovativeness. J. Serv. Mark. 32 (1), 70–82.
Lee, S., Shin, B., Lee, H.G., 2009. Understanding post-adoption usage of mobile data services: the role of supplier-side variables. J. Assoc. Inf. Syst. 10 (12), 2.
Lee, S.-G., Chae, S.H., Cho, K.M., 2013. Drivers and inhibitors of SaaS adoption in Korea. Int. J. Inf. Manag. 33 (3), 429–440.
Lemon, K.N., Verhoef, P.C., 2016. Understanding customer experience throughout the customer journey. J. Mark. 80 (6), 69–96.
Letheren, K., Martin, B.A., Jin, H.S., 2017. Effects of personification and anthropomorphic tendency on destination attitude and travel intentions. Tourism Management 62, 65–75.
Liang, H., Xue, Y., Wu, L., 2013. Ensuring employees' IT compliance: carrot or stick? Inf. Syst. Res. 24 (2), 279–294.
Liew, T.W., Tan, S.M., Ismail, H., 2017. Exploring the effects of a non-interactive talking avatar on social presence, credibility, trust, and patronage intention in an e-commerce website. Hum. Centr. Comput. Inf. Sci. 7 (1), 42.
Lim, J.S., Hwang, Y., Kim, S., et al., 2015. How social media engagement leads to sports channel loyalty: mediating roles of social presence and channel commitment. Comput. Hum. Behav. 46, 158–167.

Liu, H., Lobschat, L., Verhoef, P.C., Zhao, H., 2019. App adoption: the effect on purchasing of customers who have used a mobile website previously. J. Interact. Mark. 47, 16–34.
Lo, L.Y.S., Lin, S.W., Hsu, L.Y, 2016. Motivation for online impulse buying: a two-factor theory perspective. Int. J. Inf. Manag. 36 (5), 759–772.
Lombart, C., Labbé-Pinlon, B., Filser, M., Anteblian, B., Louis, D., 2018. Regional product assortment and merchandising in grocery stores: strategies and target customer segments. J. Retail. Consum. Serv. 42, 117–132.
Longoni, C., Bonezzi, A., Morewedge, C, 2019. Resistance to medical artificial intelligence. Longoni, C., Bonezzi, A., & morewedge, CK resistance to medical artificial intelligence. J. Consum. Res. (in press).
MacDorman, K.F., Chattopadhyay, D., 2016. Reducing consistency in human realism increases the uncanny valley effect; increasing category uncertainty does not. Cognition 146, 190–205.
Marketo (2019). "Improve customer acquisition with an engagement strategy". Retrieved 16 April 2019 from https://www.marketo.com/ebooks/customer-acquisition-engagement-strategy/.
McCarthy, E.J., 1960. Basic Marketing: A Managerial Approach. Richard D. Irwin, Homewood, IL.
McKinsey (2014). "Designing a great customer engagement strategy". Retrieved 16 April 2019 from https://www.evergage.com/blog/mckinsey-on-designing-a-great-customer-engagement-strategy/.
Melis, K., Campo, K., Breugelmans, E., Lamey, L., 2015. The impact of the multi-channel retail mix on online store choice: does online experience matter? J. Retail. 91 (2), 272–288.
Millennial Marketing Production, 2010. Millennials want deals, not discounts. Retrieved October 5 2015, from http://www.millennialmarketing.com/2010/08/millennialswant-deals-not-discounts/.
Moriuchi, E., 2021. An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re-use behavior. Psychol. Mark. 38 (1), 21–42.
Ndubisi, N.O., Nataraajan, R., 2018. Customer satisfaction, Confucian dynamism, and long-term oriented marketing relationship: a threefold empirical analysis. Psychol. Mark. 35 (6), 477–487.
Newman, C.L., Wachter, K., White, A., 2018. Bricks or clicks? Understanding consumer usage of retail mobile apps. J. Serv. Mark. 32 (2), 211–222.
Osei-Frimpong, K., McLean, G., 2018. Examining online social brand engagement: a social presence theory perspective. Technol. Forecast. Soc. Change 128, 10–21.
Ostrom, A.L., Fotheringham, D., Bitner, M.J., 2019. Customer acceptance of AI in service encounters: understanding antecedents and consequences. Handbook of Service Science. Springer, Cham, pp. 77–103. Volume II.
Otim, S., Grover, V., 2006. An empirical study on web-based services and customer loyalty. Eur. J. Inf. Syst. 15 (6), 527–541.
Ou, C.X., Pavlou, P.A., Davison, R., 2014. Swift guanxi in online marketplaces: the role of computer-mediated communication technologies. MIS Q. 38 (1), 209–230.
Ozcelik, A.B., Varnali, K., 2019. Effectiveness of online behavioral targeting: a psychological perspective. Electron. Commer. Res. Appl. 33, 100819.
Pansari, A., Kumar, V., 2017. Customer engagement: the construct, antecedents, and consequences. J. Acad. Mark. Sci. 45 (3), 294–311.
Pantano, E., Timmermans, H., 2014. What is smart for retailing? Procedia Environ. Sci. 22, 101–107.
Park, S.C., Ryoo, S.Y., 2013. An empirical investigation of end-users' switching toward cloud computing: a two factor theory perspective. Comput. Hum. Behav. 29 (1), 160–170.
Park, S., Gupta, S., 2012. Handling endogenous regressors by joint estimation using copulas. Mark. Sci. 31 (4), 567–586.
Park, Y.W., Lee, A.R., 2019. The moderating role of communication contexts: how do media synchronicity and behavioral characteristics of mobile messenger applications affect social intimacy and fatigue? Comput. Hum. Behav. 97, 179–192.
Parment, A., 2013. Generation Y vs. Baby Boomers: shopping behavior, buyer involvement and implications for retailing. J. Retail. Consum. Serv. 20 (2), 189–199.
Pelet, J.É., Ettis, S., Cowart, K., 2017. Optimal experience of flow enhanced by telepresence: evidence from social media use. Inf. Manag. 54 (1), 115–128.
Peng, Y., Ke, D., 2015. Consumer trust in 3D virtual worlds and its impact on real world purchase intention. Nankai Bus. Rev. Int. 6 (4), 381–400.
Petit, O., Velasco, C., Spence, C., 2019. Digital sensory marketing: integrating new technologies into multisensory online experience. J. Interact. Mark. 45, 42–61.
Pierce, J.R., Aguinis, H., 2013. The too-much-of-a-good-thing effect in management. J. Manag. 39 (2), 313–338.
Poushneh, A., 2018. Augmented reality in retail: a trade-off between user's control of access to personal information and augmentation quality. J. Retail. Consum. Serv. 41, 169–176.
Puzakova, M., Kwak, H., Bell, M., 2015. Beyond seeing McDonald's fiesta menu: the role of accent in brand sincerity of ethnic products and brands. J. Advert. 44 (3), 219–231.
Rauschnabel, P.A., Hein, D.W., He, J., Ro, Y.K., Rawashdeh, S., Krulikowski, B., 2016. Fashion or technology? A fashnology perspective on the perception and adoption of augmented reality smart glasses. I Com 15 (2), 179–194.
Resnick, S.M., Cheng, R., Simpson, M., Lourenço, F., 2016. Marketing in SMEs: a "4Ps" self-branding model. Int. J. Entrep. Behav. Res. 22 (1), 155–174.
Righetti, F., Kumashiro, M., 2012. Interpersonal goal support in achieving ideals and oughts: the role of dispositional regulatory focus. Pers. Individ. Dif. 53 (5), 650–654.
Robertson, N., McDonald, H., Leckie, C., McQuilken, L., 2016. Examining customer evaluations across different self-service technologies. J. Serv. Mark. 30 (1), 88–102.
Rodrigues, D.L., Huic, A., Lopes, D., Kumashiro, M., 2019. Regulatory focus in relationships and conflict resolution strategies. Pers. Individ. Dif. 142, 116–121.
Roy, R., 2017. The effects of regulatory focus and mixed valence imagery and analytical attributes on product decisions. Mark. Intell. Plann. 35 (3), 397–407.
Roy, R., Naidoo, V., 2021. Enhancing chatbot effectiveness: the role of anthropomorphic conversational styles and time orientation. J. Bus. Res. 126, 23–34.
Roy, R., Ng, S., 2012. Regulatory focus and preference reversal between hedonic and utilitarian consumption. J. Consum. Behav. 11 (1), 81–88.
Ryan, D., Jones, C., 2012. The Best Digital Marketing Campaigns: Mastering the Art of Customer Engagement. Kogan Page Ltd, London, UK.
Sambhanthan, A., Good, A., 2013. Critical success factors for positive user experience in hotel websites: applying Herzberg's two factor theory for user experience modeling. Int. J. E Serv. Mobile Appl. 5 (1), 1–25.
Sanford, C., Oh, H., 2010. The role of user resistance in the adoption of a mobile data service. Cyberpsychol. Behav. Soc. Netw. 13 (6), 663–672.
Sarstedt, M., Cheah, J.-.H., 2019. Partial least squares structural equation modeling using SmartPLS: a software review. J. Mark. Anal. 7 (3), 196–202.
Sarstedt, M., Becker, J.-.M., Ringle, C.M., et al., 2011. Uncovering and treating unobserved heterogeneity with FIMIX-PLS: which model selection criterion provides an appropriate number of segments? Schmalenb. Bus. Rev. 63 (1), 34–62.
Sarstedt, M., Hair, J.J.F., Cheah, J.-.H., et al., 2019a. How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australas. Mark. J. 27 (3), 197–211.
Sarstedt, M., Ringle, C.M., Hair, J.F., 2017. Treating unobserved heterogeneity in PLS-SEM: a multi-method approach. In: Latan, H., Noonan, R. (Eds.), Partial Least Squares Path Modeling. Springer Nature, Cham, Switzerland, pp. 197–217.
Sarstedt, M., Ringle, C.M., Cheah, J.-.H., et al., 2019b. Structural model robustness checks in PLS-SEM. Tour. Econ. (in press).
Scholz, J., Smith, A.N., 2016. Augmented reality: designing immersive experiences that maximize consumer engagement. Bus. Horiz. 59 (2), 149–161.
Schultze, U., Brooks, J.A.M, 2019. An interactional view of social presence: making the virtual other "real. Inf. Syst. J. 29 (3), 707–737.
Shin, D., 2019. How does immersion work in augmented reality games? A user-centric view of immersion and engagement. Inf. Commun. Soc. 22 (9), 1212–1229.
Shin, D.H., 2013. Defining sociability and social presence in Social TV. Comput. Hum. Behav. 29 (3), 939–947.
Shin, D.H., & Choo, H. (2011). Modeling the acceptance of socially interactive robotics: social presence in human–robot interaction, 12(3), 430–460.
Shmueli, G., Sarstedt, M., Hair, J.F., et al., 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. Eur. J. Mark. (in press).
Slade, E.L., Dwivedi, Y.K., Piercy, N.C., Williams, M.D., 2015. Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. Psychol. Mark. 32 (8), 860–873.
Statista (2020). Percentage of mobile apps that have been used only once from 2010 to 2019. Retrieved 14 January 2021 from https://www.statista.com/statistics/271628/percentage-of-apps-used-once-in-the-us/.
Steinhoff, L., Arli, D., Weaven, S., et al., 2019. Online relationship marketing. J. Acad. Mark. Sci. 47 (3), 369–393.
Steuer, J., 1992. Defining virtual reality: dimensions determining telepresence. J. Commun. 42 (4), 73–93.
Stone, M., 1974. Cross-validation and multinomial prediction. Biometrika 61 (3), 509–515.
Streukens, S., Leroi-Werelds, S., 2016. Bootstrapping and PLS-SEM: a step-by-step guide to get more out of your bootstrap results. Eur. Manag. J. 34 (6), 618–632.
Sunny, S., Patrick, L., Rob, L., 2019. Impact of cultural values on technology acceptance and technology readiness. Int. J. Hosp. Manag. 77, 89–96.
Tak, P., Panwar, S., 2017. Using UTAUT 2 model to predict mobile app-based shopping: evidences from India. J. Indian Bus. Res. 9 (3), 248–264.
Talpau, A., 2014. The marketing mix in the online environment. Bull. Transilv. Univ. Brasov. Econ. Sci. Ser. V 7 (2), 53.
Taylor, D.G., Levin, M., 2014. Predicting mobile app usage for purchasing and information-sharing. Int. J. Retail Distrib. Manag. 42 (8), 759–774.
Taylor, D.G., Strutton, D., 2010. Has e-marketing come of age? Modeling historical influences on post-adoption era Internet consumer behaviors. J. Bus. Res. 63 (9–10), 950–956.
ThaiChon, P., Liyanaarachchi, G., Quach, S., Weaven, S., Bu, Y., 2019. Online relationship marketing: evolution and theoretical insights into online relationship marketing. Mark. Intell. Plann. 38 (6), 676–698.
Thakur, R., 2019. The moderating role of customer engagement experiences in customer satisfaction–loyalty relationship. Eur. J. Mark. 53 (7), 1278–1310.
The Manifest (2018). Mobile App Usage Statistics 2018. Retrieved 24 February 2019 from https://themanifest.com/app-development/mobile-app-usage-statistics-2018.
Tuškej, U., Podnar, K., 2018. Consumers' identification with corporate brands: Brand prestige, anthropomorphism and engagement in social media. J. Prod. Brand Manag. 27 (1), 3–17.
Tuškej, Podnar, 2018. Consumers' identification with corporate brands: Brand prestige, anthropomorphism and engagement in social media. Journal of Product & Brand Management 27 (1), 3–17.
Van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P., Verhoef, P.C., 2010. Customer engagement behavior: theoretical foundations and research directions. J. Serv. Res. 13 (3), 253–266.
van Esch, P., Arli, D., Gheshlaghi, M.H., et al., 2019. Anthropomorphism and augmented reality in the retail environment. J. Retail. Consum. Serv. 49, 35–42.
van Heerde, H.J., Dinner, I.M., Neslin, S.A., 2019. Engaging the unengaged customer: the value of a retailer mobile app. Int. J. Res. Mark. 36 (3), 420–438.
Vaughn, L.A., 2017. Foundational tests of the need-support model: a framework for bridging regulatory focus theory and self-determination theory. Person. Soc. Psychol. Bull. 43 (3), 313–328.

Vivek, S.D., Beatty, S.E., Dalela, V., et al., 2014. A generalized multidimensional scale for measuring customer engagement. J. Mark. Theory Pract. 22 (4), 401–420.
Wang, R.J.-H., Krishnamurthi, L., Malthouse, E.C., 2018. When reward convenience meets a mobile app: increasing customer participation in a coalition loyalty program. J. Assoc. Consum. Res. 3 (3), 314–329.
Wang, W., Chen, R.R., Ou, C.X., Ren, S.J., 2019. Media or message, which is the king in social commerce? An empirical study of participants' intention to repost marketing messages on social media. Comput. Hum. Behav. 93, 176–191.
Wang, Y., So, K.K.F., Sparks, B.A, 2017. Technology readiness and customer satisfaction with travel technologies: a cross-country investigation. J. Travel Res. 56 (5), 563–577.
Wottrich, V.M., van Reijmersdal, E.A., Smit, E.G., 2018. The privacy trade-off for mobile app downloads: the roles of app value, intrusiveness, and privacy concerns. Decis. Support. Syst. 106, 44–52.
Wu, L.L., Chuang, Y.L., Chen, P.Y., 2008. Motivation for using search engines: a two-factor model. J. Am. Soc. Inf. Sci. Technol. 59 (11), 1829–1840.
Wu, W.-Y., Ke, C.-C., 2015. An online shopping behavior model integrating personality traits, perceived risk, and technology acceptance. Soc. Behav. Pers. 43 (1), 85–97.
Wu, Y.-L., Li, E.Y., 2018. Marketing mix, customer value, and customer loyalty in social commerce: a stimulus-organism-response perspective. Internet Res. 28 (1), 74–104.
Yuan, L., Dennis, A.R., 2019. Acting like humans? Anthropomorphism and consumer's willingness to pay in electronic commerce. J. Manag. Inf. Syst. 36 (2), 450–477.
Zhang, C., Ha, L., Liu, X., Wang, Y., 2018. The role of regulatory focus in decision making of mobile app download: a study of Chinese college students. Telemat. Inform. 35 (8), 2107–2117.
Zhang, P., Von Dran, G.M., 2000. Satisfiers and dissatisfiers: a two-factor model for website design and evaluation. J. Am. Soc. Inf. Sci. 51 (14), 1253–1268.
Zhou, T., 2013. Understanding continuance usage of mobile sites. Ind. Manag. Data Syst. 113 (9), 1286–1299.
Zou, L.W., Chan, R.Y., 2019. Why and when do consumers perform green behaviors? An examination of regulatory focus and ethical ideology. J. Bus. Res. 94, 113–127.

Xin Jean Lim is a PhD candidate under research fellowship scheme in School of Business and Economics, Universiti Putra Malaysia. She is also a tutor in business research methods class. Her research interests include consumer behavior, social media marketing, online marketing and customer relationship management. Her papers are published in British Food Journal, Marketing Intelligence and Planning, Young Consumers, Asia Pacific Journal of Marketing and Logistics, and Journal of Retailing and Consumer Services.

Jacky Cheah Jun Hwa is a senior lecturer in School of Business and Economics, Universiti Putra Malaysia (UPM) as well as external member of relationship marketing for impact cluster at Griffith University. He teaches Principle of Marketing, Research Methods, and Statistics. His-research interests include consumer behavior, marketing strategy, quantitative studies, and methodological issue in business research. His-papers are published in European Journal of Marketing, Marketing Intelligence and Planning, Internet Research, Australasian Marketing Journal, and Asia Pacific Journal of Marketing and Logistics.

Siew Imm Ng is an Associate Professor in School of Business and Economics, Universiti Putra Malaysia. She has authored and co-authored many articles in refereed and professional journals including Tourism Management, International Marketing Review, Journal of Hospitality & Tourism Research and Journal of Air Transport Management. Her current research interests are in the area of values, cultures, tourist behavior and employee behavior.

Norazlyn Kamal Basha graduated with a BBA from University Sains Malaysia in 2006, an MBA from Universiti Putra Malaysia (UPM) in 2009, and a PhD in Marketing from the University of Western Australia in 2016. Currently, I am Senior Lecturer in the Department of Marketing and Management in UPM. In terms of research, I look forward to collaborations with colleagues and students alike in the areas of International Marketing, Services Marketing, Consumer Behaviour, Higher Education, Societal Marketing, and the like. My special interests outside academia include animal welfare conservation and long-distance running.

Geoff Soutar is a Winthrop Professor of Marketing at the University of Western Australia Business School. He was Foundation Professor of Management at Curtin University of Technology from 1986 to 1994 and Executive Dean of the Faculty of Business and Public Management at Edith Cowan University from 1994 until 1999. He was also Director of the Graduate School of Management at UWA from 2000 until 2007 and Head of the Marketing Discipline Group at UWA from 2008 to 2016. He received his PhD from Cornell University in the US.