Please cite as: Sharma P, Ueno A, Dennis C, Paydas C (2023) 'Emerging digital technologies and consumer decision-making in retail sector: Towards an integrative conceptual framework', *Computers in Human Behavior*, 148.

Emerging digital technologies and consumer decision-making in retail sector: Towards an integrative conceptual framework

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Abstract
This paper explores the influence of digital technologies on the consumer decision-making in retail sector with two online survey-based studies. Study 1 identifies unique attributes of six digital technologies, including two current (Internet and Mobile Platform) and four emerging (Artificial Intelligence, Augmented, Mixed and Virtual Reality) technologies. Study two focuses on older consumers to understand their decision-making process when shopping for products or services using new digital technologies. We extend the AISAS (Awareness, Interest, Search, Action, and Sharing) model to show that with digital technologies, consumer decision journey is no longer linear. For example, attention can lead directly to action, without going through the interest or search stages. Similarly, purchase can lead to sharing that may lead to loyalty and psychological engagement, and reinforce attention. We found no significant difference in these effects between older and younger consumers. Besides providing useful insights about consumer decision-making process with emerging digital technologies for future academic researchers, these results also give useful ideas to marketing practitioners interested in introducing these emerging technologies to deliver superior value to their customers.

Keywords: artificial intelligence; augmented reality; consumer decision-making; digital technologies; mixed reality; virtual reality

1. Introduction

Digital technologies and platforms such as computers, mobile devices and social media have changed the way consumers and marketers interact with each other (Moffett et al., 2020; Yadav & Pavlou, 2014; 2020). Recently, many new digital technologies (e.g., artificial intelligence, virtual reality etc.) have emerged and transformed the way firms market and deliver their products and services to their customers and the way customers interact with firms in return (Grewal et al., 2020a, 2020b). These emerging technologies are also changing how consumers search for information, evaluate products and services, make purchase decisions, and share their experiences with others (Schweidel et al., 2022). With about $50 billion estimated to be spent on these technologies globally by 2023 (VanBoskirk et al., 2019), we need to understand how these technologies can be used by marketers to influence customers and optimize their returns on investment (Grewal & Roggeveen, 2020).

Emerging digital technologies are reshaping retailing (Ameen et al., 2021; Roggeveen & Sethuraman, 2020a; 2020b) by increasing the accessibility of information, helping customers receive personalized services, and enabling marketers to send targeted communications (Wang et al., 2022). These emerging technologies have made interaction with brands a regular part of the customers' daily lives, whereby user activities can be continuously traced during the entire customer journey. These technologies are fast becoming the main source of automated delivery processes and personalized customer experiences (Lajante et al., 2023). Despite growing research interest in the role and impact of emerging digital technologies, most marketing studies have been either conceptual or descriptive in nature, with hardly any attempt to empirically examine the consumer perceptions, attitudes and behaviors towards all these emerging digital technologies and to examine the influence of the unique attributes of these technologies on the different stages in the consumer decision-making process.

For example, many articles document the growing popularity of AI across a wide range of applications, such as customer service, healthcare, retailing, and transportation (e.g., Davenport & Kirby, 2016; Davenport & Ronanki, 2018). More recently, Davenport et al. (2020) offer a framework to organize AI applications using their task automation timeframe and form (digital vs. robot) and suggest future research agenda to test the predictive ability of AI applications and the challenges in their adoption and usage by consumers (e.g., loss of autonomy, privacy, bias and ethics).

Similarly, Tong et al. (2020, p.66) offer a framework for personalized mobile marketing incorporating five Ps (product, price, place, promotion, and prediction) to help marketers customize their offers using hyper contextual information about their customers, including "physical location, temporal information, cross-channel behaviors, surrounding environment, shopping companion, and market competition". They also propose many ideas for future research, such as a comparison of how customers use the different new technologies and how do these influence customer engagement and purchase behaviors. Researchers have also called for more research on the differences in the unique features of different technologies in the shopping context (Tong et al., 2020) and the factors that may hinder the customers' decision to adopt the new digital technologies for their shopping (Blut & Wang, 2020).

As a result, despite their growing importance there is still no comprehensive conceptual framework to guide academic researchers and marketing managers about the influence of these emerging digital technologies on consumer decision-making and purchase behavior. In this paper, we address this important research gap by focusing on four emerging digital technologies, namely artificial intelligence - AI (Davenport et al., 2020; Huang & Rust, 2020; Rai, 2020), virtual reality - VR (Burke 1997, 2002; Sample et al., 2020), augmented – AR and mixed reality - MR (Hilken et al., 2017, 2020), to develop an integrative conceptual framework to investigate the influence of emerging digital technologies on consumer decision-making and purchase behavior in the retail shopping context. To summarize, this paper addresses the following specific research objectives:

1. Identify the unique attributes of various digital technologies (both current and new) and categorize them based on their common elements.
2. Explore the influence of these attributes and the consumers' demographic and behavioral characteristics on their shopping experience, choice and usage as well as on the five stages of consumer decision-making process (need recognition, information search, alternative evaluation, purchase and post-purchase).
3. Examine consumer decision-making process with AISAS when shopping for products or services using emerging digital technologies, and extend AISAS model incorporating the effect of emerging digital technologies.
4. Investigate the influence of technology-related individual traits on the participants' level of technology anxiety, technology innovativeness, need for human interaction, social influence, and hedonic motivation.

We begin this paper with a review of the growing literature on the influence of emerging digital technologies on the consumers' attitudes, perceptions, and behaviors. Next, we conceptualize the attributes of new digital technologies as a multidimensional construct and develop a conceptual model with specific hypotheses about the influence of these attributes on the consumer decision-making stages (i.e., need recognition, information search, alternative evaluation, purchase and post-purchase). We then used an online survey (Study 1) to identify and categorize the unique attributes of six digital technologies, including internet, mobile platform, artificial intelligence, augmented, mixed, and virtual reality. We also tested the influence of these attributes and the participants' demographic and behavioral characteristics on important customer outcomes (future usage and decision-making stages) and found many useful insights about the influence of emerging digital technologies.

Notwithstanding its useful findings, study 1 had a relatively smaller sample size (N=50) for each of the six digital technologies and a relatively young sample (Under 44 years, 77%), which may restrict the generalizability of its findings. To address these limitations, we conducted another online survey (Study 2) with only those participants who claimed to be at least somewhat familiar with emerging digital technologies (e.g., artificial intelligence; augmented, mixed and virtual reality) among mainly older consumers. We also assessed the influence of the new digital technologies on the five stages in the AISAS (Awareness, Interest, Search, Action, and Sharing) model (Sugiyama & Andree, 2011) that has been offered as an alternative to the traditional AIDMA model (Moriarty, 1983) in response to the growing influence of digital technologies on consumer behavior. We also measured perceived usefulness (Moriuchi, 2019) of new digital technologies, responsiveness of interactivity (Park & Yoo, 2020), performance expectancy (Gursoy et al., 2019) as factors which affect AISAS, participates' attitude toward emerging digital technologies (Moriuchi, 2019) to test any influence on AISAS, customer loyalty (Moriuchi, 2019) and psychological engagement (Flavián et al., 2019) as the outcomes.

Study 1 identifies unique attributes of six digital technologies and study two focuses on older consumers to understand their decision-making process when shopping for products or services using new digital technologies. We also extend the AISAS (Awareness, Interest, Search, Action, and Sharing) model to show that under the influence of emerging digital technologies, consumer decision-making is no longer a linear process. For example, attention can lead directly to action, without going through the interest or search stages. Similarly, purchase can lead to sharing that may lead to loyalty and psychological engagement, and reinforce attention. We found no significant difference in these effects between older and younger consumers. Besides providing unique insights about consumer decision-making process with emerging digital technologies for future academic researchers, these results also give useful ideas to marketing practitioners interested in introducing these emerging technologies to deliver superior value to their customers.

2. Literature review

2.1. Consumer decision-making process

Consumer decision-making process is one of the basic concepts in the study of consumer behavior and it consists of five stages - need recognition, information search, alternative evaluation, purchase decision, and post-purchase behavior (Kotler et al., 2020). One of the earliest consumer decision-making model to represent these five stages, is the Attention-Interest-Desire-Memory-Action (AIDMA) model (Hall 1924). More recently, researchers at the Japanese advertising giant, Dentsu, have introduced Attention-Interest-Search-Action-Share (AISAS) model in response to the growing influence of digital technologies on consumer behavior (Sugiyama & Andree, 2011). AISAS model maps the five stages of consumer decision-making as, need recognition (attention, interest, desire), information search (memory, search), evaluation of alternative (search, action, sharing), purchase decision (action), and post-purchase behavior (action, sharing).

AISAS model has become a cornerstone of digital marketing strategy, and as a successor to the AIDMA model, it captures the consumer's journey to purchase in the digital age (Sugiyama & Andree, 2011; Wei & Lu, 2013). The initial stage of the customer journey is Attention, where the goal is to capture the attention of potential consumers towards a brand or product (Kim et al., 2020). The next stage is that consumers develop an interest in the brand or product and starts to see its potential value. After sparking interest, customers often engage in an information search process. In the digital space, consumers easily search for information regarding their desired products or services (Xue et al., 2021). The action stage involves consumers making the purchase decision. The final stage of the AISAS model -

sharing', has become increasingly important in the digital age. After purchasing, consumers might share their experiences or opinions on various platforms such as social media, review websites, or personal blogs (Kim et al., 2020). This stage is particularly important as it could generate word-of-mouth marketing and foster trust among prospective customers.

One of the key differences between the AIDMA and AISAS models is that AIDMA model assumes a linear sequential progression from one stage to the next, whereas AISAS model allows for consumers to use technology to jump from one stage to another without having to go through the stages between them (Wei & Lu, 2013). In this paper, we argue that it makes AISAS almost like a circular process wherein customers could jump from any point on the circle to another point on the circle without having to travel along its perimeter. This is unlike the traditional AIDMA model, which is more like a straight line that prevents customers from skipping any stage and move from one stage to the next in a linear manner.

2.2. Digital technologies in the retail sector

In the constantly evolving digital age, the retail sector has been subjected to transformative changes shaped by digital technologies. These advancements play a pivotal role in enhancing business operations, customer experiences, and revenue growth (Mostaghel et al., 2022). Pervasive technologies such as AI, IoT, AR/VR, blockchain, and big data analytics have been adopted extensively in retail, reshaping the industry's operations and strategic decision-making processes (Shankar et al., 2021). They offer businesses unprecedented capabilities to engage with consumers in a more personalized and interactive manner (Ameen et al., 2022). AI and data analytics are particularly significant, allowing businesses to offer hyper-personalized shopping experiences by analyzing and predicting customer behavior and trends (Silva et al., 2020).

2.2.1. Artificial Intelligence (AI) In the current digital transformation, AI stands at the front, serving as an indispensable tool for retailers to enhance consumer satisfaction and engagement. AI, with its programs, algorithms, systems and machines, simulates multiple aspects of human intelligence, embodying mechanical, analytical, intuitive, and empathetic intelligence (Huang & Rust, 2018; Shankar, 2018). AI uses a range of sophisticated tools such as deep learning, machine learning, natural language processing, neural networks, robotic process automation, and rule- based expert systems (Davenport et al., 2020). These tools help AI's capabilities to collect, interpret and learn from a vast amount of data, revolutionizing marketing and business applications, such as business process automation, profound marketing research, innovative customer engagement and relationship management, new product development, and service delivery innovation (Davenport & Ronanki, 2018).

AI's ability to analyze consumer behavior and preferences has been instrumental in offering personalized product recommendations, significantly elevating the consumer shopping experience (Silva et al., 2020). A multitude of AI applications in retail demonstrates its transformative influence. For example, Amazon.com's Prime Air uses drones for shipping and delivery; Macy's On Call serves as an in-store personal assistant using natural language processing; Stitch Fix uses AI to match clothing styles with different customers. Moreover, AI-powered chatbots, such as Conversica's AI bot and 1–800-Flowers' AI bot, that offers sales and customer service support (Davenport et al., 2020; Huang & Rust, 2020) have revolutionized customer service, providing instant, 24/7 support, thus contributing to increased customer satisfaction and loyalty. The AI platform of RedBalloon that identifies new customers, Affectiva's use of affective analytics to study consumers' emotions when watching advertisements, and Replika's machine learning-based chatbot to mimic customers' communication styles, exemplify the diverse applications of AI in the retail sector.

2.2.2. Augmented Reality (AR)

AR is an 'immersive technology', which "blurs the boundary between the physical and virtual words and enables users to experience a sense of immersion" (Suh & Prophet, 2018, p. 77). This 'smart' technology helps enhance the customers' online service experiences by providing them with an intuitive and context-sensitive interface to process information in a natural manner, ultimately improving service quality and make online shopping more effective and enjoyable for the customers (Marinova et al., 2017). AR tools such as Facebook's innovative lenses and filters, Google's ARCore, Apple's ARKit, and cloud-based platforms have led the rapid development of AR content (Petrock, 2018). The transformative and potentially disruptive nature of AR has gathered significant interest among marketers who seek to leverage its capabilities (Huang & Rust, 2018; Rauschnabel et al., 2019).

AR applications such as the Ikea app, virtual make-up trials, and 'Pokémon Go' are a few examples of how firms increase customer engagement and excitement through AR (Hinsch et al., 2020). By providing simulated physical control and environmental embedding, AR enhances the customer experience (Hilken, 2017), allowing shoppers to augment the physical world with context-specific information at or near the point of purchase. This holds the potential to revolutionize the retail sector and transform the shopping experience (Heller et al., 2019; Hilken et al., 2020; Jessen et al., 2020). With AR's ability to provide an engaging and immersive shopping experience, it emerges as a powerful technology that fosters customer satisfaction and loyalty in the retail industry (Riar et al., 2022).

2.2.3. Virtual Reality (VR)

VR is a computer-generated environment that simulates an immersive, lifelike experience grounded in reality (Burke, 1997; 2002). In the retail sector, VR can be leveraged to simulate a virtual shopping experience, replicating physical stores down to product details and store layout (Branca et al., 2023). VR allows people to experience the feeling of actually being in 'another place' (e.g., a retail store, restaurant, hotel room, or tourist destination) above and beyond the information made available by the computer (Boyd & Koles, 2019). VR is different from AR as it uses devices such as 3-D glasses, headsets and gloves to simulate the real-life like experience for the customers, whereas AR can be employed using normal devices such as computers and smartphones (Wedel et al., 2020). For example, VR allows customers to 'try on' clothes virtually, providing a realistic and interactive shopping experience (https://www.zyler.com), while AR can superimpose a piece of furniture onto the customer's living room through their smartphone camera (e.g., https://www.ikea.com/au/en/customer-service/mobile-apps/say-hej-to-ikea-place-pub1f8af050).

VR mainly relies on virtual stimuli to create a realistic experience but AR uses additional computer-generated content to enhance the customers' perceptions of reality (Wedel et al., 2020). VR holds great potential for marketers by engaging the customers and helping them visualize, interact with, and experience the products or services, and thus increase their likelihood to purchase and use the product (Flavián et al., 2019; Sample et al., 2020). In the retail sector, VR provides customers with an immersive, engaging and novel shopping experience that can boost customer loyalty and increase sales. VR has been used to develop applications in many industries, including gaming, medicine, education, travel, entertainment, and marketing (Wedel et al., 2020). However, its application in the retail sector is particularly promising due to the scope for innovation in enhancing the shopping experience.

2.2.4. Mixed Reality (MR)

MR, an innovative blend of both AR and VR, holds significant promise in revolutionizing the retail landscape by merging real and virtual worlds, thereby creating new environments where physical and digital objects co-exist in real-time. This combination creates integrated physical and virtual experiences, which offers enhanced customer experience and greater potential for physical stores to improve their service offers (Dekimpe et al., 2020). MR applications in the retail sector include Sephora's 'Magic Mirror', an interactive tool that uses a smart engine not only to help its customers visualize different make-up treatments but also to recommend personalized makeup, skincare, and fragrances with unprecedented accuracy. This ensures an immersive, hyper-personalized shopping experience that extends beyond the conventional boundaries of retail (Jain et al., 2023).

Similarly, an RFID-enabled interactive touch-screen mirror developed by Oaks Labs have shown great potential in transforming the in-store shopping experience. These advanced mirrors can identify all the items taken by a consumer into a fitting room, and act as a digital sales assistant. Customers can request other sizes, colors, or matching items from a human salesperson, creating a seamless blend of digital convenience and human service. All these MR applications are designed to create frictionless experiences for the customers, reducing their effort and discomfort in the shopping process. Such convenience and personalized service ultimately result in higher levels of customer satisfaction and store loyalty (Dekimpe et al., 2020). This clearly underlines the significance of MR in the retail industry, showing its potential to redefine the way businesses interact with and satisfy their customers.

In view of the above unique features and benefits from the new digital technologies, marketing firms, particularly retailers, are rapidly adopting these to improve customer experience and interactivity (Grewal et al., 2017; 2018). With such growing popularity, it is not surprising to see an increase in academic research on the role of these new digital technologies in the marketing discipline. However, many of these articles focus on either the specific technical aspects of these technologies used to solve marketing problems or other managerial and strategic issues related to their use, such as their influence on jobs and society, with relatively little attention to the customers' psychological reactions to these technologies (Grewal et al., 2020a, 2020b). We address this research gap by identifying the unique attributes of these new technologies and exploring their influence on all the stages in the consumer decision-making process and on important customer outcomes.

2.3. New digital technologies and consumer decision-making process

Past research used AIDMA (Hall 1924) to study consumer decision-making (CDM) process to show that consumers go through different stages. However, this model assumes CDM to be a linear process and did not account for the changes in CDM due to the advent of new technologies like Internet and Mobile platforms. Dentsu addressed this gap with their AISAS model that extended the AIDMA model to be able to study CDM in the online and mobile environments (Sugiyama & Andree, 2011). In this research, we aim to further extend this line of research by exploring the need to adapt, modify or extend the AISAS model to account for the recent digital technologies e.g., AR, VR and MR. Digital technologies have lowered the threshold for shopping, and stimulated repeat purchase; hence, skips information search and evaluation of alternative stage. Impulse buying means consumers make a purchase purely based on their impulses and emotions, and attractive presentation of products is said to be the one of the causes of impulse buying. Digital technologies have enabled a presentation of products in real life setting (e.g., IKEA furniture, Dulux paint, L'Oreal test beauty product at home), hence may have contributed more impulse buying.

Once buyers acknowledge a problem or a need, they are likely to search for information regard with the problem or the need. It is expected that these new digital technologies are likely to change information searches and product trials (Javornik, 2016), and ultimately to facilitate purchasing decisions (Boletsis & Karahasanvic, 2018). The most effective source of information tends to be word of mouth (Chen & Xie, 2008). Recent research on digital technologies confirmed that product recommendations through social augmented reality contribute to other's purchase decisions (Hilken et al., 2020). Therefore, use of digital technologies enables information search and sharing information easier and speedier, and which in turn result in faster buying decision marking. Research on online shopping shows a positive relationship between each stage of consumer decision making process and volume of Online purchase. For example, consumers who used the internet more also purchased more online (Comegys et al., 2006). Buyers' satisfaction with the purchase is determined by a comparison of the consumer's expectations and the product's perceived performance. When the perceived performance falls below expectations, then, the consumer is dissatisfied, and which in turn may lead to cognitive dissonance. However, as customers are able to test a product before buying, digital technologies make users feel happier and more confident with their buying decision, and experience less cognitive dissonance (Hilken et al., 2017).

Due to unique characteristics of services, these cannot be readily displayed or easily communicated to customers' (Wilson et al., 2021, p.16). Therefore, services which have no tangible elements cannot be seen, touched, tested or inspected before buying the same way as products. Lack of demonstration increases the uncertainly when evaluating among alternative service offers (Palmer, 2014). Digital technologies allow consumers to inspect and try the products before buying (Javornik, 2016). Hence, digital technologies provide 'a pre-purchase service for customers' or 'a complemental service to the existing products' (Boletsis & Karahasanvić, 2018, p. 52). Therefore, digital technologies seem to have changed the consumer decision making process of product purchase, but may not have influenced the consumer decision making process of service purchase. Thus, to fully understand the effect of digital technologies on consumer decision making process, different contexts for shopping (e.g., service vs. product, tangible vs. intangible) need to be considered as moderators (Darley et al., 2010; Suh & Prophet, 2018).

We address the above research gaps by identifying the major attributes of six digital technologies, including two current (Internet and Mobile Platform) and four new (Artificial Intelligence, Augmented, Mixed and Virtual Reality) technologies. We then test the influence of these attributes and the participants' demographic and behavioral characteristics on their shopping experience, choice and usage of these new digital technologies and on the five stages of consumer decision-making process (need recognition, information search, alternative evaluation, purchase and post-purchase) in Study 1. Next, in Study 2, we focus on participants familiar with the new digital technologies (e.g., artificial intelligence; augmented, mixed and virtual reality) and their perceptions on specific products or services for which they have either shopped in the past or may shop in near future, using four emerging digital technologies. We also assessed the influence of the new digital technologies on the five stages in the AISAS (Awareness, Interest, Search, Action, and Sharing) model and the influence of technology-related individual traits on the participants' level of technology anxiety, technology innovativeness, need for human interaction, social influence and hedonic motivation. In the next section, we present our conceptual framework and hypotheses.

3. Conceptual framework and hypotheses

3.1. Non-linear nature of AISAS model

AISAS maps the five stages of consumer decision-making as need recognition (attention, interest, desire), information search (memory, search), evaluation of alternative (search, action, sharing), purchase decision (action), and post-purchase behavior (action, sharing) (Sugiyama & Andree, 2011; Wei & Lu, 2013), which forms the foundation of our Study 2 model. Some links in the AISAS model (e.g., Awareness → Interest, Interest → Search, Search → Action, and Action → Sharing) are well-researched, so we do not seek to test these as hypotheses. Building on Lemon and Verhoef (2016) and Darley et al. (2010), we examine the non-linear nature of consumer decision-making that allows customers to use technology to jump back and forth in between stages, especially allowing transition from post-purchase to both purchase and pre-purchase stages, as illustrated in Figure 1 created by us.

< Insert Figure 1 about here >

Digital technologies influence consumers at every stage of the customer shopping journey from pre- to post-transaction period (Hoyer et al., 2020). With the use of emerging digital technologies, consumers are increasingly connected and empowered to seek information and create experiences with brands (Hoyer et al., 2020). Hence, digital technologies affect how consumers search for products and services, evaluate and choose them, consume and build relationships with them (Libai et al., 2020). In the pre-transaction stage of the consumer decision making journey, digital technologies facilitate visualization and imagination of the future experience with the products or services in real-time. This not only increases the knowledge of consumers about the products or services they are considering purchasing, but also increases their enjoyment of experiencing emerging digital technologies (Hilken et al., 2018). Consumers in this stage evaluate the effort (i.e., money, time, and energy) required to purchase the product or service and the expected benefits they will derive from the purchase (Dowling et al., 2020). They decide to proceed to the next stage, transactions stage, based on their assessment in the pre-transaction stage. If consumers decide to proceed further, they can seamlessly move from pre-transaction to the transaction stage where they can authorize a transaction in a convenient and fast way.

In the post-transaction stage, consumers continue to engage with digital technologies, which not only enhances their consumption experience but also helps them reflect on their experience and share with others (Dellaert, 2019). At this stage, consumers actively review and assess the strengths and weaknesses of the product or service after experiencing it (e.g., through word-of-mouth, blog posts, tweets). This engagement can affect their overall attitude of the product, their satisfaction with the purchase experience and choice, and finally intention to repurchase (Dowling et al., 2020). Attention, interest, search, action and sharing do not necessarily take place in a linear and sequential way (Dowling et al., 2020). For example, consumers may skip some of the stages as in the case of search to share and iterate through these stages multiple times in the case of repeat purchases (Dowling et al., 2020). Based on this discussion, we hypothesize as follows:

H1: The AISAS customer journey model is non-linear, such that customers may skip from one stage to another stage without going through a linear path.

3.2. AISAS Stages – Antecedents

Consumers' perceptions of interactivity refer to a person using machine interactions that simulate interpersonal exchange while using digital technologies (Park & Yoo, 2020). As technology develops, interactive capabilities continue to evolve. Controllability, responsiveness and playfulness are dimensions of interactivity for digital technologies (Zhao & Lu, 2012). Controllability is the extent of individuals' manipulation of communication, timing and content search through digital technologies. Responsiveness refers to the speed of digital technologies' responses while consumers navigate to access information (Wu, 2019). Playfulness is defined as the perceived enjoyment while interacting with the digital technologies. Hence, consumers' perceptions of interactivity with the digital technologies play a crucial role in attracting attention while shopping. Customers who are responsive to digital interactivity are more likely to be attracted to use digital technologies as part of the shopping process. Grewal et al. (2018) find that customers use of mobile phones whilst shopping increases shelf attention (as measured by eye tracking). Giombi et al. (2022) also find that interactivity features influence consumer engagement, recall, and understanding in different ways depending on the type of ad, the product category, and the consumer characteristics. Hence, we hypothesize:

H2: Responsiveness to digital interactivity is positively associated with digital technologies drawing attention to shopping opportunities.

Mental imagery is defined as the visualization of a concept or relationship (Park & Yoo, 2020). Mental imagery plays an important role in information processing. Especially in virtual environments, where consumers do not have access to the actual physical products or services that they are interested in purchasing, mental imagery plays a crucial role as a source of information when making purchase decisions. Consumers can create mental images of their future experience with the product or service they are considering purchasing through digital technologies (Park & Yoo, 2020). Consumers can elaborate more vivid information through digital technologies to build more favorable attitude toward the product and services (Babin & Burns, 1998). Activating a mental imagery, hence, plays an important role in the pre-transaction stage in customer decision making process. However, consumers engage with digital technologies when they expect to receive value from the interactive experiences.

In this context, perceived usefulness refers to the perception of a consumer regarding the behavioral outcome (Moriuchi, 2019). When consumers want to acquire more information about the product or service, they engage with digital technologies as they think it will be useful while shopping. Hence, perceived usefulness of digital technologies has a positive influence on attitude towards digital technologies and is positively related to arousing interest in the consumer decision making while shopping. In line with Hoyer et al.'s (2020) conceptual study, we expect digital technologies to influence the stages of the AISAS model. First, customers are unlikely to buy unless they consider the product or service useful. Moriuchi (2019) finds that perceived usefulness influences attitude towards using a voice-assisted buying process. Thus, a potential customer is unlikely to be interested in buying using digital technologies unless they perceive digital technologies to be useful. Accordingly, as follows:

H3: The perceived usefulness of digital technologies is positively associated with (a) interest, and (b) attitude towards using digital technologies in the buying process.

Drawing upon the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Gansser & Reich, 2021), Schmitz et al. (2022) report that performance expectancy is one of the most important drivers to the intention to use virtual appointment, especially for people over the age of 35 years old. Performance expectancy of digital technologies refers to the perceived benefits derived from the use of digital technologies (Gursoy et al., 2019). When consumers think that digital technologies can help them in their decision-making process by providing fast, convenient and reliable services, they will have a positive attitude towards using digital technologies. For example, Gursoy et al. (2019) find that performance expectancy is associated with higher levels of willingness to use AI. Thus, we expect that performance expectancy will influence AISAS, possibly in multiple ways but likely on the start of the process (attention) and attitude to using digital technologies. Accordingly, we hypothesize:

H4: Performance expectancy is positively associated with (a) attention, and (b) attitude towards using digital technologies.

3.3. AISAS Stages – Outcomes

In the AISAS model, successful purchases are expected to lead to sharing on social media (e.g., Sugiyama & Andree, 2011). Evidence from traditional purchasing (i.e. not necessarily digital technologies) indicates that sharing builds loyalty and psychological engagement (He et al., 2019). Indeed, Moriuchi (2019) finds that loyalty and engagement are associated with each other and are both outcomes of using voice assistants. Digital technologies not only help consumers in the pre-transaction and transaction stages of their decision-making journey, but also provide a tool for interaction in the post-transaction stage (Moriuchi, 2019). The interactive consumer experiences with digital technologies are defined as consumer engagement (Moriuchi, 2019). Sharing feedback about the product or service through digital technologies helps to build attachment to a product or service. Therefore, sharing through digital technologies is positively related to engagement and loyalty.

Digital technologies provide consumers with necessary information to form relevant product or service expectation. Therefore, digital technologies help to reduce the risk of dissatisfaction with the purchased product or service (Meißner et al., 2020). The interactivity with digital technologies will help consumers to visualize the use and the fit of the product or service and hence, make purchase decisions more comfortable. Hence, satisfaction with choice made and the experience itself will be positively related to willingness to re-purchase and loyalty in the post-transaction stage. Accordingly, we hypothesize as follows:

H5: Sharing information about shopping using digital technologies is positively associated with (a) loyalty, and (b) psychological engagement.

Figure 2 summarizes our conceptual framework with all these hypotheses.

< Insert Figure 2 about here >

4. Methodology

4.1. Study 1 – Online survey

We conducted an online survey with a sample drawn from Amazon Mechanical Turk (MTurk) panel members (N=300) in the US with 50 participants in each of six digital technologies (Internet, Mobile, AI, AR, VR, MR). MTurk is a popular crowdsourcing platform that uses a distributed workforce to perform virtual tasks, such as online surveys. We also collected the participants' demographic data to classify their responses (Table 1). Our sample has more males (71%) and younger (< 44 years, 77%), Full-time employees (89%), White Collar workers (61%), well educated (≥ bachelors, 91%), higher income (> $25,000 per annum, 84%), frequent internet users (≥ 4 hours every day, 72%), and those using a desktop or laptop as their primary device to access internet (88%).

< Insert Tables 1 & 2 about here >

We used a structured questionnaire with the level of familiarity, usage, and satisfaction as well as the perceived attributes, benefits, choice, and usage of new digital technologies. We adapted 69 items from well-established scales to operationalize all the constructs in this study (Table 2). Exploratory factor analysis (EFA) with SPSS 26.0 revealed eight dimensions, which we interpreted as, utilitarian, hedonic, entertainment, performance, perceived risk, versatility, virtualization, and human-like attributes of emerging digital technologies. In addition, we measured the five stages of consumer decision-making (need recognition, information search, alternative evaluation, purchase and post-purchase) using two items each. Finally, we also measured three important customer outcomes, including customer experience (efficiency and enjoyment), customer choice and future usage. All the items have high factor loadings (> .70) that load significantly on their respective factors, demonstrating convergent validity. Table 3 confirms discriminant validity as the square-roots of the AVE for all the constructs are higher than their correlations with all the other constructs in our model.

< Insert Tables 3 & 4 about here >

We analyzed the data using multiple regression and mean comparison analysis with SPSS 26.0, to test the influence of the unique attribute of six digital technologies and the participant demographic and behavioral characterizes on future usage and each decision making stage. Table 4 shows that the participants' future usage is mainly driven by the performance ($\beta = .22$, $p < .001$), versatility ($\beta = .14$, $p < .05$), and choice ($\beta = .37$, $p < .001$). In contrast, the first stage of CDM, need recognition is only influenced by the utilitarian ($\beta = .37$, $p < .001$) attribute of the digital technologies, whereas the second stage, information search is affected by familiarity with the digital technologies ($\beta = .16$, $p < .001$), utilitarian attribute ($\beta = .38$, $p < .001$) of the digital technologies and need recognition ($\beta = .12$, $p < .05$).

Similarly, alternative evaluation is influenced by performance attribute ($\beta = .36$, $p < .001$) of the digital technologies and need recognition ($\beta = .13$, $p < .05$), whereas purchase behavior is driven by independence ($\beta = .27$, $p < .001$), information search ($\beta = .15$, $p < .05$) and alternative evaluation ($\beta = .17$, $p < .01$). Finally, post-purchase behavior is influenced by many attributes of digital technologies, including utilitarian ($\beta = .33$, $p < .001$), independence ($\beta = .24$, $p < .01$), performance ($\beta = .20$, $p < .05$), and versatility ($\beta = .17$, $p < .05$), enjoyment dimension of customer experience ($\beta = .37$, $p < .001$) as well as need recognition ($\beta = .19$, $p < .001$) and information search ($\beta = .20$, $p < .001$).

< Insert Table 5 about here >

Table 5 shows a comparison of the values of all the variables across the six digital technologies included in this study. As expected, Internet seems to be the most popular technology with highest scores on information search, purchase behavior, familiarity, past usage and utilitarian attributes. In contrast, augmented reality shows highest scores on virtualization and human-like attributes. Interestingly, mobile platform shows the lowest scores on many attributes and CDM stages as well as customer outcomes, which seems in line with the lower use of mobile phones as primary internet device in this sample (12%).

Overall study 1 provides many useful insights about the consumers' perceptions about the digital technologies. However, this study had a few limitations. First, it included many participants who were not quite familiar with all the digital technologies. Second, we did not focus on any specific product or service category. We did this to cover a broad cross-section of consumers and their perceptions about these digital technologies in general. However, all this may limit the generalizability of its findings. Finally, we had a relatively smaller sample size (N=50) for each of the six digital technologies, hence we could not test the influence of all the attributes of the digital technologies as well as the demographic and behavioral characteristics of the participants on the customers outcomes and the five CDM stages.

4.2. Study 2 – Online survey

We addressed Study 1's limitations with Study 2, an online survey with the members of

Dynata, a leading global provider of first-party data contributed by consumers and others with a reach of about 70 million people globally. As we needed participants who were at least somewhat familiar with the four new digital technologies (i.e., AI, AR, VR and MR), we asked a screening question asked at the start of the survey to filter out participants not familiar with the emerging technologies. Out of 2737 participants, 26% stated that they were somewhat or more familiar (4 or more out of 7 in a Likert scale) with the digital technologies, making them eligible to take the study. To ensure the quality of responses, we also asked an attention-checking question twice in the survey, one at the beginning of the questionnaire, and another towards to the end. Fifty-six percent of the eligible participants passed both attention-checking questions, leaving the total sample size to be 400 participants in total. Table 1 includes the respondent profile for study 2.

Most of the participants (86.4%) in study 2 are aged 56 and over. Generally, individuals aged 56 and over are classified as elderly, while those aged 55 and below are often categorized as middle-aged (Wang et al., 2022). This distinction is particularly salient in the context of digital technology usage. Older adults, often slower and less likely to achieve their objectives through digital means, tend to use digital technology at a lower rate than middle-aged individuals (Johnson, 2022). We asked the participants to choose a specific product or service for which they have either shopped in the past or may shop in near future, using the new digital technologies. We also assessed the influence of the new digital technologies on the five stages in the AISAS model (Sugiyama & Andree, 2011).

We developed our questionnaire on Qualtrics platform, using items adapted from well-established scales drawn from our extensive literature review. Specifically, AISAS was measured using 22 items from Tseng and Wei (2020) and Kim et al (2020), slightly modified to allow respondents to concentrate on shopping using the emerging digital technologies. Eight items were adopted from Moriuchi (2019) to capture the perceived usefulness of digital technologies. For responsiveness to interactivity, 4 items were adopted from Park and Yoo (2020), reflecting the speed of accessing information using digital technologies while shopping. Scale items for performance expectancy were adopted from Gursoy et al. (2019) and for customer loyalty from Moriuchi (2019) with seven items. Psychological engagement was measured with nine items adopted from Flavián et al. (2019) to capture engagement with shopping using digital technologies. Five items of attitude towards digital technologies during shopping were adopted from Moriuchi (2019) to identify respondents' attitude towards digital technology for information seeking. The scales for all items above except attitude used seven-point Likert-type response format (1=strongly disagree to 7=strongly agree). Five dimensions of attitude were measured using a Bipolar Semantic Differential scale.

All the scale items are reported in Appendix 1. Before the survey, all scales were critically evaluated by a number of academics whose main area of expertise lies in the areas covered in the survey. The survey was also pre-tested with 20 respondents, and useful feedback was incorporated. All the variables were examined using confirmatory factor analysis (CFA) with AMOS 26.0 software and two items were dropped due to low convergent validity and cross-loading (Appendix 1). The CFA yielded a satisfactory fit (χ^2 = 2676, df = 979; normed χ^2 = 2.73 comparative fit index (CFI) = .926; root mean square error of approximation (RMSEA) = .066), with all items loading greater than 0.70 and Construct Reliability greater than 0.80 for each latent variable. We also established discriminant validity, as the square root of the average variance extracted (AVE) for each of the constructs was greater than the correlation between them (Table 6).

< Insert Tables 6 and 7 about here >

Next, all the hypothesized paths were tested using structural equation modeling (SEM) with AMOS 26.0. This model also yielded a satisfactory fit (χ^2 = 3042, df = 1010; normed χ^2= 3.01, CFI = .909; RMSEA = .071). The results confirm significant relationships for our AISAS model, (i.e., Attention → Interest → Search → Action → Share). As shown in Table 7, we found support for the non-linear nature of AISAS with a positive effect of Share on Attention (H1: β = .173, t = 2.7, p < .01). Responsiveness to digital interactivity also has a positive effect on Attention (H2: β = .174, t = 3.04, p < .01). Perceived usefulness has a positive effect on Interest (H3a: β = .360, t = 9.95, p < .001), and on Attitude (H3b: β = .578, t = 9.54, p < .001). Performance expectancy also has a positive effect on Attention (H4a: β = .222, t = 3.37, p < .001) and on Attitude (H4b: β = .166, t = 2.81, p < .01). Finally, Share has a positive effect on Loyalty (H5a: β = .397, t = 9.13, p < .001) and on Psychological engagement (β = .211, t = 4.07, p < .001). Thus, all of our hypotheses are supported by the data collected in our Study 2. In addition, we checked for moderating factors that might affect the strength of paths from antecedents to AISAS: need for human interaction, technology innovativeness, social influence, technology anxiety, hedonic motivation, service vs. product, and age. As none of these were significant, we do not report the results here.

5. General discussion

In this paper, we use two empirical studies (online surveys with consumer panel members) to investigate the effects of two existing (Internet and Mobile Platform) and four emerging (Artificial Intelligence, Augmented, Mixed and Virtual Reality) technologies on the different stages of consumer decision-making process. Specifically, in Study 1, we identified eight dimensions of attributes (utilitarian, hedonic, entertainment, performance, perceived risk, versatility, virtualization, and human-like). We also found significant differences in the influence of these attributes on the participants' choice and future usage of these technologies as well as the five stages of consumer decision-making process. Among the eight dimensions, utilitarian, performance, independence, and versatility appeared to play a more important role than the other four dimensions, although we would expect differences in their roles across the six technologies. For example, virtualization and human-like attributes are likely to play a more important role for the AR, VR and MR technologies compared to the others. However, we could not test these differences due to the relatively small sizes of our samples for each of the six digital technologies included in our first study. We also did not find significant differences in the overall scores for many of these attributes across the six technologies, except utilitarian, virtualization, and human-like, possibly because we did not distinguish among our participants based on their level of familiarity with the digital technologies.

We addressed these limitations in our second study, by including only those participants who were familiar with four new digital technologies (artificial intelligence; augmented, mixed and virtual reality) to test our specific hypotheses about the various antecedents and outcomes of the five stages in the AISAS (awareness, interest, search, action, and sharing) consumer decision-making model in the context of these new digital technologies. In addition, recognizing that the use of digital technologies might be considered a young person's activity, we gathered data for Study 2 from an older sample. The finding that influences on the AISAS process are not moderated by age, increases the generalizability of the findings. We found support for the non-linear nature of AISAS with a positive effect of sharing on attention (H1). In addition, responsiveness to digital interactivity had a positive effect on attention (H2). Similarly, perceived usefulness had a positive effect on interest and attitude (H3); performance expectancy had a positive effect on attention and attitude (H4); and sharing had a positive effect on loyalty and psychological engagement (H5). All these findings highlight the need to examine the influence of digital technologies on each stage of consumer decision-making more closely to account for its increasingly non-linear nature.

6. Theoretical and practical implications

This paper builds upon previous research by exploring the need to adapt and extend the AISAS model to account for the recent digital technologies AI, AR, VR and MR. Previous research has highlighted the crucial role of technology in transforming the interactions between the customers and firms (Yadav & Pavlou, 2020). Lemon and Verhoef (2016) conceptualize this customer experience with the firm over time from pre- to post-transaction as the customer shopping journey. The findings of this research demonstrate that digital technologies (e.g., AI, AR, VR and MR) influence customers along the shopping journey from pre- to post-transaction (Hoyer et al., 2020). Consumers are more connected and empowered to seek information and create experiences with brands through digital technologies (Hoyer et al., 2020). Therefore, consumer decision journey is no longer linear.

Our findings demonstrate this to be the case as our prediction that sharing influences consumption was confirmed, making AISAS into a circular model. In addition, consumers can skip some of the stages and follow many possible routes. We found, for example, that attention can lead directly to action, meaning that, with the help of digital technologies, customers might buy as soon as they are aware of an opportunity, without needing to go through the interest and search stages. This finding has an important practical implication for retailers. If customers' attention can be drawn to the possibilities of using digital technologies, say augmented reality to demonstrate how a room might look with particular furniture or color scheme, they may be motivated to buy without further consideration, making purchase from a competitor much less likely.

Results indicate that purchase leads to sharing and sharing leads to loyalty and psychological engagement. Psychological engagement itself also builds loyalty. In addition, the circular nature of the AISAS model, with the confirmed path from sharing to attention, means that use of digital technologies is likely to lead to repeat purchase, constituting a further route to loyalty. Thus, customers' use of digital technologies can help marketers tackle competitors more effectively and build repeat business. These results are as strong for older customers as for younger ones, which suggests that the emerging digital technologies may help a section of the older generation market segment become technology-savvy.

Our findings also confirm prior research showing that digital technologies affect how consumers search for products and services, evaluate and choose them, consume and build relationships with them (Libai et al., 2020). The digital interactivity and performance expectancy of technologies have significant influence on various stages in consumer decision journey such as arousing interest and attracting attention to shopping in the pre-transaction stage. Customers interact with brands at various touchpoints through digital technologies (Lee et al., 2018). Our results provide promising implications for both academics and managers who are interested in understanding the influence of digital technologies on consumer decision-making process throughout the customer shopping journey.

To conclude, this paper uses two online survey-based studies to first identify the unique attributes of four emerging technologies (AI, AR, VR and MR) and then study their influence on consumer decision-making process during shopping for products or services using new digital technologies. We also extend the AISAS (Awareness, Interest, Search, Action, and Sharing) model to show that the emerging digital technologies are making fundamental changes in the consumer decision-making process to make it non-linear. These findings indicate the need to examine the influence of digital technologies on each stage of consumer decision-making more closely in order to account for its increasingly non-linear nature.

7. Limitations and future research

This paper has a few limitations that future research may address. First, we used two different online consumer panels based in the US for our two studies, hence, our results may not be generalizable to other parts of the world, such as the emerging markets that may have very different socio-economic and cultural environment compared to the US. Second, in both our studies we included four new digital technologies and studied their influence on consumer decision-making in overall terms. Future research may focus on each new technology to understand its influence on the different stages in the consumer decision-making process. Finally, future research may also extend the AISAS model by accounting for the non-linear nature of consumer decision-making and by identifying new stages in this process.

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Figure 1. Non-linear AISAS model.

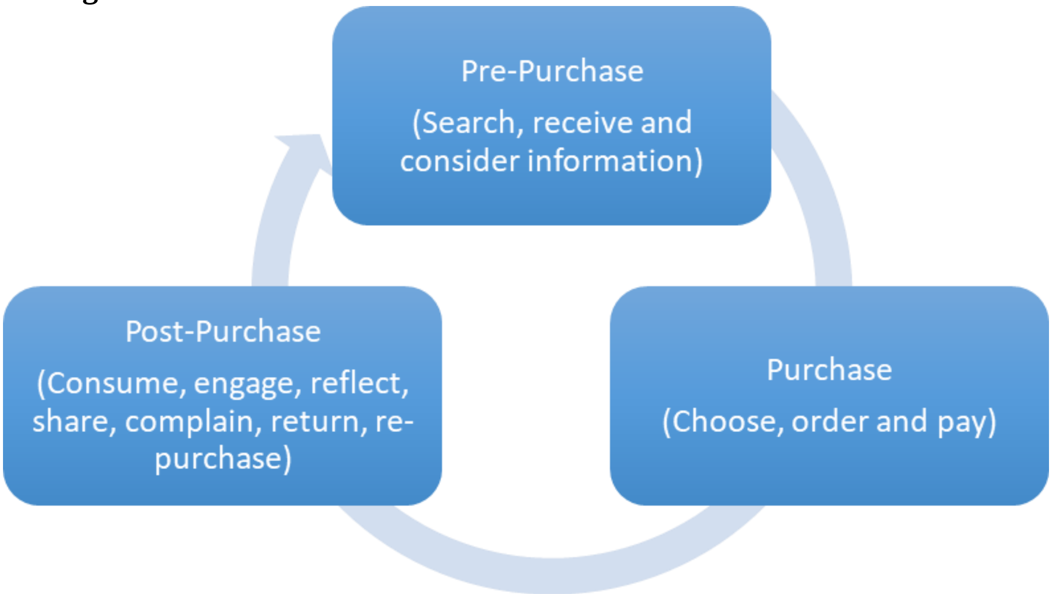

Figure 2. Conceptual model – AISAS Stages (Antecedents and Outcomes)

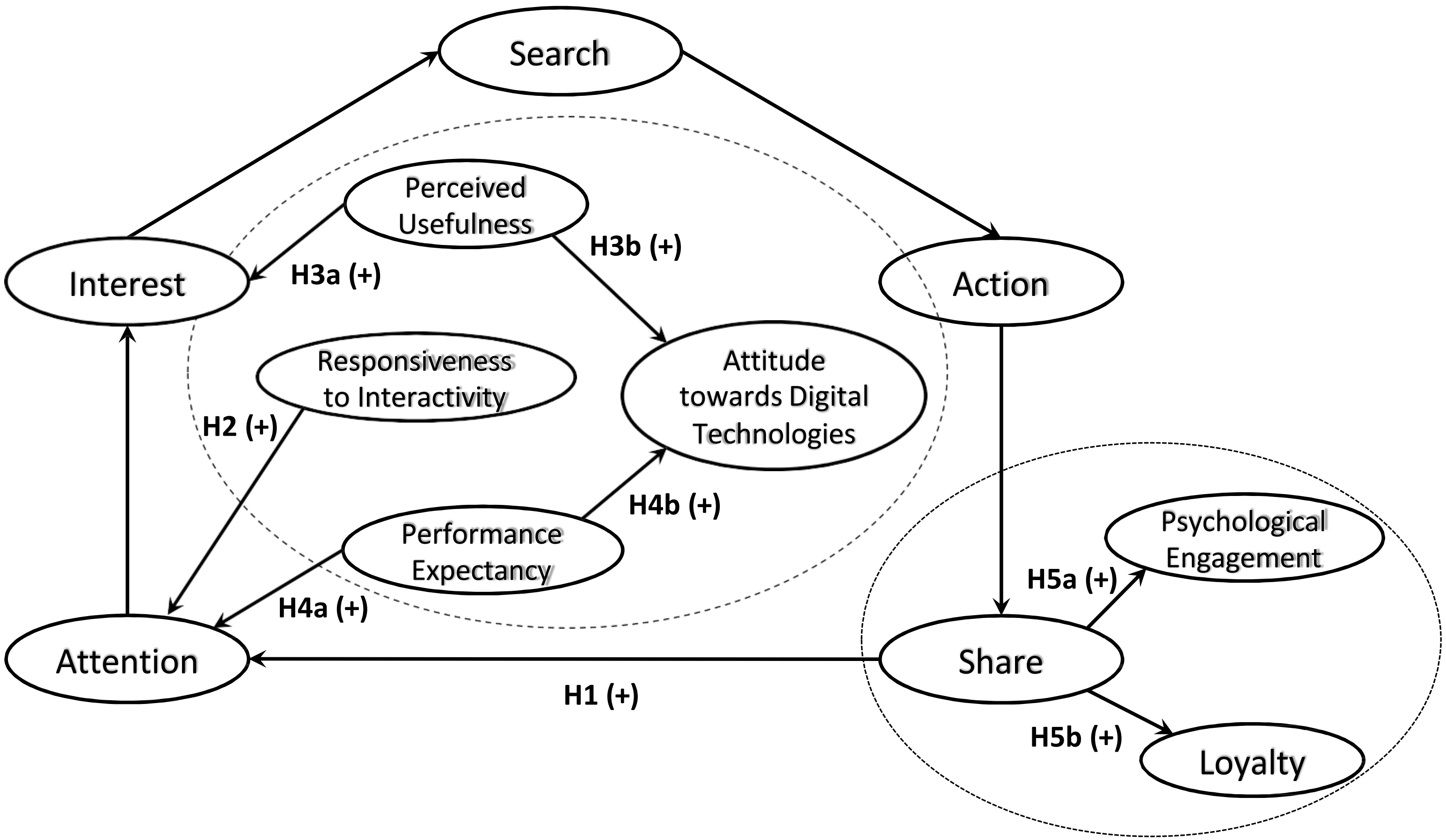

Table 1. Sample profiles

Variables	Categories	Study 1 (N=300)	Study 2 (N=400)
Gender	Female	87 (29.0%)	121 (30.3%)
	Male	213 (71.0%)	279 (69.8%)
Age	21 years or below	14 (4.7%)	6 (1.5%)
	22-43 years	217 (72.3%)	27 (6.8%)
	44-55 years	46 (15.3%)	21 (5.3%)
	56 years and above	23 (7.7%)	346 (86.4%)
Employment Status	Full-time	268 (89.3%)	81 (20.2%)
	Others	32 (12.7%)	319 (79.8%)
Employment Industry	Education	36 (12.0%)	14 (13.3%)
	Financial services	41 (13.7%)	12 (11.4%)
	IT services	107 (35.7%)	10 (9.5%)
	Manufacturing	48 (16.0%)	7 (6.7%)
	Others	68 (22.6%)	62 (59.1%)
Education Level	High school or below	29 (9.7%)	47 (11.7%)
	Bachelor's degree	219 (73.0%)	164 (41.0%)
	Master's degree or higher	52 (17.3%)	136 (34.0%)
Personal Annual Income (US Dollars)	Less than $25,000	47 (15.7%)	38 (9.5%)
	$25,000-$49,999	102 (34.0%)	60 (15.0%)
	$50,000-$74,999	70 (23.3%)	70 (17.5%)
	$75,000-$99,999	49 (16.3%)	73 (18.3%)
	$100,000 or more	32 (10.7%)	140 (35%)
Daily Internet Usage	Less than 2 hours	12 (4.0%)	40 (10.0%)
	2 - 4 hours	71 (23.7%)	171 (42.8%)
	4 - 6 hours	110 (36.7%)	92 (23%)
	6 - 8 hours	50 (16.6%)	33 (8.3%)
	More than 8 hours	57 (19.0%)	64 (26.0%)
Primary Internet Device	Desktop	97 (32.3%)	151 (37.8%)
	Laptop	168 (56.0%)	153 (38.3%)
	Smartphone or tablet	35 (11.7%)	92 (23.0%)

Table 2. Scale items and descriptives (Study 1)

Scale items	λ	M	SD
Decision making stage adopted from Comegys et al. (2009)			
Need Recognition			
Realize that I need something	0.73	5.18	1.27
Remind me about something I need	0.73	5.34	1.25
Information Search			
Browse for things that I may need	0.74	5.43	1.22
Search for information to fulfil my need	0.72	5.58	1.11
Alternative Evaluation			
Compare different options based on relevant features	0.71	5.47	1.20
Decide my order of preference for different options	0.75	5.33	1.21
Purchase			
Make my choice from various options	0.60	5.35	1.26
Make my purchase decision	0.70	5.35	1.29
Post-purchase			
Share my purchase experience with others	0.62	5.30	1.31
Make the same purchase decision again	0.68	5.33	1.25
Utilitarian adopted from Lysonski et al. (1996); Park and Stangl (2020)			
Quick to access	0.79	5.41	1.30
Easy to access	0.80	5.48	1.26
Ease of use	0.79	5.47	1.23
Portable	0.76	5.41	1.23
Informative	0.62	5.55	1.21
Increase knowledge	0.79	5.45	1.20
Inexpensive	0.72	5.05	1.42
Hedonic adopted from Biocca and Delaney (2013); Azuma (1997); Yusoff et al. (2011); Silva et al. (2003); Kirkley and Kirkley (2005); Park and Stangl (2020);			
Creative	0.74	5.34	1.30
Engaging	0.66	5.56	1.20
Interactive in real time	0.62	5.46	1.14
Independent	0.75	5.47	1.22
Impersonal	0.63	5.14	1.36
Do the unthinkable	0.66	5.03	1.46
Entertainment adopted from Kirkley and Kirkley (2005); Brito (2012); Park and Stangl (2020)			
Entertainment (audio, video)	0.63	5.39	1.25
Entertaining	0.66	5.54	1.10
Fun	0.72	5.35	1.25
Playing games	0.78	5.34	1.43
Self-learning system	0.67	5.30	1.16
Performance adopted from Kirkley and Kirkley (2005); Fisher et al. (2006)			
Personalized	0.63	5.37	1.16

Realistic	0.66	5.42	1.18
Trustworthy	0.69	5.35	1.19
Accuracy	0.67	5.50	1.15
Fast performance	0.80	5.38	1.24
Impartial	0.67	5.35	1.30
Perceived Risk adopted from Yoon et al. (2009); Brito (2012)			
Data security	0.62	5.21	1.33
Easy to hack	0.76	4.65	1.56
Damage mental health	0.86	4.61	1.68
Damage physical health	0.86	4.50	1.79
Lack of privacy	0.83	4.84	1.54
Virus prone	0.89	4.66	1.70
Versatility adopted from Young (2010); Brito (2012); Park and Stangl (2020)			
Ability to engage with others entities (e.g., humans, machines, objects)	0.71	5.18	1.30
Ability to perform a variety of tasks (e.g., play game, shop, communicate etc.)	0.89	5.31	1.23
Ability to mimic real-world responses	0.71	5.25	1.14
Ability to capture attention	0.76	5.43	1.29
Ability to create online content, e.g., website, blog, etc.	0.74	5.12	1.30
Ability to share online content, e.g., posts, photos, etc.	0.78	5.32	1.20
Ability to download information	0.79	5.46	1.14
Virtualization adopted from Azuma (1997); Azuma et al. (2001); Silva et al. (2003); Vince (2004); Guttentag (2010); Yusoff et al. (2011); Parsons et al. (2017)			
Combines real and virtual objects in a real environment	0.79	5.19	1.24
Incorporate social cues from computer-simulated avatars	0.69	5.17	1.23
Incorporates spatial environments	0.66	5.24	1.24
Matches real and virtual objects with each other	0.75	5.27	1.23
Use of a computer-generated 3D environment	0.75	5.35	1.17
Displaying in three dimensions	0.82	5.19	1.26
Humanlike adopted from Geetha and Bhanu (2018)			
Look like humans	0.80	5.01	1.45
Act like humans	0.82	4.94	1.45
Think like human	0.86	5.02	1.40
Act rationally	0.82	5.18	1.32
Think rationally	0.79	5.10	1.30
Intelligent	0.71	5.32	1.23
Work like a human brain	0.83	5.21	1.40

Efficiency adopted from Lysonski et al. (1996); Park and Stangl (2020)

Choose the right brand/product for me	0.69	5.35	1.29
Meet my expectations	0.46	5.44	1.14
Make the right choice	0.58	5.55	1.16
Process information	0.64	5.31	1.26
Search for value	0.75	5.53	1.16
Accomplish what I want	0.44	5.50	1.12
Find the item(s) I look for	0.80	5.43	1.29
Save my time	0.76	5.41	1.22
Make quick decisions	0.80	5.43	1.33
Easy to compare prices	0.75	5.32	1.31
Reduce my overall effort	0.69	5.51	1.16
Enjoyment adopted from Lysonski et al. (1996); Alavi et al. (2016)			
Enjoy the shopping experience	0.64	5.37	1.22
Look fashionable	0.65	5.37	1.28
Seek new experiences	0.61	5.48	1.21
Search for variety	0.88	5.57	1.17
Buy on impulse	0.85	5.07	1.44
Match the experience of traditional shopping	0.84	5.42	1.19
Choice adopted from Yoon et al. (2009); Van Boom (2011)			
Complexity of shopping task	0.65	5.13	1.31
Duration of a shopping task	0.72	5.27	1.26
Number of stages to complete a shopping task	0.82	5.32	1.20
Accuracy of information to complete a shopping task	0.76	5.40	1.25
Quantity of information to complete a shopping task	0.72	5.35	1.14
Clarity of information to complete a shopping task	0.73	5.37	1.19
Time of the day carrying out a task	0.68	5.31	1.26
Time pressure for a task to complete	0.70	5.28	1.23
Usage adopted from Jacoby et al. (1986); Yoon et al. (2009); Bearden et al. (2001)			
Experience of using the technology	0.75	5.30	1.20
Shopping goals for using the technology	0.78	5.32	1.20
Knowledge of the technology	0.81	5.47	1.21
Memory of how to use the technology	0.79	5.39	1.20
Motivation to use the technology	0.79	5.36	1.18
Confidence in using the technology	0.81	5.56	1.19

Table 3. Correlations table (Study 1)

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Need Recognition	*.75*																			
2. Info Search	.63**	*.73*																		
3. Alternative Eval	.62**	.61**	*.73*																	
4. Purchase Behavior	.57**	.57**	.60**	*.75*																
5. Post-purchase	.55**	.56**	.47**	.41**	*.75*															
6. Utilitarian	.73**	.71**	.67**	.60**	.53**	*.77*														
7. Hedonic	.61**	.60**	.63**	.64**	.58**	.74**	*.74*													
8. Entertainment	.61**	.58**	.64**	.62**	.49**	.72**	.75**	*.75*												
9. Performance	.67**	.66**	.71**	.62**	.60**	.71**	.70**	.73**	*.74*											
10. Perceived Risk	.32**	.27**	.29**	.30**	.39**	.40**	.55**	.37**	.42**	*.76*										
11. Versatility	.57**	.52**	.58**	.57**	.54**	.68**	.71**	.67**	.69**	.63**	*.77*									
12. Virtualization	.56**	.49**	.56**	.55**	.46**	.61**	.74**	.71**	.68**	.49**	.74**	*.75*								
13. Human-like	.44**	.34**	.41**	.45**	.40**	.48**	.63**	.53**	.59**	.57**	.71**	.68**	*.81*							
14. Efficiency	.71**	.69**	.68**	.64**	.58**	.75**	.72**	.73**	.73**	.37**	.72**	.69**	.55**	*.73*						
15. Enjoyment	.66**	.65**	.62**	.58**	.63**	.72**	.71**	.70**	.70**	.41**	.71**	.70**	.65**	.64**	*.78*					
16. Familiarity	.42**	.41**	.41**	.33**	.37**	.43**	.33**	.31**	.35**	.25**	.34**	.27**	.23**	.42**	.34**	*NA*				
17. Past Usage	.34**	.26**	.32**	.26**	.29**	.35**	.30**	.24**	.30**	.32**	.35**	.23**	.31**	.31**	.30**	.62**	*NA*			
18. Satisfaction	.38**	.29**	.35**	.29**	.32**	.40**	.29**	.31**	.35**	.15**	.34**	.28**	.25**	.36**	.34**	.50**	.49**	*NA*		
19. Choice	.59**	.54**	.58**	.53**	.48**	.67**	.70**	.62**	.71**	.53**	.68**	.70**	.61**	.71**	.71**	.35**	.25**	.28**	*.73*	
20. Future Usage	.60**	.55**	.60**	.49**	.56**	.70**	.66**	.63**	.72**	.45**	.67**	.62**	.50**	.73**	.70**	.42**	.36**	.39**	.70**	*.79*

Note: Figures in italics on the diagonal are the square roots of the average variance extracted (AVE)

Table 4. Multiple regression analysis output

Independent Variables	Future Usage	p-value	Need Recog	p-value	Info Search	p-value	Alternate Eval	p-value	Purchase Behavior	p-value	Post-Purchase	p-value
Familiarity	.04	.37	.08	.17	**.16**	**.00**	.09	.10	.01	.82	.12	.06
Past Usage	.08	.08	.03	.54	-.06	.24	.05	.32	-.01	.80	-.03	.56
Satisfaction	.06	.13	.04	.46	-.07	.17	.02	.75	.02	.69	.07	.16
Utilitarian	-.02	.77	**.37**	**.00**	**.38**	**.00**	.00	.97	-.11	.26	**-.33**	**.00**
Independence	-.09	.21	-.01	.88	.14	.07	.01	.91	**.27**	**.00**	**.24**	**.01**
Entertainment	.07	.26	.04	.57	-.01	.87	.14	.04	.12	.09	-.01	.86
Performance	**.22**	**.00**	.04	.66	.10	.24	**.36**	**.00**	-.03	.73	**.20**	**.04**
Concerns	.06	.22	-.05	.36	-.07	.22	-.10	.09	-.08	.21	.11	.08
Versatility	**.14**	**.03**	-.02	.75	.03	.69	.11	.16	.10	.21	**.17**	**.04**
Virtualization	-.02	.71	.10	.15	.01	.90	.05	.50	-.01	.94	-.13	.10
Humanlike	-.10	.09	-.01	.90	-.12	.07	-.05	.44	.05	.49	-.09	.21
Efficiency	.09	.30	.19	.06	.09	.35	-.04	.71	.17	.10	.01	.90
Enjoyment	.11	.12	.04	.65	.09	.26	-.04	.67	-.08	.37	**.37**	**.00**
Choice	**.37**	**.00**	.05	.43	-.04	.53	.07	.30	-.02	.83	-.13	.09
Need Recognition	-	-	-	-	**.12**	**.04**	**.13**	**.03**	.12	.07	**.19**	**.00**
Information Search	-	-	-	-	-	-	.12	.06	**.15**	**.02**	**.20**	**.00**
Alternative Evaluation	-	-	-	-	-	-	-	-	**.17**	**.01**	-.05	.48
Purchase Behavior	-	-	-	-	-	-	-	-	-	-	-.09	.15
Gender	.02	.54	.02	.55	.04	.36	.05	.25	-.05	.26	.07	.14
Age	.00	.91	.04	.33	-.02	.56	.05	.22	.00	.93	.03	.50
Employment Category	.09	.01	-.02	.60	-.02	.63	.03	.40	-.10	.03	.05	.23
Daily Internet Usage	.06	.10	-.06	.20	-.09	.04	.04	.33	.00	.99	.00	.93
Highest Education	.01	.83	.06	.13	.12	.00	.02	.63	-.02	.72	.06	.19
Personal Annual Income	.01	.81	-.01	.88	-.03	.50	-.05	.26	-.05	.25	-.02	.69
R-Square	.68		.57		.59		.57		.51		.50	
F-value	32.35		20.44		20.99		19.34		14.31		13.28	
P-value	.001		.001		.001		.001		.001		.001	

Table 5. Mean comparison - One Way ANOVA (Study 1)

Constructs	INT	MOB	AI	AR	VR	MR	F-value	P-value
Need Recognition	5.54	5.02	5.27	5.33	5.12	5.31	1.39	0.23
Information Search	**5.80**	5.29	5.64	5.71	*5.23*	5.40	2.77	**0.02**
Alternative Evaluation	5.63	5.34	5.38	5.57	5.14	5.35	1.41	0.22
Purchase Behavior	**5.65**	*5.04*	5.18	5.60	5.27	5.37	2.56	**0.03**
Post-purchase Behavior	5.38	5.16	5.43	5.43	5.11	5.38	0.78	0.56
Utilitarian	**5.82**	5.28	5.45	5.46	5.14	5.29	3.15	**0.01**
Hedonic	5.53	5.19	5.20	5.53	5.19	5.36	1.73	0.13
Entertainment	5.69	5.23	5.29	5.56	5.35	5.31	1.69	0.14
Performance	5.55	5.27	5.39	5.52	5.21	5.38	1.18	0.32
Perceived Risk	4.98	4.77	4.77	4.83	4.85	4.81	0.23	0.95
Versatility	5.45	5.10	5.30	5.28	5.15	5.24	0.93	0.46
Virtualization	5.36	*4.91*	5.15	**5.45**	5.22	5.33	2.07	**0.07**
Human-like	5.07	*4.71*	5.11	**5.34**	5.22	5.24	2.05	**0.07**
Efficiency	5.72	5.30	5.41	5.46	5.25	5.48	1.83	0.11
Enjoyment	5.48	5.26	5.28	5.51	5.25	5.51	0.99	0.43
Familiarity	**5.57**	4.98	4.84	5.00	4.96	*4.49*	2.38	**0.04**
Past Usage	**5.31**	4.96	4.28	*4.27*	4.36	4.47	3.66	**0.00**
Satisfaction	5.20	4.94	4.64	4.96	4.98	4.57	0.87	0.50
Choice	5.29	5.11	5.36	5.44	5.26	5.37	0.84	0.52
Future Usage	5.64	5.26	5.39	5.51	5.26	5.35	1.24	0.29

Note: INT: Internet, MOB: Mobile; AI: Artificial Intelligence; AR: Augmented Reality; VR: Virtual Reality; MR: Mixed Reality

Table 6. Correlations table (Study 2)

Constructs	1	2	3	4	5	6	7	8	9	10	11
1. Customer Loyalty	**0.897**										
2. Perceived Usefulness	0.808	**0.867**									
3. Attitude toward digital technologies	0.569	0.685	**0.915**								
4. Responsiveness of Interactivity	0.581	0.709	0.590	**0.875**							
5. Interest	0.689	0.791	0.622	0.580	**0.909**						
6. Search	0.603	0.720	0.531	0.504	0.748	**0.827**					
7. Action	0.762	0.842	0.640	0.603	0.873	0.804	**0.895**				
8. Share	0.772	0.644	0.423	0.434	0.588	0.546	0.699	**0.908**			
9. Psychological engagement	0.830	0.802	0.611	0.645	0.774	0.583	0.750	0.632	**0.832**		
10. Performance Expectancy	0.681	0.689	0.569	0.693	0.566	0.506	0.586	0.528	0.677	**0.844**	
11. Attention	0.747	0.791	0.582	0.555	0.869	0.681	0.859	0.640	0.717	0.580	**0.935**

Notes: figures in bold in the diagonal are square roots of AVEs

Table 7. Hypotheses tests (Study 2)

	Hypothesised path	β (t-value)	S.E	Result
H1	Share → Attention	.173** (2.74)	.058	Supported
H2	Responsiveness of Interactivity → Attention	.174** (3.04)	.083	Supported
H3a	Perceived Usefulness → Interest	.360*** (9.95)	.036	Supported
H3b	Perceived Usefulness → Attitude toward digital technologies	.578*** (9.54)	.064	Supported
H4a	Performance Expectancy → Attention	.222*** (3.37)	.084	Supported
H4b	Performance Expectancy → Attitude toward digital technologies	.166*** (2.80)	.064	Supported
H5a	Share → Psychological Engagement	.211*** (4.07)	.038	Supported
H5b	Share → Customer Loyalty	.397*** (9.13)	.38	Supported

Notes: B = standardised structural weight. * = p < .05, ** = p < .01, *** = p < .001

Appendix 1: Survey items (Study 2)
AISAS (Tseng & Wei 2020; Kim et al., 2020)
Attention CR = .955, AVE = .875

- Digital Technologies would attract me to shop for {respondent choice for a product or a service}. (1)
- Digital Technologies would draw my full attention to shop for {respondent choice for a product or a service}. (2)
- Digital Technologies would catch my eye to shop for {respondent choice for a product or a service}. (3)

Interest CR = .950, AVE = .826

- Shopping for {respondent choice for a product or a service} using Digital Technologies would be interesting. (1)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would be fun. (2)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would be enjoyable. (3)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would give me a good idea of what to look for. (4)

Search CR = .811, AVE .685

- I can use Digital Technologies to search for information while shopping {respondent choice for a product or a service}. (1)
- ~~I can use Digital Technologies to search for online word-of-mouth while shopping for {respondent choice for a product or a service}. (2)~~
- I can use Digital Technologies to compare prices while shopping for {respondent choice for a product or a service}. (3)

Action CR = .924, AVE = .801

- Shopping for {respondent choice for a product or a service} using Digital Technologies would be worthwhile. (1)
- I would be willing to shop for {respondent choice for a product or a service} using Digital Technologies. (2)
- I would make a good decision by shopping for {respondent choice for a product or a service} using Digital Technologies. (3)

Share CR = .934, AVE = .825

- I would tell my friends about my purchase while shopping for {respondent choice for a product or a service} using Digital Technologies. (1)
- I would share information about my purchase with my friends while shopping for {respondent choice for a product or a service} using Digital Technologies. (2)
- I would share my comments about my purchase on the internet shopping for {respondent choice for a product or a service} using Digital Technologies. (3)

Responsiveness of Interactivity (Park & Yoo 2020) CR = .929, AVE = .766

- Shopping for {respondent choice for a product or a service} using Digital Technologies would process my input very quickly. (1)
- Getting information when shopping for {respondent choice for a product or a service} would be very fast using Digital Technologies. (2)
- When shopping for {respondent choice for a product or a service} using Digital Technologies, I would be able to obtain the information I wanted without any delay. (3)
- When shopping for {respondent choice for a product or a service} using Digital Technologies, I would feel I were getting instantaneous information. (4)

Perceived Usefulness of digital technologies (Moriuchi, 2019) CR = .955, AVE = .751

- Shopping for {respondent choice for a product or a service} using Digital Technologies would improve my shopping experiences. (1)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would help me utilize my time more effectively. (2)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would enable me to make better shopping decisions. (3)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would make my shopping decisions easier. (4)
- Shopping for {respondent choice for a product or a service} using Digital Technologies would enhance my repurchases. (5)
- ~~Shopping for {respondent choice for a product or a service} using Digital Technologies would be better than using real customer agents. (6)~~
- Shopping for {respondent choice for a product or a service} using Digital Technologies would save me the time to gather information for making my shopping decisions. (7)
- Overall, I would find shopping for {respondent choice for a product or a service} using Digital Technologies useful to gather information for making my shopping decisions. (8)

Performance Expectancy (Gursoy et al., 2019) CR = .908, AVE = .712

- Digital Technologies used when shopping for {respondent choice for a product or a service} would be more accurate than human beings. (1)
- Digital Technologies used when shopping for {respondent choice for a product or a service} would make less errors than humans. (2)
- Digital Technologies used when shopping for {respondent choice for a product or a service} would provide me with more consistent service than human beings. (3)
- Information provided by Digital Technologies during shopping for {respondent choice for a product or a service} would be more consistent. (4)

Customer loyalty (Moriuchi, 2019) CR = .961, AVE = .805

- I would recommend a company to others because of their integration of Digital Technology on their website or messaging app. (1)
- I would do more shopping with companies that integrate Digital Technology on their website or messaging app in the future. (2)
- I would encourage friends and relatives to search information from companies that integrate Digital Technology on their website or messaging app. (3)
- I would say positive things to other people about a company if they use Digital Technology integrated on their website or messaging app. (4)
- A company that integrates Digital Technology on their website or messaging app would be my destination for shopping for {respondent choice for a product or a service}. (5)
- I would encourage friends and relatives to do business with the company using Digital Technologies. (6)
- I would recommend the company using Digital Technologies to someone who seeks my advice. (7)

Psychological engagement (Flavián et al., 2019) CR = .931, AVE = .692

- I would lose myself in the shopping experience for {respondent choice for a product or a service} using Digital Technologies. (1)
- I would be absorbed in the shopping experience for {respondent choice for a product or a service} using Digital Technologies. (2)
- The time I would spend in the shopping experience for {respondent choice for a product or a service} using Digital Technologies just slipped away. (3)
- The shopping experience for {respondent choice for a product or a service} using Digital Technologies would be attractive. (4)
- The shopping experience for {respondent choice for a product or a service} using Digital Technologies would be aesthetically appealing. (5)
- The shopping experience for {respondent choice for a product or a service} using Digital Technologies would appeal to my senses. (6)
- The shopping experience for {respondent choice for a product or a service} using Digital Technologies would be worthwhile. (7)
- My shopping experience for {respondent choice for a product or a service} using Digital Technologies would be rewarding. (8)
- I would feel interested in the shopping experience using Digital Technologies. (9)

Attitude toward digital technologies (Moriuchi, 2019) CR = .963, AVE = .838

I think using digital technology devices for information seeking during shopping is …

- Useful—not useful (1)
- Realistic—not realistic (2)
- Informative—not informative (3)
- Specific—unspecific (4)
- Logical—illogical (5)

Notes: Items shown as ~~strikethrough~~ were deleted from the model due to low convergent validity and cross-loading. CR = Construct Reliability, AVE = Average Variance Extracted