ORIGINAL RESEARCH

Check for
updates

Conversational commerce: entering the next stage of AI-powered digital assistants

Janarthanan Balakrishnan[1] · Yogesh K. Dwivedi[2]

© The Author(s) 2021

Abstract

Digital assistant is a recent advancement benefited through data-driven innovation. Though digital assistants have become an integral member of user conversations, but there is no theory that relates user perception towards this AI powered technology. The purpose of the research is to investigate the role of technology attitude and AI attributes in enhancing purchase intention through digital assistants. A conceptual model is proposed after identifying three major AI factors namely, perceived anthropomorphism, perceived intelligence, and perceived animacy. To test the model, the study employed structural equation modeling using 440 sample. The results indicated that perceived anthropomorphism plays the most significant role in building a positive attitude and purchase intention through digital assistants. Though the study is built using technology-related variables, the hypotheses are proposed based on various psychology-related theories such as uncanny valley theory, the theory of mind, developmental psychology, and cognitive psychology theory. The study's theoretical contributions are discussed within the scope of these theories. Besides the theoretical contribution, the study also offers illuminating practical implications for developers and marketers' benefit.

Keywords Anthropomorphism · Intelligence · Animacy · Artificial intelligence · Digital assistants · Purchase intention

1 Introduction

Mayer and Harrison (2019) emphasized the term "conversational commerce". Conversational commerce refers to buying activity by a customer through a digital assistant. Since the term was first introduced in 2016 (Messina, 2016), it has received adequate

✉ Yogesh K. Dwivedi
  ykdwivedi@gmail.com; y.k.dwivedi@swansea.ac.uk

  Janarthanan Balakrishnan
  reachjanarthanan@gmail.com; jana@nitt.edu

[1] Department of Management Studies, National Institute of Technology, Tiruchirappalli, Tamil Nadu, India

[2] Emerging Markets Research Centre (EMaRC), School of Management, Swansea University Bay Campus, Fabian Way, Swansea SA1 8EN, UK

 Springer

attention in industry reports. A recent research survey (Humanizing Digital 2020) found that consumers prefer proactive product recommendations when purchasing through an online channel and using digital assistants. The survey also quoted that 88% of consumers demand businesses to integrate digital assistants to choose the right product and brand (Linder, 2020). A report by PWC published that consumers apart use digital assistants mostly to order food, buy groceries, books, homecare, hotel reservations (PWC, 2018). Mayer and Harrison (2019) proposed that digital assistants will significantly impact a commercial scenario. Given that conversation data and product recommendations are inbuilt inside digital assistants, the same could challenge the present e-commerce scenario in the promoting their brand. Data analytic have already played a more vital role in e-commerce (Akter & Wamba, 2016). Shi (2019) explains that conversational commerce involves messaging with consumers and allowing them to make purchases over platforms like Facebook Messenger, WhatsApp, Alexa, and other digital assistants. Though the term digital assistant is interchangeably used with the voice assistant, chatbot assistant, and AI (Artificial Intelligence) agents, "Digital Assistant" is an umbrella term that covers all these functions. Digital assistants mainly integrate AI-powered algorithmic chatbots, which use Natural Language Processing (NLP) to converse with customers (Pantano & Pizzi, 2020). The complete digital assistant architecture operates based on processing user conversation data to provide optimized results for their queries and recommendations. Also, digital assistants are more than AI pilots (Davenport & Bean, 2018), given that their scale of improvements has grown considerably year by year. While human-assisted chatbot is available across different business verticals (Ransbotham et al., 2017; Wilson & Daugherty, 2018), digital assistants employ satisfying AI experience without the interference of human dialogues. Notably, Kiron and Unruh (2019) quoted that AI applications are becoming human alternatives or in addition to them.

Though digital assistants and conversational commerce's growth is evident in a practical scenario, very little attention was given to empirical research ground (Bavaresco et al., 2020). There are few studies to explain how customers position their attitude towards digital assistants from a technology perspective. Digital assistants can be used through various devices with numerous queries. Buying a product through digital assistants can be one of its functions. Given its vast function and user involvement level, it is essential to understand users' disposition towards it, especially from a technology perspective. Though digital assistants can be regarded as a growing technology, their primary function, which sophisticates its success, is grounded based on AI-related attributes and data tools empowered within it. Developers associated with digital assistants deploy various algorithms to amplify the AI performance for optimized output. However, it is also essential to understand how consumers perceive these AI attributes in the same line. Though implementing AI is perceived to be a lucrative opportunity for business, but at the same time, it can be challenging as well (Wilson & Daugherty, 2018). AI and data have become an integral part of human life, and it is inevitable to ignore them (Wang et al., 2018). The same has now extended towards customers seeking an opportunity to purchase through digital assistants (McLean & Osei-Frimpong, 2019). This research is built from the practical gap stated above. The importance of understanding the technology and AI perspective in digital assistants in the customer purchase journey is gaining momentum, but no research has tried to unveil the phenomenon both conceptually and empirically. Most importantly, Moriuchi (2019), in his recent research, supported that future research should investigate different perspectives that emerge when consumers engage with digital assistants, especially in commercial view.

Though the advancement of digital assistants was well available during the last decade, limited research has extended to build any empirical framework that benefits businesses. The present research uses TAM (Technology Acceptance Model) integrating with AI (Artificial Intelligence) attributes to understand the attitude towards digital assistants and its reaction towards customer purchase intention via digital assistants. By employing TAM in this framework, it gives a basic idea of customer positioning towards digital assistants, and at the same time, it will contribute to the theory in the context of digital assistants. Besides TAM, this research identified and deployed three AI functional attributes: perceived anthropomorphism, perceived intelligence, and perceived animacy, which are regarded as important functional attributes of AI-powered technology (Bartneck et al., 2009). Next to TAM, by employing the AI attributes in the model, the study contributes extensively to theories related to digital assistants and online retailing. Building from the practical and theoretical gap, the study proposes the following research question.

RQ What are the impact of technology and AI functional attributes on user's attitude toward digital assistants and purchase intention through digital assistants?

The study will provide valuable insight into conversational commerce from the perspective of AI and TAM variables by exploring this research question. The study results will enable a greater understanding of literature concerned with technology based purchases. Besides the spectrum of conversational commerce, the study will enable understanding of the AI functional attributes which can contribute to improvising operational performance (Roden et al., 2017). Besides the core theoretical frameworks, the study has built its hypothetical background through metacognitive psychological theories, uncanny valley theory, perception theories (theory of mind), development psychology, and the theory of media equation. Besides theoretical implications, the study results will provide meaningful insights to practitioners in designing the digital assistants based on AI attributes. The results will also enable the practitioners to design the voice or pictorial avatars accordingly.

The present research follows cross-section research with data collected from 440 users who have prior purchasing experience through digital assistants. The research first explains the theoretical background of the model, then proposes the hypotheses. Subsequently, the methodology and results sections are explained. Finally, the results are discussed with specific reference to the study contributions from a theoretical and practical perspective.

2 Theoretical background

2.1 Technology acceptance model

Technology Acceptance Model (TAM) was proposed by Davis (1989), which is derived from the Theory of Reasoned Action (TRA) postulated by Ajzen and Fishbein (1980). Studies have discussed TAM applications in e-commerce and m-commerce perspectives (Dennis et al., 2009; Faqih & Jaradat, 2015; Pavlou, 2003; Wu & Wang, 2005). In their paper, Gefen et al. (2003) proposed that technology will play a crucial role in customer purchase scenario now and in the future. Now this research extends the theoretical application concerning conversational commerce with specific reference to digital assistants. Various research has supported the importance of TAM in e-commerce. In their seminal research, Pavlou (2003) supported the same argument by their model, which converged

the technology acceptance and intention to purchase through e-commerce websites. Subsequently, many research supported the argument of investigating the role of TAM constructs namely, perceived ease of use and perceived usefulness with relevant to online buying intention (Gefen et al., 2003; Juaneda-Ayensa et al., 2016). But though TAM is derived from TRA, minimal studies have used attitude as a substantial construct that creates behavioral intention. Alike TRA, the Theory of Planned Behaviour (TPB) supports that any behavioral intention is formed through a positive attitude (Ajzen, 1991). Most of the studies on online purchases have supported that behavioral intention is derived from a positive attitude. Thus, theoretically, while TAM helps to understand the acceptance parameters, it is important to build it through a positive attitude (Dwivedi et al., 2019). Various relationships associated with TAM were explored previously in the context of e-commerce, such as; electronic commerce acceptance with trust and risk (Pavlou, 2003), technology acceptance and adoption with electronic commerce (Dennis et al., 2009), integrating task technology fit with TAM (Klopping & McKinney, 2004; Sinha et al., 2019), TAM with information, system, and service quality in building online buying attitude (Shih, 2004), technology adaptation towards virtual stores acceptance (Chen & Tan, 2004), customer loyalty intentions (Chiu et al., 2009), TAM with e-shopping quality (Ha & Stoel, 2009), augmented TAM (Vijayasarathy, 2004). Notably, Hsiao and Yang (2011) supported that e-commerce is one of TAM's most investigated areas. Like e-commerce, various studies have applied TAM to understand mobile commerce acceptance (Faqih & Jaradat, 2015; Kalinic & Marinkovic, 2016; Pipitwanichakarn & Wongtada, 2019; Wu & Wang, 2005). However, previous studies have also employed the Unified Theory of Acceptance and Use of Technology (UTAUT; Im et al., 2011; San Martín & Herrero, 2012) and Information Adoption Model (IAM; Gunawan & Huarng, 2015) to investigate purchase intention and behavioral intention. However, given the functionalities of digital assistants, TAM (perceived ease of use and perceived usefulness) will provide an outline to understand them better. Table 1 shows the relevant studies related to digital assistants and the theoretical framework employed by the researchers. From the table, it is evident that, except Moriuchi's (2019) study, no study has attempted to incorporate TAM related to attitude. Also, no study has tried to build a holistic model in digital assistants using TAM to relate with purchase intention. Overall, though TAM has been predominantly used relevant to online shopping intention and other technologies, no literature integrates AI properties and digital assistants in a single framework. Brill et al. (2019) supported that digital assistants' literature should also emphasise on AI application to get a complete understanding of the technology. Thus, besides TAM, this study also brings in three major constructs which portray AI properties in digital assistants.

2.2 Attributes of artificial intelligence

While some common attributes are available to synthesize with AI, three main functional attributes that can be uniquely assigned to AI are: perceived anthropomorphism, perceived intelligence, and perceived animacy (Bartneck et al., 2009). Present research employs the three AI functional attributes in the proposed framework.

2.2.1 Perceived anthropomorphism

Anthropomorphism at the human–computer interface involves both hardware features (physical replication) and software features (internal replication) which triggers an

Table 1 Studies related to digital assistants

Context/investigated variable in the study	Technology type	Study	Theoretical foundation/background variables
Social versus task orientation	Conversational digital assistants	Chattaraman et al. (2019)	Social response theory
Attitude and loyalty	Voice assistants	Moriuchi (2019)	TAM
Satisfaction	Digital assistants	Brill et al. (2019)	Expectation confirmation theory
Continuation intention	AI-powered service agents	Ashfaq et al. (2020)	Expectation confirmation theory and TAM
Choice satisfaction	Chatbots	Pizzi et al. (2020)	Reactance theory
Purchase intention	Chatbots	Yen and Chiang (2020)	Machine communication quality, human uses and gratification, human–computer interaction
Acceptance of digital voice assistants	Digital voice assistants	Fernandes and Oliveira (2021)	Functional, relational and social model
Consumer brand engagement and purchase intention	Voice assistants	McLean et al. (2021)	AI attributes, technology attributes, situational foundation
Satisfaction and willingness to continue	Voice assistants	Poushneh (2021)	Voice assistants personality trait
Intention to voice order	Voice-activated smart home devices	Canziani and MacSween (2021)	Opinion seeking, hedonic perception
Intention to re-use	Voice assistant	Moriuchi (2021	UTAUT
Trust	Artificial agent	Sullivan et al. (2020)	Moral appraisal
Customer experience performance	AI based voice assistants	Bawack et al., (2021)	Personality traits, trust and privacy concerns

anthropomorphic design (Qiu & Benbasat, 2009). In other words, anthropomorphism can be explained as assigning humanlike characteristics to a non-human agent or object (Aggarwal & McGill, 2012; Pfeuffer et al., 2019). Studies have supported that anthropomorphic characteristics can induce high-level trust through an emotional connection with the object, which sustains a stronger relationship with the non-human objects (Mourey et al., 2017; Touré-Tillery & McGill, 2015). Previous research has investigated different anthropomorphic implementations such as avatar extensions, facial modifications, character definitions etc. (Qiu & Benbasat, 2009; Riedl et al., 2014). The term "Anthropomorphism" is also widely used in marketing literature with relevance to brand and in advertising research on how marketers use it (Hudson et al., 2016; Rauschnabel & Ahuvia, 2014). In their research, Chandler and Schwarz (2010) confirmed that anthropomorphism played a crucial role in product decisions and brand switchovers. Likewise, various marketing research has supported that anthropomorphic characteristics imposed on the brand characters can lead to the brand's build attitude and purchase intention (Payne et al., 2013). Though anthropomorphism has received considerable attention from marketing literature, its primary application lies in Information Systems (IS) research. In IS domain, anthropomorphism has received prominent attention from the robotics area. Some of the considerable research that connected robotic functions with anthropomorphism are robot's sociability (Kiesler et al., 2008), artificialness (Bartneck et al., 2009), consciousness and emotions (Waytz et al., 2014), and humanness (Haslam et al., 2008). Złotowski et al. (2014) explained two dimensions of anthropomorphism; uniquely human and human nature. They represented uniquely human characteristics with cognitive ability and human nature with emotional being that is represented towards anthropomorphic object. Though anthropomorphism is mainly attributed to robotic features, Moussawi et al. (2020) supported that anthropomorphism will be an important construct to investigate personal and digital assistants' relevance. Prior research has supported different views associated with functions of digital assistants such as text to speech interface (Link et al., 2001), voice replication (Nass & Lee, 2001), vividness (Hess et al., 2009), etc. The successful implementation of anthropomorphism lies in the perception of the users and consumers. Moussawi and Koufaris (2019) explain perceived anthropomorphism as the degree to which users perceive the agent as humanlike. Brahnam (2009) found that by applying anthropomorphic characteristics cues in chatbot conversations, they received social acceptance from them. Digital assistants use both voice and chat facilities with human-like cues to increase the likeability of anthropomorphic characteristics. However, minimal research has investigated digital assistants' technology and anthropomorphic aspects, especially in commercial terms. This research adds perceived anthropomorphism as an important construct to the study model.

2.2.2 Perceived intelligence

Like anthropomorphism, researchers have found intelligence as an important characteristic of artificial intelligence (Bartneck et al., 2009). Intelligent systems started playing an important role in the information systems area from the 1950s, and the topic emerged to solve complex problems which are difficult for human beings to process (McCarthy & Hayes, 1969). Recent developments in intelligent systems include IBM Watson and other chatbots (Ferrucci et al., 2010) and many more, which use series of connected algorithms and data predictions to exhibit more human-like intelligence (Akter et al., 2019). Nevertheless, since the cognitive and reasoning capacity in processing data has become an integral part of any AI algorithms (Hossain et al., 2020), intelligence has become an important

identity for any AI-powered systems (Ogiela & Ko, 2018; Russell & Norvig, 2010). From a business perspective, intelligence plays a role in users' perception, especially when injecting human-like characteristics into an object. Perceived intelligence denotes the user's perception of the technology intelligence and its capacity (Johnson et al., 2008). Bartneck et al. (2009), in their paper, commented that intelligence is mostly perceived based on the system's competence level. Previous research has investigated knowledge, sensibleness, and responsibility as the critical variables associated with intelligence (Bartneck et al., 2009; Kiesler et al., 1996; Parise et al., 1996). Moussawi et al. (2020) introduced digital and voice assistants as Personal Intelligent Agents (PIA), which acts intelligently to answer and assist users based on the conversation data. PIA's or digital assistants are recognized as intelligent systems based on their performance and intellectual architecture, which solves human queries. Though digital assistants emerged as a useful tool to support users' daily activities, they later started playing an important role by enhancing its touchpoint in every aspect of user's life (Parise et al., 2016). One of the major successes and improvements in the digital assistants can be attributed to the learning rate it captures from the user's interaction and transforms it into an intelligent quotient, leading to a better outcome and performance. Seeber et al. (2020) said that digital assistants had become collaborators in the consumer decision-making process, besides its functional operation as a tool. Dellermann et al. (2019) supported the same by emphasizing how these tools have started playing an important role in human life, and its intelligence is compounding based on the learning. In their research, Yang et al. (2020) explained that machine intelligence could enhance retail operations and provide personalized consumer service. While various literature has supported that digital assistants, chatbots, and PIA's are growing intelligent, their interactive system facilitates human queries. However, how do users or customers react by perceiving its intelligence at a higher level? remains unexplored. There is no literature to support that digital assistants' perceived intelligence can affect users' attitudes and enhance intention to purchase through it. This research attempts to propose the hypothesis in theoretical background.

2.2.3 Perceived animacy

One major task for autonomous agent developers is to bring lifelike elements into the system (Maes, 1995). In recent times the concept of animacy is used predominantly in IS research (Bartneck et al., 2009), but its origin is rooted in psychology research (Nielsen et al., 2015; Tremoulet & Feldman, 2006). Human when strongly attached to a tool, they personify at least to an abstract level. However, they may not wholly perceive it as a living thing but animate it to that level. Psychology research state this phenomenon as perceived animacy (Shultz & McCarthy, 2014). Animacy can be defined as believing objects as living beings that can interact and move on with their own rules. Such belief and phenomenon associated with animacy are fundamentally derived from social perception (Michotte, 1963). In one of their seminal studies, Heider and Simmel (1944) demonstrated that individuals perceive the motion of geometric shapes as animated. In support of this view, Tremoulet and Feldman (2006) reason that any object movement may inject a feel of animacy in an individual mind.

While anthropomorphism precisely imports human-like characteristics, which also involves personality and traits (Aggarwal & McGill, 2012), animacy brings in lifelike form to the object, which may not necessarily represent human form but mostly associated with the movement and graphic texture (Gao et al., 2019). Most of the research has

supported animacy in shapes and how humans perceive shapes in control with animacy. For example, Farid and Bravo (2012) spoke about face-animacy, which represents animatic face-like movements in a computer-generated environment (Balas et al., 2017; Cheetham et al., 2011; Koldewyn et al., 2014). Likewise, most of the research has attributed animacy perceptions with shapes and objects. Nielsen et al. (2015) extended this theory by experimenting that single object sounds can also emerge and form animacy perception among the IS users, including animal and human sounds such as human speaking and mosquito sounds. Meanwhile, Another section of studies has given a view that perception of animacy is more oriented with the humans' cognitive ability. Notably, Gao et al. (2019) found that the perception of animacy that emerges from the humans' cognitive architecture. While the literature of animacy has been derived mainly from a psychology background, its application in recent years is predominantly used in information systems research. The growth of AI-oriented applications is increasing day by day, so does the involvement of humanistic characteristics and animatic involvement. Digital assistants are one such example, in which the developers use multi-functional AI attributes with human embedded features to create a perceived animatic environment. One good example is Amazon-Alexa, a well-known digital assistant, creates human-like voices and intelligent algorithms to recreate a human–human experience rather than a human–machine experience. Building upon these theories and practical examples, this research assumes that digital assistants create animacy perceptions among the users. In this study, we propose that the AI attributes can build purchase intention through digital assistants. In their framework, Pappas et al. (2016) proposed that both cognitive and affective perception can instill positive purchase intention. In a similar line, Hu et al. (2021) proposed that AI components consist of cognitive and affective components. Given that the above three components are more related to both cognitive and affective attributes of AI, we attempt to build our argument in this line. Overall we build our approach as given in Fig. 1. Based upon the above theoretical discussion, the study proposes a conceptual model and hypotheses in the following section.
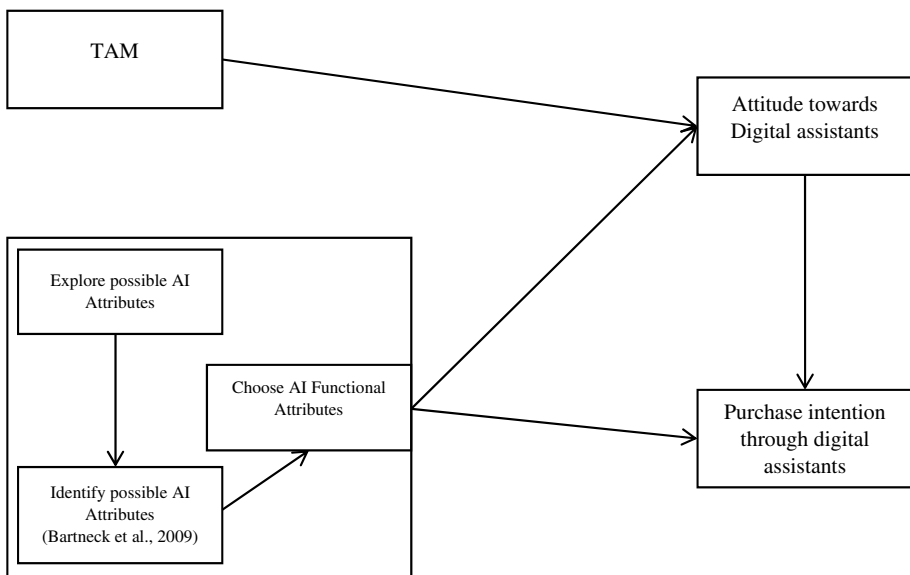

Fig. 1 Approach to the conceptual model

3 Conceptual model and hypotheses

Perceived ease of use denotes how users perceive the technology and system are easy to use than the existing way of performing the work. The construct, ease of use, is one of the important constructs in TAM. A plethora of studies have used the ease of use in different technology contexts like social media (Rauniar et al., 2014), Massive Open Online Courses (MOOCs) (Wu & Chen, 2017), smartphone usage (Joo & Sang, 2013), e-commerce and m-commerce (Chen & Tan, 2004; Dennis et al., 2009; Wu & Wang, 2005), etc. However, no studies have attempted to investigate this construct in the context of digital assistants. The use of digital assistants has become growingly important and necessary. It is important to understand the basis of the technology's attitude before understanding the technology's outcome to arrive at a sustainable decision (Akter et al., 2016; Wamba et al., 2017). Digital assistants operate at different levels based on the devices in which it is used, based on the AI algorithms (Chattaraman et al., 2019), and based on the product provider. Given these customized features, it is important to analyze whether the users perceive whether digital assistants are easy to use. Also, it is equally important to ascertain its relationship with the attitude of digital assistants. Based on the discussion above, the following hypothesis is proposed.

Hypothesis 1 (H1) Perceived ease of use will positively enhance users' attitude towards digital assistants.

Another vital construct in TAM is perceived usefulness (Davis, 1989). Similar to ease of use, usefulness has been used in most technology-oriented research. Previous researchers have found that perceived usefulness can be a strong determinant for positioning a positive attitude towards technology (Purnawirawan et al., 2012). In digital assistants' case, perceived usefulness denotes the extra utility that the technology can provide compared to the existing technology. Studies have found that technology use in the context of wearables (Chuah et al., 2016), virtual reality (Düking et al., 2018), electronic health records (Fan et al., 2018; Malik et al., 2018; Tubaishat, 2018), e-commerce and m-commerce (Gefen et al., 2003; Wu & Wang, 2005), etc. Given that digital assistants can be utilized for multifunctional tasks such as booking tickets, location navigation, buying goods, health checking, etc., the utility derived from these devices can be much higher. It is important and necessary to investigate the role of digital assistants' usefulness and how subsequently, it builds a positive attitude towards digital assistants.

Hypothesis 2 (H2) Perceived usefulness will positively enhance users' attitude towards digital assistants.

Social psychology research explains attitude as positive or negative evaluations and thoughts of an object of human (Bohner & Dickel, 2011). There are no studies that have studied the role of AI factors that can build a positive attitude towards technology. Perceived anthropomorphism is mostly investigated in the context of robotic uses (Ho & MacDorman, 2017). Nevertheless, no research has investigated the role of anthropomorphism and its effect in the digital assistant environment. Previous literature has built arguments about anthropomorphism from Uncanny Valley Theory's base (Mori, 1970). The theory suggests that an object with the human characteristics can enhance the user's comfortability in using it (Broadbent, 2017; Mori et al., 2012). The theory also stated that perceived

anthropomorphic characteristics included in an object could increase the users' emotional state (Mori, 1970). However, the theory does not directly propose the relationship between anthropomorphism and attitude. Nevertheless, the earlier studies' findings have supported that human likeliness can induce more technology-oriented interactions (Goudey & Bonnin, 2016) and user intentions (Fan et al., 2016). From the light of the above discussion and the argument set based upon uncanny valley theory, the following hypothesis is proposed.

Hypothesis 3 (H3) Perceived anthropomorphism will positively enhance users' attitude towards digital assistants.

In continuation from the discussion above, it is evident that human likeliness can enhance behavior aspects (Mori et al., 2012). Previous studies have supported that anthropomorphic impersonation induces purchase intention. For example, Payne et al. (2013) supported that brand anthropomorphic personalities can enhance purchase intention. The same can be extended to the e-commerce buying domain. To support this view, the study by Qiu and Benbasat (2009) found that the anthropomorphic recommendation agents used in e-commerce websites can aid the consumer purchase process. Guthrie (1995) found that anthropomorphic features can ease understanding of the product by familiarising the experience. Notably, Labroo et al. (2008) supported that the accumulation of humanlike experience can induce more likelihood to purchase the product. Digital assistants embed human voice-like characteristics that can induce consumers to book through digital assistants. These findings align with the propositions made from uncanny valley theory that human likelihood can induce more involvement and engagement towards the object. Building upon this view, the study proposes the following hypothesis.

Hypothesis 4 (H4) Perceived anthropomorphism will positively enhance users' purchase through towards digital assistants.

Sakamoto et al. (2015) explain virtuality as a background that does not exist but still affects the consumers' lives. Digital assistants offer enhanced experience through a virtual space but with embedded intelligence. Literature which has examined the aspects of technology intelligence and its relationship with user perceptions is very scarce. Koda (1996) expresses technology intelligence as a competence-based mechanism. On the other hand, Cohen (2000) describes systems intelligence as exhibiting cognitive processes which come as a replica of human reasoning. Though literature in psychology has addressed and compared IQ and self-efficacy in the context of perceived intelligence (Furnham & Buchanan, 2005), there is no theory available to directly link between perceived intelligence and user attitude. Digital assistants are well-known intelligent systems, but no studies have reported how users perceive this intelligence. Developers keep building new algorithms to improvise the digital assistants' intellectual capacity, but at the same time, marketers and developers need to understand how this builds a positive attitude among the users. The following hypothesis is proposed based on the above discussion.

Hypothesis 5 (H5) Perceived intelligence will positively enhance users' attitude towards digital assistants.

Retailers attempt various technology formats to maximize their conversion potential (Vukadin et al., 2019). When it comes to buying through a developed technology,

competence plays a significant role. Ihtiyar and Ahmad (2014) found that intercultural communication competence and its positive impact on purchase intention. Bassellier et al. (2001) supported that technology competence can be mainly attributed to system intelligence. Though there is no direct link or theoretical background to build a relationship between intelligence and purchase intention, through the route of competence, it can be proposed that intelligence can enhance purchase intention through digital assistants since previous studies have supported that technology competence can attribute positive user behavior (Ma et al., 2005). Given the recommendation and query handling possibility that digital assistants offer, their intelligence can be highly regarded by the users and influence them to purchase through the technology. The following hypothesis is proposed below based on the discussion above.

Hypothesis 6 (H6) Perceived intelligence will positively enhance users' purchase intention through digital assistants.

Animacy is perceived based on the cues and stimuli received and interpreted in the human perceptual system (Shultz & McCarthy, 2014). However, animacy is derived from the roots of development psychology (Piaget, 1926) and psychology of perception theories (Heider and Simmel, 1944). In recent times the application of animacy is extensively used in information and communication technology. The theory of media equation (Reeves & Nass, 1998) supports that people tend to build a favorable positioning towards the system while interacting with human-like artifacts. Research by Nass and others investigated and found that the human voice's effects can create animatic beliefs among the users (Nass & Gong, 2000; Nass & Lee, 2001). The above characteristics and beliefs can apply to the digital assistants, and digital assistants may create a positive attitude. Developers impart possible implementation of voice applications to infuse the most desirable animatic features. Notably, Davis (1993) found that system design and characteristics can build a positive attitude. Consolidating from the above thought and theoretical support, we propose the following hypothesis.

Hypothesis 7 (H7) Perceived animacy will positively enhance users' attitude towards digital assistants.

Theory of mind states that human behavior aspects are more tuned towards social psychology aspects in which they perceive the animatic interaction (Scholl & Leslie, 2001). Though most of the literature in psychology has informed that animacy can influence user behavior (Bartneck et al., 2009), no research has precisely investigated specific behaviors. Digital assistants can be perceived with high animacy levels, especially with the integrated AI attributes its human-like features react both in stimuli and intelligence contexts. Previous studies have supported that emerging technology formats can support purchase intention through digital modes (Kim, 2019). Given the emergence of digital assistants, it has become increasingly possible that users have started using them for commercial purposes. It is pertinent from psychology theories that perceived animacy is built from animated cues and stimuli through artificial agents (Shultz & McCarthy, 2014). Digital assistants provide voice and speech cues with human aspects to bring human-like features. It will be interesting and valuable to investigate how these animacy features enhance purchase intention

through digital assistants in a theoretical and practical context. The following hypothesis is proposed based on this discussion.

Hypothesis 8 (H8) Perceived animacy will positively enhance users' purchase intention through digital assistants.

Theory of Planned Behaviour (TPB) stated that a positive attitude could influence positive purchase intention (Ajzen, 1991). The theory is predominantly used in marketing literature to understand product attitude and brand attitude towards purchase intention. Similarly, the same was extended in the e-commerce domain to analyze the portal attitude and purchase intention through the portal (Kim, 2019). Most technology models have used technology acceptance as an important predictor of purchase intention (Juaneda-Ayensa et al., 2016). Limited studies have used technology attitude as a precursor to understanding purchase intention. Dwivedi et al. (2019) emphasized in their paper that attitude will play a significant role in technology-oriented models. Theories in psychology have described the attitude as a favorable or unfavorable disposition towards a human or object. Attitude facilitates the consumer purchase process (Ajzen, 1991). In digital assistants' case, users' favorable attitudes can positively interact and enable purchases through digital assistants. Building from this viewpoint, we propose the following hypothesis.

Hypothesis 9 (H9) Users' attitude towards digital assistants will positively enhance users' purchase intention through digital assistants.

Studies related to technology adoption and behavioral intention have addressed prior experience in using the technology as an important predictor and moderator of technology use (Speier & Venkatesh, 2002). Epley et al. (2007), in their three-factor theory of anthropomorphism, predicted that people elicited agent knowledge, effectance motivation, and sociality motivation from their continuous learning. According to the theory, it is predicted that people are more likely to anthropomorphize the agent when it is more accessible and applicable. It can be interpreted that the more the experience of the anthropomorphic agent, the more it can yield anthropomorphic perception. Various studies have used usage experience as a significant moderator of technology behavior (Chang & Chen, 2008; Shi & Chow, 2015). With the support of previous technology models and building from the recommendations from the three-factor theory of anthropomorphism, we propose that digital assistants' usage experience can enhance the anthropomorphic perception, which can subsequently enhance the positive relationship between anthropomorphism and purchase intention.

Hypothesis 10 (H10) Usage experience in digital assistants will positively moderate the relationship between perceived anthropomorphism and users' purchase intention through digital assistants.

Artificial intelligence builds its predictability and outcome-based learning data curve (Song et al., 2018). The more the users interact, it can naturally exhibit a higher level of predictability and optimized results. In other words, their perceived intelligence can accordingly increase based on the user's interaction with the digital assistants. Krening and Feigh (2018), in their paper, supported this view by finding that users' continuous interaction can

develop perceived intelligence among the robots. These results can be extended in the context of digital assistants too. Naives theory of intelligence suggests that people's experience in processing information can increase their perceived comprehension (Miele & Molden, 2010). The same can be applied to the digital assistants and how they comprehend them during the usage process. From this rational view, we propose that users with more experience with digital assistants can enhance their ability to perceive the digital assistants' intelligence. Thus, when usage experience interacts with perceived intelligence, it can build a positive intention to purchase through digital assistants.

Hypothesis 11 (H11) Usage experience in digital assistants will positively moderate the relationship between perceived intelligence and users' purchase intention through digital assistants.

The effects of animacy perception are built from the psychological perception theories and theory of mind. Tremoulet and Feldman (2006) showed that animacy perception is closely related to other entities, which the user identifies overtime as possessing a "mind". Their arguments stated that human perception towards animatic objects increases in parallel to the movements and patterns. The same can apply to voice-based animatic agents. In their research, Santos et al. (2008) found that animacy perception can increase based on experiencing more modulations. The research precisely found that users tend to understand different animatic variations when exposed to the condition more. From the above insights, it can be rationally understood that digital assistants can increase the animatic feeling among the users' overtime. Consequently, it can increase purchase intention through digital assistants. Based on the above discussion, the following hypothesis is proposed.

Hypothesis 12 (H12) Usage experience in digital assistants will positively moderate the relationship between perceived animacy and users' purchase intention through digital assistants (Fig. 2).
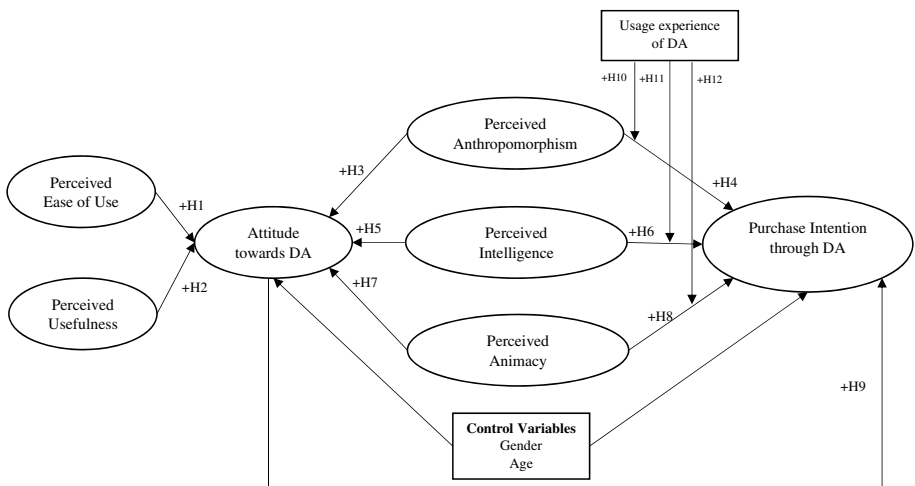

Fig. 2 Conceptual model with hypotheses

4 Methodology

4.1 Study participants

The study participants are users who have prior experience of commercial activity through the digital assistants. The participants were recruited using the non-probabilistic sampling method from colleges, universities, and work offices in India. WatConsult (2020) expects the Indian voice recognition technology market to reach ₹ 415.71 crores by 2020. Also, the source confirms that among the existing users of voice/digital assistants, 30% have used voice assistants for shopping of various product categories. Also, India's study sample can be represented as a case for emerging economies and Asia countries. Given the growth of technology has localized the global aspects; thus the study's results can be generalized globally.

4.2 Data collection

In the first stage – for identifying the sampling frame, we circulated a form asking for interest to participate in our research for an incentive of receiving ₹ 200 worth of online purchase coupons. The form consisted of two questions in a categorical format (yes/no); (1). Are you willing to participate in a survey investigating your intention to purchase through digital and voice assistants? (2) Do you have any experience purchasing through mobile voice or digital assistants? The form was circulated to various colleges/university contacts, employees belonging to private and public sector companies. With more than 8000 email recipients, we found 600 participants who provided "Yes" to both the questions. In the second stage – for data collection, data were collected by the authors through personal interaction, either by direct or telephone conversation with the respondents for three months. Based on the extended interest level and knowledge towards voice/digital assistants, we were able to arrive at collecting482 data, of which 440 usable responses are finally considered for the study sample. The socio-demographic characteristics of the participants are provided in Table 2.

4.3 Questionnaire and measures

A detailed questionnaire was prepared in English language consisting of scale measurement items and six questions about socio-demographic information (gender, education, age, occupation, usage intensity of digital assistants, experience in purchasing or ordering through digital assistants). The constructs' scale was derived from the previous studies (Bartneck et al., 2009; Hsu & Lin, 2008; Juaneda-Ayensa et al., 2016; Pantano & Viassone, 2015; Zhu et al., 2019). The questionnaire included all nominal, ordinal, interval, and ratio. The items for perceived ease of use, perceived usefulness, and attitude towards digital assistants is derived from Hsu and Lin (2008); The items for perceived anthropomorphism, perceived intelligence, and perceived animacy is derived from the godspeed questionnaire proposed by Bartneck et al. (2009); and finally, the scale for purchase intention through digital assistants is derived from Pantano and Viassone (2015), Juaneda-Ayensa et al. (2016), and Zhu et al. (2019). The questionnaire was pilot tested with 25 respondents representing the population and ten experts to evaluate the understandability, repetition, and clarity. Based on a qualitative evaluation, minor changes were accommodated in the scales

Table 2 Social demographic information about the study participants

Socio-demographic		Frequency	Percentage
Variables	Characteristics		
Gender	Male	211	47.95
	Female	229	52.05
Age	30 and less than 30 years	171	38.86
	31 to 40 years	154	35.00
	41 to 50 years	82	18.64
	Above 50 years	33	7.50
Occupation	Students	209	47.50
	Private sector employee	121	27.50
	Public sector employee	68	15.45
	Business	42	9.55
Education	Under-graduation	210	47.73
	Post-graduation	187	42.50
	PhD	43	9.77
Usage experience of digital assistants	Fortnightly once	57	12.95
	Weekly once	141	32.05
	Weekly twice	115	26.14
	Daily once	127	28.86
Experience in purchasing or ordering through digital assistants	More than 10 Occasions	55	12.50
	6 to 9 occasions	148	33.64
	2 to 5 occasions	214	48.64
	At least once	23	5.22

without deviating actual measurement. All the scale items were measured in a seven-point rating scale (7 being "Very Strongly Agree" and 1 being "Very Strongly Disagree").

4.4 Non-response bias

Armstrong and Overton (1977) emphasized the importance of testing the non-response bias for survey designs. To test non-response bias, we tested a significant difference in all the measurement items corresponding between early and later data collection stages (Dubey et al., 2019; Srinivasan & Swink, 2018; Wamba et al., 2020). The 30% of the data collected during the first 32 days is compared with the 30% of the data collected during the last 25 days to operationalize the test. The results indicate that there is no significant difference between the data collected during the two waves. Of the investigated variables third item of Animacy is found to have the least value (t=0.197; p=0.844), and the first item in Attitude is found to have a high value (t=1.793; p=0.074). Overall, it can be inferred that non-response bias is not a major issue in this study.

4.5 Analysis

The study model hypotheses were investigated using the two-step Structural Equation Modelling (SEM) technique. First, the confirmatory factor analysis is performed to check

the reliability, content validity, convergent validity, and discriminant validity requirements. Common Method Bias (CMB) analysis was used to confirm the constructs' measurements are free from common method bias. Subsequently, SEM was used to test the model; previous studies have supported using SEM for hypothesis testing models (Fornell & Larcker, 1981; Gefen et al., 2000; MacCallum & Austin, 2000). All analyses are performed using SPSS statistics 24 and AMOS 20 graphics. The estimates are calculated using the maximum likelihood method. The factor scores of each construct were calculated using the imputation method in AMOS software, and the same was further used to calculate the interaction effect with the variable usage intensity of digital assistants. Following that, the moderation path was included in the statistical model. Therefore, two models were calculated, i.e., one without moderation effect (model 1) and the other with moderation effect (model 2).

5 Results

5.1 Measurement model

Table 3 shows the measurement model range for all the constructs. The values of Cronbach's Alpha are well above the threshold value of 0.70, which confirms the presence of scale reliability (Portney & Watkins, 2000). The standardized estimates (factor loadings) of all the items representing all constructs are above 0.74, confirming the content validity requirements. Table 4 shows the values of Average Variance Extracted (AVE), Composite Reliability (CR), and the inter-correlation values between each construct with the squared root of AVE values represented in the diagonals. The AVE values are above 0.50, and this confirms the convergent validity requirements. The table also shows that AVE values' squared root is higher than the inter-correlation values for respective constructs. This result shows the confirmation of discriminant validity. All validity requirements met the expectation proposed by Bagozzi et al. (1991) and Fornell and Larcker (1981). The fit indices of the measurement model are given in Table 5, which shows the model reflects a good fit. From the above suggestions.

5.2 Common method bias

Analyzing Common Method Bias (CMB) has become increasingly necessary in social science research (Podsakoff et al., 2003). Two well-known methods are used in social science research to test CMB; the first method involves testing the construct items within a single construct known as Harman's one-factor examination. To examine this model, we performed factor analysis by imputing all the items under a single factor. The total variance extracted resulted in 45.86%, which is well under the threshold limit of 50%. This process confirms the data is free from common bias as per Harman's one-factor examination (Harman, 1967; Lindell & Whitney, 2001). Though Harman's model is well accepted in social science research, Podsakoff and Organ (1986) argue to conduct a Common Latent Factor (CLF) approach to analyze the CMB, since Harman's one-factor model can be conservative to some data. CLF aims to measure the difference between the common variance shared by the model with the individual measurement constructs (Podsakoff et al., 2003). CLF is performed through AMOS, in which the standardized estimates of the CLF model are compared with the Non-CLF model.

Table 3 Items and measurement model loadings

Constructs	Items	Mean	Std. loadings	Cronbach alpha
Perceived ease of use	I feel digital assistants are easy to use	4.709	0.949***	0.964
	I feel learning to operate digital assistants is easy	4.793	0.938***	
	Overall, I believe it is easy to work with digital assistants	4.781	0.958***	
Perceived usefulness	Using digital assistants enables to accomplish my work/learning/life more quickly	4.736	0.940***	0.926
	Using digital assistants would improve my work/learning/life performance	4.743	0.937***	
	Using digital assistants would enhance my work/learning/life effectiveness	4.840	0.960***	
	Using digital assistants can increase productivity when performing my tasks at work/learning/life	4.606	0.899***	
Attitude towards digital assistants	I like using digital assistants	4.272	0.924***	0.928
	I feel good about using digital assistants	4.327	0.911***	
	Overall, my attitude towards digital assistants is favorable	4.254	0.905***	
Perceived anthropomorphism	Digital assistants are natural; I do not feel fake about it	5.136	0.961***	0.965
	Digital assistants are more humanlike	5.027	0.940***	
	Digital assistants are conscious of their actions	4.936	0.965***	
	Digital assistants feel lifelike and not artificial	4.906	0.938***	
	Digital assistants are elegant in engaging	4.875	0.935***	
Perceived intelligence	Digital assistants are competent	4.838	0.962***	0.897
	Digital assistants are knowledgeable	4.813	0.948***	
	Digital assistants exhibits responsibility	4.697	0.958***	
	Digital assistants have intelligent functions	4.700	0.936***	
	Digital assistants are sensible during replies	4.647	0.945***	
Perceived animacy	Digital assistants feel to be alive	4.068	0.925***	0.854
	Digital assistants are lively	3.656	0.814***	
	Digital assistants fell to be organic	4.252	0.961***	
	Digital assistants engagement are mostly lifelike	3.827	0.918***	
	Digital assistants are more interactive	3.970	0.912***	
	Digital assistants are responsive	4.711	0.737***	

Table 3 (continued)

Constructs	Items	Mean	Std. loadings	Cronbach alpha
Purchase intention through digital assistants	I would like to purchase through digital assistants	4.468	0.914***	0.919
	I would like to repeat my experience in digital assistants	4.595	0.944***	
	I will execute my next purchase through digital assistants	5.636	0.938***	
	I am inclined to purchase products through digital assistants	4.472	0.944***	

***Significat at $p < 0.05$

Table 4 Inter-construct correlations and AVE values

	CR	AVE	1	2	3	4	5	6	7
1. Perceived animacy	0.953	0.773	*0.879*						
2. Perceived ease of use	0.964	0.899	0.266	*0.948*					
3. Perceived usefulness	0.928	0.873	0.331	0.858	*0.934*				
4. Attitude towards DA	0.938	0.834	0.483	0.662	0.714	*0.913*			
5. Perceived anthropomorphism	0.965	0.905	0.465	0.579	0.655	0.708	*0.951*		
6. Perceived intelligence	0.897	0.902	0.392	0.483	0.581	0.617	0.722	*0.950*	
7. Purchase intention through DA	0.919	0.874	0.406	0.439	0.521	0.680	0.634	0.574	*0.935*

1. AVE represents average variance extracted; 2. CR represents Composite Reliability; 3. Squared root of AVE's are presented in the diagonal for each construct in italic format; 4. All values in the correlation matrix are significant at 99% confidence level; 5. DA represents Digital Assistants

Table 5 Fit indices results

Fit indices	Measurement model	Structural model	Recommended value	Reference
X^2	869.076	1119.513	Not applicable	Hu and Bentler (1998)
df	377	385	Not applicable	
X^2/df	2.305	2.908	≤ 3.00	
GFI	0.890	0.865	≥ 0.900	
NFI	0.956	0.944	≥ 0.900	
CFI	0.975	0.962	≥ 0.900	
RMSEA	0.055	0.066	≤ 0.080	

It was found that the range of the differences lies from 0.054 to 0.002. Given that the CLF method requires the difference of all the items should be below 0.05, except one item (0.054), the remaining 29 items are well below the threshold. With the satisfactory examination and the values are well within the threshold limits of Harman's one-factor model and CLF estimation (MacKenzie & Podsakoff, 2012), we confirm that constructs are free from common method bias.

5.3 Structural equation modelling

Table 6 shows the results of the hypothetical model provided in Fig. 2. Model 1 indicates the hypothetical results without any moderation-interaction effects of digital assistants' usage experience, whereas model 2 indicates the results, including the moderation-interaction effects from digital assistants' usage experience. The r^2 values for the purchase intention through digital assistants (0.333) and attitude towards digital assistants (0.389) indicated the total variance extracted by the model for the respective endogenous constructs. The overall model fit for the structural model indicated a good fit (refer to Table 5), which supported the hypothetical model framing. In terms of technology variables, usefulness showed a high significant coefficient value than the ease of use. In the case of AI-related variables, anthropomorphism showed high coefficient value than perceived intelligence

Table 6 Standardised estimates of the model

Endogenous factor (dependent)	Exogenous factor (independent)	Standardized coefficient (Model 1)	Standardized coefficient (Model 2)	r^2
Attitude towards digital assistants	Perceived ease of use	0.250***	0.256***	0.389
	Perceived usefulness	0.334***	0.333***	
	Perceived anthropomorphism	0.361***	0.359***	
	Perceived intelligence	0.165***	0.165***	
	Perceived animacy	0.240***	0.240***	
	Age (control variable)	−0.070ns	−0.070ns	
	Gender (control variable)	0.015ns	0.015ns	
Purchase intention through digital assistants	Perceived anthropomorphism	0.250***	0.272***	0.333
	Perceived intelligence	0.175***	0.311***	
	Perceived animacy	0.061ns	0.102***	
	Attitude towards DA	0.370***	0.224***	
	Usage experience × perceived Anthropomorphism		0.479***	
	Usage experience × perceived Intelligence		0.101***	
	Usage experience × perceived animacy		0.116***	
	Age (control variable)	−0.038ns	−0.038ns	
	Gender (control variable)	0.009ns	0.009ns	

***Significant at 99% confidence level; ns represents non-significant relationship

The r^2 values represents pertaining to model 1

DA digital assistants

and perceived animacy. In the case of building positive intention to purchase through digital assistants, digital assistants' attitude and anthropomorphism play a more vital role. In model 1, all the hypotheses significantly supported the proposed model, except the relationship between perceived animacy and purchase intention through digital assistants. A detailed discussion of the results is provided in the subsequent sections.

Usage experience of digital assistants is proposed as a moderator for paths between perceived anthropomorphism, perceived intelligence, and perceived animacy towards purchase intention through digital assistants. It is found that the increase in usage experience of digital assistants also positively strengthens the relationship between the moderated paths. This result can be observed in Table 6. The interaction between usage intensity of digital assistants and perceived anthropomorphism is found to have a higher significant coefficient. Overall, it was found that the three interactions are found to be positively significant. The interaction graph for respective variables is provided in Appendices 1–3.

Previous studies have found that age and gender can confound the relationships investigated (He et al., 2018; Kamboj et al., 2018). To check the confounding effect, we employed age and gender as control variables to test its relationship with the endogenous variables (attitude towards digital assistants and purchase intention through digital assistants). The results showed no significant relationship between the age and gender with the endogenous variables (attitude towards digital assistants purchase intention through digital assistants). Also, there is no significant change in the relationships before introducing the control variables and introducing control variables. These results confirm that the relationship does not change due to the gender and age (He et al., 2018).

6 Discussion and implications

The study investigated the role of technology and AI factors and their impact in building a positive attitude and purchase intention of digital assistants, and a hypothetical model was framed to evaluate their relationships in a practical manner. The investigation was carried out through a single cross-sectional research design using 440 samples. Overall, nine hypotheses were proposed about model 1 (without any moderation effect), whereas model 2 included another three hypotheses (including digital assistants' usage experience as moderator). Except for perceived animacy, the remaining eight hypotheses about model 1 were found to be significant. In the case of model 2, all the 12 hypotheses were found to be significant. The following paragraphs discuss the results and highlight the theoretical contributions that can be extended from the results. Finally, the practical implications and conclusion are proposed.

The results of hypotheses 1 and 2 investigate the relationship of ease of use and usefulness towards digital assistants' attitude. Though previous studies about TAM have supported these variables can influence technology adoption. This study has extended the results of TAM concerning attitude building. In digital assistants, this is a new finding since previous literature has investigated digital assistants in technical aspects, but the present study has investigated user perception. Hypothesis 3 and 4 investigated the relationship between perceived anthropomorphism and attitude towards digital assistants and purchase intention through digital assistants, respectively. Both the hypotheses were found to be significant. These hypotheses are built from the basis of uncanny valley theory (Mori, 1970). The theory proposed that a nonlinear movement in human likeliness with a robot increases human's perceived emotional response (Broadbent, 2017;

Mori et al., 2012). The present research has extended the theoretical application of this theory concerning digital assistants. While most of the literature relevant to this theory has tried to explore the perceptual categorization of robots in the context of anthropomorphism (Eyssel & Kuchenbrandt, 2012) and the relationship between anthropomorphism towards user attitude and their behavior intention remained as a gap. To fill the gap mentioned above, the present research has added value to the theory by finding that anthropomorphism can build a positive attitude and purchase intentions through digital assistants. Besides uncanny valley theory, the study results about these hypotheses can extend the literature knowledge relevant to anthropomorphism.

Hypothesis 5 and 6 investigates the relationship of perceived intelligence towards attitude and purchase intention through digital assistants. Though some of the studies have supported the argument that perceived intelligence is an integral part of AI, it is important to be analyzed (Bartneck et al., 2009). However, there was no theoretical framing to support such an argument. On the other hand, there is a growing body of literature investigating psychology theories relevant to meta-cognition (Jaccard et al., 2005), representing perceived intelligence and perceived knowledge. Given that there is no direct theoretical background to support such an argument, the study results support that perceived intelligence is an important AI factor. Hypothesis 7 and 8 tested the impact of perceived animacy on attitude and purchase intention through digital assistants. The results supported that it could improve the attitude but not the purchase intention. This result is important considering the strong theoretical background of the term "Animacy". Hypothesis 9 is derived from the argument of TPB (Ajzen, 1991), which stated that attitude could build behavioral intention. The results supported the same finding that digital assistants' positive attitudes can build intention to purchase through digital assistants. Through this result, the study brings a new perspective to TPB by investigating the hypothesis in context with digital assistants.

Hypotheses 10, 11, and 12 represented model 2, which investigates the moderation effect of usage experience on the relationship between AI factors and purchase intention through digital assistants. The results supported that the interaction between usage experience and AI factors can enhance consumer intention to purchase through digital assistants. The interaction effect of anthropomorphism with usage experience, is found to be significantly related to purchase intention. This result supports the three-factor theory's argument (Epley et al., 2007) that when people tend to get more associated with anthropomorphic agents, they tend to elicit more knowledge and stabilize anthropomorphic perception. The same can also be seen in model 2 and Appendix 1, where the relationship between anthropomorphism and purchase intention tends to increase. Though the three-factor theory's argument is supportive, the results of the hypothesis 10 provide an extended value addition to the theory by investigating the results in terms of digital assistants and through studying the argument in a human–machine interaction perspective was not explored before. Hypothesis 11 investigated the interaction effect of digital assistants' usage experience on the relationship between perceived intelligence and purchase intention through digital assistants. This hypothesis's argument was put forth based on Naives theory of intelligence (Miele & Molden, 2010). While this theory has been previously applied to understand people's knowledge improvement and information comprehension based on experience (Miele & Molden, 2010), this research has extended Naives theory application concerning intelligent agents. While research on the construct of perceived intelligence is scarce, this research has produced a meaningful contribution by introducing the perceived intelligence as one of the AI factors. Hypothesis 12 investigates the moderation effect of digital assistants' usage experience in the relationship between perceived animacy and purchase intention. Though perceived animacy was found to be insignificant towards purchase intention in model 1, the

path coefficient is found to be positively significant after introducing perceived animacy. This result supported Santos et al. (2008), in which they proposed animacy perception may increase after more exposure to modulations. The results also extended the understanding of the theory of mind (Tremoulet & Feldman, 2006). The theory, in most cases, has discussed only the perceptual inclination in human to human interaction, but this study has extended that the mind can exhibit the same in case human to machine interaction.

Overall consolidating from the above discussion, the study offers meaningful theoretical contribution on two grounds, one through the study as a whole by bringing in TAM and AI factors together to build a conceptual model in the context of digital assistants. Secondly, the study has built its argument about AI factors from the bases of psychology theories such as; uncanny valley theory, metacognitive theory, perception theories (theory of mind), development psychology, and theory of media equation, three-factor theory of anthropomorphism, and Naives theory of intelligence. Besides the theoretical, the study results also comprehend more meaning and valuable insights for practitioners discussed in the subsequent section.

6.1 Theoretical contributions

Assimilating from the above discussions, we present the highlights of the theoretical contribution arising from this research. Primarily, the study results have advanced the understanding of conversational commerce from AI and TAM variables. The findings of the study will extend the available knowledge available in the literature relevant to digital assistants (Fernandes & Oliveira, 2021), robotic (Bartneck et al., 2009), and voice-conversational purchases (Canziani & MacSween, 2021). The results concerning the relationship of AI functional attributes to purchase intention through digital assistants will yield more significant value than existing literature on technology purchase intention. The study has also extended substantial implications for the domain of operations research. Dubey, Gunasekaran, et al. (2020) emphasized that big data analytics powered by artificial intelligence can improve operational performance. The present study has provided a yardstick to assess the qualities of AI that consumers perceive. This study results will enable operational researchers to narrow their thought of AI and operations based on the variables proposed in this study. Akter, Michael, et al. (2020), Akter, Motamarri, et al. (2020) proposed that AI can help integrate different business operations. In this line, the results of the present study can provide a viewpoint for various operational improvements. For example, Gupta et al. (2021) stated that robotics could play an advanced role in inventory management systems with AI and OR. Given that the variables are broadly considered to be associated with robotic functions. The study results will enable the present and future research in OR to build their arguments accordingly.

Besides the primary contributions, the study holds series of contributions based on the arguments proposed in the hypotheses. (1) The study extends the existing knowledge of uncanny valley theory and anthropomorphism from robotic studies to digital assistants. (2). This study's results have extended the knowledge of perceived intelligence by showing that apart from human psychology and health psychology theories, perceived intelligence also applies in the context of technology and data-driven innovations. Besides, the results about this construct will add new knowledge to metacognitive psychological theories. (3). Perceived animacy has evolved from a series of studies such as psychology of perception theories (theory of mind), development psychology, and media equation theory. While the previous animacy results are more oriented with graphical objects and interfaces, the study

results have extended their theoretical validity to voice-based and data-driven technology. Given that multiple theories are associated with the argument between perceived animacy and attitude, this hypothesis's result will be multi-facet concerning the theories mentioned above. (4). The results pertaining to animacy and purchase intention extend the existing knowledge in the theory of mind (Tremoulet & Feldman, 2006). The theory, in most cases, has discussed only the perceptual inclination in human to human interaction, but this study has extended that the mind can exhibit the the same in case of human–machine interaction.

6.2 Managerial implications

The study results can present potential insights that can be valuable for both developers and marketers. First, TAM's results towards technology attitude give an overview that usefulness is relatively more important than ease of use. Given that various technology improvements are emerging very frequently, users have become adaptable for the technology transition. At the same time, users' expectations from technology usefulness have increased. In digital assistants, both marketers and AI developers demand to extend more functions in the device. Though in earlier stages, these personal digital assistants are predominantly used for queries and multimedia features, now, after especially the growth of the Internet of Things (IoT), digital assistants' role has become omnipresent across every aspect of users and consumers. The same is reflected through the results; marketers with the support of developers should integrate most of the customer journey through offering maximized functions. Also, this can help marketers to learn various aspects and produce targeting marketing efforts. Mostly, the results can induce developers to use the conversation data to optimize the marketing efforts by providing paid voice promotions (Mari et al., 2020).

Next, the results about AI factors and their impact on digital assistants extend fruitful managerial implications. From the results of model 1 and model 2, it is visible that anthropomorphism plays a significant role in building a positive attitude and purchase intention among the users. The results emphasize the importance of imposing human-like anthropomorphic features within digital assistants. Using avatars to creating anthropomorphism is suggested by various literature (Nowak & Rauh, 2005). The use of avatars in digital assistants is not available, especially with human-like characteristics. It will be worthful move if digital assistants can impose with avatar-based characters. Building character to the digital assistant based on user interaction can enhance user response (Waytz et al, 2010).

Moreover, the same can build a personality for digital assistants. Next to anthropomorphism, perceived intelligence in digital assistants is an important measure for developers to consider. Various research and algorithms in AI keep emerging to raise the learning rate and quality of response from the digital assistants. Simultaneously, developers need to make it transparent to the users to help them perceive the digital assistants' intellectual competence. Kleisner et al. (2014) proposed that intelligence can be stereotyped and associated with appearance. The same can be used to structure avatars as intelligent for both male and female characters'. The same applies to the character and personality in which the avatar can be designed. There is a possibility that this can inflict an intelligent stereotype among the avatars. Thus, it is necessary to project the intelligent perception among the users and customers.

Finally, the results found the positive role of animacy in building a positive attitude and purchase intention through digital assistants. As of now, digital assistants interact through voice with their users. There is a higher possibility to increase the animatic stature of digital assistants by following the suggestions mentioned above. Besides, developers can increase more elements such as voice modulations, voice pitches, language phenomes, etc., to create more animatic perceptions. Overall, the suggestions provided through AI factors provide a comprehensive outline of injecting more human-like elements inside the digital assistants. Besides, this study's results will provide valuable insights to gather data and optimize retail operations effectively using AI algorithms (Hu & Li, 2012; Ren et al., 2019). As mentioned in the intelligence hypothesis, the more the customers interact, the more the digital assistants can gain a learning rate and amplify their intelligence using the gathered data. It is retailers' role to create a sustainable customer journey through digital assistants.

6.3 Limitations and future research directions

This research used a single cross-sectional design to test the proposed model. Future studies can experiment with different stimuli levels of anthropomorphism, animacy, and digital assistants' intelligence to understand these variables' precise effect on technology attitude. We found that the data is free from non-response bias. However, we did not check for the endogeneity issues before proceeding to the structural equation modeling. Future research can use voice assistants (such as Google, SIRI, Alexa) as control factors to produce greater breadth to the results. Also, future studies can investigate the following gaps: (1). Research integrating the use of AI factors and technology factors to understand service delivery effectiveness through chatbots will be fruitful (Androutsopoulou et al., 2019; Nordheim et al., 2019). (2). The present study has integrated TAM with AI attributes, and future research can propose integrating UTAUT (Unified Theory of Acceptance and Use of Technology) with AI attributes to arrive at a more comprehensive overview. (3). The study only used three AI-related variables; future research can test other AI-related issues (Bag et al., 2021; Balakrishnan & Dwivedi, 2021; Bartneck et al., 2009; Duan et al., 2019; Dubey, Bryde, et al., 2020; Dwivedi et al., 2020, 2021; Grover et al., 2020; Gursoy et al., 2019; Pillai et al., 2020, 2021; Shareef et al., 2021).

7 Conclusion

The research investigated the technology and AI factors' role in creating a positive attitude and purchase intention through digital assistants. Among the factors, it was identified that anthropomorphism plays a dominant role in creating a more positive attitude and purchase intention. Besides, this research has explained the role of perceived intelligence and perceived animacy in digital assistants. This research offers a valuable contribution to research associated with IS, analytics, retail operations, and marketing. The results' scope can also be extended to evolving data-driven innovation technologies, which involve human–machine interaction.
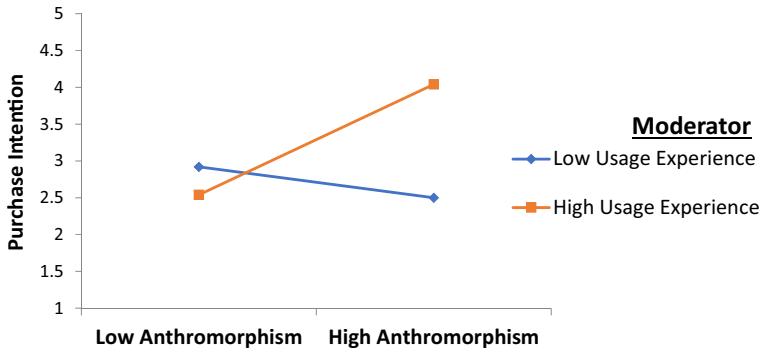
Appendix 1

See Fig. 3.

Fig. 3 Interaction effect graph pertaining to Hypothesis 10
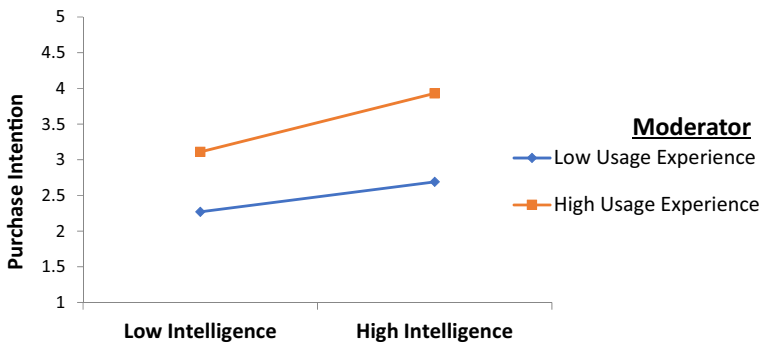
Appendix 2

See Fig. 4.

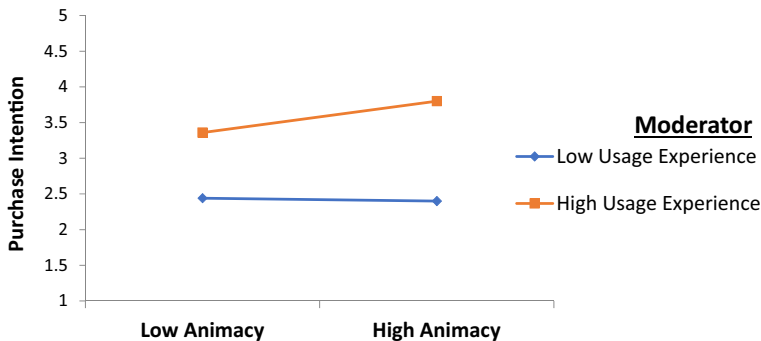**Fig. 4** Interaction effect graph pertaining to Hypothesis 11

Appendix 3

See Fig. 5.

Fig. 5 Interaction effect graph pertaining to Hypothesis 12

References

Aggarwal, P., & McGill, A. L. (2012). When brands seem human, do humans act like brands? Automatic behavioral priming effects of brand anthropomorphism. *Journal of Consumer Research, 39*(2), 307–323.

Ajzen, H., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. . Prentice-Hall.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Akter, S., Bandara, R., Hani, U., Wamba, S. F., Foropon, C., & Papadopoulos, T. (2019). Analytics-based decision-making for service systems: A qualitative study and agenda for future research. *International Journal of Information Management, 48*, 85–95.

Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2020). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03620-w.

Akter, S., Motamarri, S., Hani, U., Shams, R., Fernando, M., Babu, M. M., & Shen, K. N. (2020). Building dynamic service analytics capabilities for the digital marketplace. *Journal of Business Research, 118*, 177–188.

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electronic Markets, 26*(2), 173–194.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics, 182*, 113–131.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly, 36*(2), 358–367.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396–402.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54*, 101473.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*, 120420.

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly, 36*(3), 421–458.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*. https://doi.org/10.1002/mar.21462.

Balas, B., van Lamsweerde, A. E., Auen, A., & Saville, A. (2017). The impact of face inversion on animacy categorization. *i-Perception, 8*(4), 1–16.

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics, 1*(1), 71–81.

Bassellier, G., Reich, B. H., & Benbasat, I. (2001). Information technology competence of business managers: A definition and research model. *Journal of Management Information Systems, 17*(4), 159–182.

Bavaresco, R., Silveira, D., Reis, E., Barbosa, J., Righi, R., Costa, C., Antunes, R., Gomes, M., Gatti, C., Vanzin, M., & Silva, E. (2020). Conversational agents in business: A systematic literature review and future research directions. *Computer Science Review, 36*, 100239.

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management, 58*, 102309. https://doi.org/10.1016/j.ijinfomgt.2021.102309.

Bohner, G., & Dickel, N. (2011). Attitudes and attitude change. *Annual Review of Psychology, 62*, 391–417.

Brahnam, S. (2009). Building character for artificial conversational agents: Ethos, ethics, believability, and credibility. *PsychNology Journal, 7*(1), 9–47.

Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, Alexa, and other digital assistants: A study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management, 35*(15–16), 1401–1436.

Broadbent, E. (2017). Interactions with robots: The truths we reveal about ourselves. *Annual Review of Psychology, 68*, 627–652.

Canziani, B., & MacSween, S. (2021). Consumer acceptance of voice-activated smart home devices for product information seeking and online ordering. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2021.106714.

Chandler, J., & Schwarz, N. (2010). Use does not wear ragged the fabric of friendship: Thinking of objects as alive makes people less willing to replace them. *Journal of Consumer Psychology, 20*(2), 138–145.

Chang, H. H., & Chen, S. W. (2008). The impact of customer interface quality, satisfaction and switching costs on e-loyalty: Internet experience as a moderator. *Computers in Human Behavior, 24*(6), 2927–2944.

Chattaraman, V., Kwon, W. S., Gilbert, J. E., & Ross, K. (2019). Should AI-Based, conversational digital assistants employ social-or task-oriented interaction style? A task-competency and reciprocity perspective for older adults. *Computers in Human Behavior, 90*, 315–330.

Cheetham, M., Suter, P., & Jäncke, L. (2011). The human likeness dimension of the "uncanny valley hypothesis": Behavioral and functional MRI findings. *Frontiers in Human Neuroscience, 5*, 126.

Chen, L. D., & Tan, J. (2004). Technology adaptation in e-commerce: Key determinants of virtual stores acceptance. *European Management Journal, 22*(1), 74–86.

Chiu, C. M., Lin, H. Y., Sun, S. Y., & Hsu, M. H. (2009). Understanding customers' loyalty intentions towards online shopping: An integration of technology acceptance model and fairness theory. *Behaviour & Information Technology, 28*(4), 347–360.

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior, 65*, 276–284.

Cohen, G. (2000). Hierarchical models in cognition: Do they have psychological reality? *European Journal of Cognitive Psychology, 12*(1), 1–36.

Davenport, T. H., & Bean, R. (2018). *The problem with AI pilots, MIT sloan management review*. https://sloanreview.mit.edu/article/the-problem-with-ai-pilots/. Assessed on 1 March, 2021.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies, 38*(3), 475–487.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*(5), 637–643.

Dennis, C., Merrilees, B., Hernandez, B., Jimenez, J., & Martín, M. J. (2009). Adoption vs acceptance of e-commerce: Two different decisions. *European Journal of Marketing, 43*(9/10), 1232–1245.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Dubey, R., Bryde, D. J., Foropon, C., Tiwari, M., Dwivedi, Y. K., & Schiffling, S. (2020). An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2020.1865583.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management, 30*(2), 341–361.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226*, 107599. https://doi.org/10.1016/j.ijpe.2019.107599.

Düking, P., Holmberg, H. C., & Sperlich, B. (2018). The potential usefulness of virtual reality systems for athletes: A short SWOT analysis. *Frontiers in Physiology, 9*, 128. https://doi.org/10.3389/fphys.2018.00128.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., & Galanos, V. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., & Kumar, V. (2020). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2020.102168.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719–734.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864–886.

Eyssel, F., & Kuchenbrandt, D. (2012). Social categorization of social robots: Anthropomorphism as a function of robot group membership. *British Journal of Social Psychology, 51*(4), 724–731.

Fan, A., Wu, L. L., & Mattila, A. S. (2016). Does anthropomorphism influence customers' switching intentions in the self-service technology failure context? *Journal of Services Marketing., 30*(7), 713–723.

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2018). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research*. https://doi.org/10.1007/s10479-018-2818-y.

Faqih, K. M., & Jaradat, M. I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *Journal of Retailing and Consumer Services, 22*, 37–52.

Farid, H., & Bravo, M. J. (2012). Perceptual discrimination of computer generated and photographic faces. *Digital Investigation, 8*(3–4), 226–235.

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research, 122*, 180–191.

Ferrucci, D., Brown, E., Chu-Carroll, J., Fan, J., Gondek, D., Kalyanpur, A. A., Lally, A., Murdock, J. W., Nyberg, E., Prager, J., Schlaefer, N., & Welty, C. (2010). Building Watson: An overview of the DeepQA project. *AI Magazine, 31*(3), 59–79.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(4), 39–50.

Furnham, A., & Buchanan, T. (2005). Personality, gender and self-perceived intelligence. *Personality and Individual Differences, 39*(3), 543–555.

Gao, T., Baker, C. L., Tang, N., Xu, H., & Tenenbaum, J. B. (2019). The cognitive architecture of perceived animacy: Intention, attention, and memory. *Cognitive Science, 43*(8), e12775. https://doi.org/10.1111/cogs.12775.

Gefen, D., Karahanna, E., & Straub Pavlou, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.

Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*(1), 7. https://doi.org/10.17705/1CAIS.00407.

Goudey, A., & Bonnin, G. (2016). Must smart objects look human? Study of the impact of anthropomorphism on the acceptance of companion robots. *Recherche et Applications en Marketing (English Edition), 31*(2), 2–20.

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2020). Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03683-9.

Gunawan, D. D., & Huarng, K. H. (2015). Viral effects of social network and media on consumers' purchase intention. *Journal of Business Research, 68*(11), 2237–2241.

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2021). Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03856-6.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.

Guthrie, S. E. (1995). *Faces in the clouds: A new theory of religion*. . Oxford University Press.

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research, 62*(5), 565–571.

Harman, D. (1967). A single factor test of common method variance. *Journal of Psychology, 35*, 359–378.

Haslam, N., Loughnan, S., Kashima, Y., & Bain, P. (2008). Attributing and denying humanness to others. *European Review of Social Psychology, 19*(1), 55–85.

He, X., Zhan, W., & Hu, Y. (2018). Consumer purchase intention of electric vehicles in China: The roles of perception and personality. *Journal of Cleaner Production, 204*, 1060–1069.

Heider, F., & Simmel, M. (1944). An experimental study of apparent behavior. *The American Journal of Psychology, 57*(2), 243–259.

Hess, T. J., Fuller, M., & Campbell, D. E. (2009). Designing interfaces with social presence: Using vividness and extraversion to create social recommendation agents. *Journal of the Association for Information Systems, 10*(12), 889–919.

Ho, C. C., & MacDorman, K. F. (2017). Measuring the uncanny valley effect. *International Journal of Social Robotics, 9*(1), 129–139.

Hossain, M. A., Akter, S., & Yanamandram, V. (2020). Revisiting customer analytics capability for data-driven retailing. *Journal of Retailing and Consumer Services, 56*, 102187.

Hsiao, C. H., & Yang, C. (2011). The intellectual development of the technology acceptance model: A co-citation analysis. *International Journal of Information Management, 31*(2), 128–136.

Hsu, C. L., & Lin, J. C. C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management, 45*(1), 65–74.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to under parameterized model misspecification. *Psychological methods, 3*(4), 424.

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management, 56*, 102250.

Hu, W., & Li, Y. (2012). Retail service for mixed retail and E-tail channels. *Annals of Operations Research, 192*(1), 151–171.

Hudson, S., Huang, L., Roth, M. S., & Madden, T. J. (2016). The influence of social media interactions on consumer–brand relationships: A three-country study of brand perceptions and marketing behaviors. *International Journal of Research in Marketing, 33*(1), 27–41.

Ihtiyar, A., & Ahmad, F. S. (2014). Intercultural communication competence as a key activator of purchase intention. *Procedia-Social and Behavioral Sciences, 150*, 590–599.

Im, I., Hong, S., & Kang, M. S. (2011). An international comparison of technology adoption: Testing the UTAUT model. *Information & management, 48*(1), 1–8.

Jaccard, J., Dodge, T., & Guilamo-Ramos, V. (2005). Metacognition, risk behavior, and risk outcomes: The role of perceived intelligence and perceived knowledge. *Health Psychology, 24*(2), 161.

Johnson, R. D., Marakas, G. M., & Palmer, J. W. (2008). Beliefs about the social roles and capabilities of computing technology: Development of the computing technology continuum of perspective. *Behaviour & Information Technology, 27*(2), 169–181.

Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. *Computers in Human Behavior, 29*(6), 2512–2518.

Juaneda-Ayensa, E., Mosquera, A., & Sierra Murillo, Y. (2016). Omnichannel customer behavior: Key drivers of technology acceptance and use and their effects on purchase intention. *Frontiers in Psychology, 7*, 1117.

Kalinic, Z., & Marinkovic, V. (2016). Determinants of users' intention to adopt m-commerce: An empirical analysis. *Information Systems and e-Business Management, 14*(2), 367–387.

Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: Applying the paradigm of Stimulus-Organism-Response. *International Journal of Information Management, 39*, 169–185.

Kiesler, S., Powers, A., Fussell, S. R., & Torrey, C. (2008). Anthropomorphic interactions with a robot and robot–like agent. *Social Cognition, 26*(2), 169–181.

Kiesler, S., Sproull, L., & Waters, K. (1996). A prisoner's dilemma experiment on cooperation with people and human-like computers. *Journal of Personality and Social Psychology, 70*(1), 47–65.

Kim, M. (2019). Digital product presentation, information processing, need for cognition and behavioral intent in digital commerce. *Journal of Retailing and Consumer Services, 50*, 362–370.

Kiron, D., & Unruh, G. (2019). Even if AI can cure loneliness-should it? *MIT Sloan Management Review, 60*(2), 1–4.

Kleisner, K., Chvátalová, V., & Flegr, J. (2014). Perceived intelligence is associated with measured intelligence in men but not women. *PLoS ONE, 9*(3), e81237.

Klopping, I. M., & McKinney, E. (2004). Extending the technology acceptance model and the task-technology fit model to consumer e-commerce. *Information Technology, Learning & Performance Journal, 22*(1), 35–48.

Koda, T. (1996). *Agents with faces: A study on the effect of personification of software agents*. . MIT Media Lab.

Koldewyn, K., Hanus, P., & Balas, B. (2014). Visual adaptation of the perception of "life": Animacy is a basic perceptual dimension of faces. *Psychonomic Bulletin & Review, 21*(4), 969–975.

Krening, S., & Feigh, K. M. (2018, September). Characteristics that influence perceived intelligence in AI design. In *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 62, No. 1, pp. 1637–1641). SAGE Publications.

Labroo, A. A., Dhar, R., & Schwarz, N. (2008). Of frog wines and frowning watches: Semantic priming, perceptual fluency, and brand evaluation. *Journal of Consumer Research, 34*(6), 819–831.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121.

Linder, M. (2020). *Humanizing digital 2020—What consumers expect from you today*. https://zoovu.com/blog/humanizing-digital-2020-report/. Accessed on 9 January 2020.

Link, K. E., Kreuz, R. J., Graesser, A. C., & Tutoring Research Group. (2001). Factors that influence the perception of feedback delivered by a pedagogical agent. *International Journal of Speech Technology*, *4*(2), 145-153.

Ma, W. W. K., Andersson, R., & Streith, K. O. (2005). Examining user acceptance of computer technology: An empirical study of student teachers. *Journal of Computer Assisted Learning, 21*(6), 387–395.

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology, 51*(1), 201–226.

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing, 88*(4), 542–555.

Maes, P. (1995). Artificial life meets entertainment: lifelike autonomous agents. *Communications of the ACM, 38*(11), 108–114.

Malik, M. M., Abdallah, S., & Ala'raj, M. . (2018). Data mining and predictive analytics applications for the delivery of healthcare services: a systematic literature review. *Annals of Operations Research, 270*(1–2), 287–312.

Mari, A., Mandelli, A., & Algesheimer, R. (2020, July). The evolution of marketing in the context of voice commerce: A managerial perspective. In *International conference on human–computer interaction* (pp. 405–425). Springer.

Mayer, R. D., & Harrison, N. (2019). *As customers begin to shop through voice assistants, what can brands do to stand out?* https://hbr.org/2019/08/as-customers-begin-to-shop-through-voice-assistants-what-can-brands-do-to-stand-out#comment-section. Accessed on 5th January 2020.

McCarthy, J., & Hayes, P. (1969). Some philosophical problems from the standpoint of artificial intelligence. In *Machine intelligence* (pp. 463–502). Edinburgh University Press.

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

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement? Examining the role of AI powered voice assistants in influencing consumer brand engagement. *Journal of Business Research, 124*, 312–328.

Messina, C. (2016). *2016 will be the year of conversational commerce.* https://medium.com/chris-messina/2016-will-be-the-year-of-conversational-commerce-1586e85e3991#.bsdskkyji. Accessed on 1 March 2021.

Michotte, A. (1963). *The perception of causality.* . Basic Books.

Miele, D. B., & Molden, D. C. (2010). Naive theories of intelligence and the role of processing fluency in perceived comprehension. *Journal of Experimental Psychology: General, 139*(3), 535.

Mori, M. (1970). The uncanny valley. *Energy, 7*(4), 33–35.

Mori, M., MacDorman, K. F., & Kageki, N. (2012). The uncanny valley [from the field]. *IEEE Robotics & Automation Magazine, 19*(2), 98–100.

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing, 36*(5), 489–501.

Moriuchi, E. (2021). An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re-use behavior. *Psychology & Marketing, 38*(1), 21–42.

Mourey, J. A., Olson, J. G., & Yoon, C. (2017). Products as pals: Engaging with anthropomorphic products mitigates the effects of social exclusion. *Journal of Consumer Research, 44*(2), 414–431.

Moussawi, S., & Koufaris, M. (2019). *Perceived intelligence and perceived anthropomorphism of personal intelligent agents: Scale development and validation.* In Paper presented at the Hawaii international conference on system sciences (HICSS). Maui: HI. http://hdl.handle.net/10125/59452.

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2020). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electron Markets.* https://doi.org/10.1007/s12525-020-00411-w.

Nass, C., & Gong, L. (2000). Speech interfaces from an evolutionary perspective. *Communications of the ACM, 43*(9), 36–43.

Nass, C., & Lee, K. M. (2001). Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *Journal of Experimental Psychology: Applied, 7*(3), 171–181.

Nielsen, R. H., Vuust, P., & Wallentin, M. (2015). Perception of animacy from the motion of a single sound object. *Perception, 44*(2), 183–197.

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An initial model of trust in chatbots for customer service—Findings from a questionnaire study. *Interacting with Computers, 31*(3), 317–335.

Nowak, K. L., & Rauh, C. (2005). The influence of the avatar on online perceptions of anthropomorphism, androgyny, credibility, homophily, and attraction. *Journal of Computer-Mediated Communication, 11*(1), 153–178.

Ogiela, M. R., & Ko, H. (2018). Cognitive systems and operations research in big data and cloud computing. *Annals of Operations Research, 265*(2), 183–186.

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services, 55*, 102096.

Pantano, E., & Viassone, M. (2015). Engaging consumers on new integrated multichannel retail settings: Challenges for retailers. *Journal of Retailing and Consumer Services, 25*, 106–114.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of Business Research, 69*(2), 794–803.

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

Parise, S., Kiesler, S., Sproull, L., & Waters, K. (1996). *My partner is a real dog: Cooperation with social agents.* Paper presented at the proceedings of the 1996 ACM conference on computer supported cooperative work. Boston, Massachusetts, United States (pp. 399–408).

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.

Payne, C. R., Hyman, M. R., Niculescu, M., & Huhmann, B. A. (2013). Anthropomorphic responses to new-to-market logos. *Journal of Marketing Management, 29*(1–2), 122–140.

Pfeuffer, N., Benlian, A., Gimpel, H., & Hinz, O. (2019). Anthropomorphic information systems. *Business & Information Systems Engineering, 61*(4), 523–533.

Piaget, J. (1926). The child's conception of the world. Harcourt Brace Jovanovich, New York (English translation in 1929).

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services, 57*, 102207.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control*. https://doi.org/10.1080/09537287.2021.1882689.

Pipitwanichakarn, T., & Wongtada, N. (2019). Leveraging the technology acceptance model for mobile commerce adoption under distinct stages of adoption. *Asia Pacific Journal of Marketing and Logistics*. https://doi.org/10.1108/APJML-10-2018-0448.

Pizzi, G., Scarpi, D., & Pantano, E. (2020). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.11.006.

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

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management, 12*(4), 531–544.

Portney, L. G., & Watkins, M. P. (2000). *Foundations of clinical research: Applications to practice*. . Prentice Hall Health.

Poushneh, A. (2021). Humanizing voice assistant: The impact of voice assistant personality on consumers' attitudes and behaviors. *Journal of Retailing and Consumer Services, 58*, 102283. https://doi.org/10.1016/j.jretconser.2020.102283.

Purnawirawan, N., De Pelsmacker, P., & Dens, N. (2012). Balance and sequence in online reviews: How perceived usefulness affects attitudes and intentions. *Journal of Interactive Marketing, 26*(4), 244–255.

PWC. (2018). *Consumer intelligence series: Prepare for the voice revolution*. https://www.pwc.com/us/en/advisory-services/publications/consumer-intelligence-series/voice-assistants.pdf. Accessed on 9 January 2020.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145–182.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). *Reshaping business with artificial intelligence* (No. 59181). MIT Sloan Management Review and The Boston Consulting Group.

Rauniar, R., Rawski, G., Yang, J., & Johnson, B. (2014). Technology acceptance model (TAM) and social media usage: an empirical study on Facebook. *Journal of Enterprise Information Management, 27*(1), 6–30.

Rauschnabel, P. A., & Ahuvia, A. C. (2014). You're so lovable: Anthropomorphism and brand love. *Journal of Brand Management, 21*(5), 372–395.

Reeves, B., & Nass, C. (1998). *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge University Press.

Ren, S., Chan, H. L., & Siqin, T. (2019). Demand forecasting in retail operations for fashionable products: Methods, practices, and real case study. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03148-8.

Riedl, R., Mohr, P. N., Kenning, P. H., Davis, F. D., & Heekeren, H. R. (2014). Trusting humans and avatars: A brain imaging study based on evolution theory. *Journal of Management Information Systems, 30*(4), 83–114.

Roden, S., Nucciarelli, A., Li, F., & Graham, G. (2017). Big data and the transformation of operations models: A framework and a new research agenda. *Production Planning & Control, 28*(11–12), 929–944.

Russell, S., & Norvig, P. (2010). *Artificial intelligence: A modern approach* (Vol. 25, Third edn.). Pearson Education.

Sakamoto, M., Nakajima, T., & Alexandrova, T. (2015). Enhancing values through virtuality for intelligent artifacts that influence human attitude and behavior. *Multimedia Tools and Applications, 74*(24), 11537–11568.

San Martín, H., & Herrero, Á. (2012). Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management, 33*(2), 341–350.

Santos, N. S., David, N., Bente, G., & Vogeley, K. (2008). Parametric induction of animacy experience. *Consciousness and Cognition, 17*(2), 425–437.

Scholl, B. J., & Leslie, A. M. (2001). Minds, modules, and meta-analysis. *Child Development, 72*(3), 696–701.

Seeber, I., Bittner, E., Briggs, R. O., De Vreede, T., De Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., & Schwabe, G. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management, 57*(2), 103174.

Shareef, M. A., Kumar, V., Dwivedi, Y. K., Kumar, U., Akram, M. S., & Raman, R. (2021). A new health care system enabled by machine intelligence: Elderly people's trust or losing self control. *Technological Forecasting and Social Change, 162*, 120334.

Shi, H. (2019). *Will 2019 be the breakout year for conversational commerce in the U.S.?* https://www.forbes.com/sites/forbestechcouncil/2019/05/07/will-2019-be-the-breakout-year-for-conversational-commerce-in-the-u-s/#1de3a6904ac9. Accessed on 5 April 2020.

Shi, S., & Chow, W. S. (2015). Trust development and transfer in social commerce: Prior experience as moderator. *Industrial Management & Data Systems, 115*(17), 1182–1203.

Shih, H. P. (2004). An empirical study on predicting user acceptance of e-shopping on the Web. *Information & Management, 41*(3), 351–368.

Shultz, S., & McCarthy, G. (2014). Perceived animacy influences the processing of human-like surface features in the fusiform gyrus. *Neuropsychologia, 60*, 115–120.

Sinha, A., Kumar, P., Rana, N. P., Islam, R., & Dwivedi, Y. K. (2019). Impact of internet of things (IoT) in disaster management: A task-technology fit perspective. *Annals of Operations Research, 283*(1–2), 759–794.

Song, M. L., Fisher, R., Wang, J. L., & Cui, L. B. (2018). Environmental performance evaluation with big data: Theories and methods. *Annals of Operations Research, 270*(1–2), 459–472.

Speier, C., & Venkatesh, V. (2002). The hidden minefields in the adoption of sales force automation technologies. *Journal of Marketing, 66*(3), 98–111.

Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management, 27*(10), 1849–1867.

Sullivan, Y., de Bourmont, M., & Dunaway, M. (2020). Appraisals of harms and injustice trigger an eerie feeling that decreases trust in artificial intelligence systems. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03702-9.

Touré-Tillery, M., & McGill, A. L. (2015). Who or what to believe: Trust and the differential persuasiveness of human and anthropomorphized messengers. *Journal of Marketing, 79*(4), 94–110.

Tremoulet, P. D., & Feldman, J. (2006). The influence of spatial context and the role of intentionality in the interpretation of animacy from motion. *Perception & Psychophysics, 68*(6), 1047–1058.

Tubaishat, A. (2018). Perceived usefulness and perceived ease of use of electronic health records among nurses: Application of technology acceptance model. *Informatics for Health and Social Care, 43*(4), 379–389.

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use on-line shopping: The case for an augmented technology acceptance model. *Information & Management, 41*(6), 747–762.

Vukadin, A., Lemoine, J. F., & Badot, O. (2019). Store artification and retail performance. *Journal of Marketing Management, 35*(7–8), 634–661.

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics, 222*, 107498.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126*, 3–13.

WatConsult. (2020). *India's voice market to grow 40% this year*. https://www.warc.com/newsandopinion/news/indias-voice-market-to-grow-40-this-year/43252, Assessed on 1st March 2021.

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology, 52*, 113–117.

Waytz, A., Morewedge, C. K., Epley, N., Monteleone, G., Gao, J. H., & Cacioppo, J. T. (2010). Making sense by making sentient: Effectance motivation increases anthropomorphism. *Journal of Personality and Social Psychology, 99*(3), 410–435.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review, 96*(4), 114–123.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior, 67*, 221–232.

Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management, 42*(5), 719–729.

Yang, G., Ji, G., & Tan, K. H. (2020). Impact of artificial intelligence adoption on online returns policies. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03602-y.

Yen, C., & Chiang, M. C. (2020). Trust me, if you can: A study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments. *Behaviour & Information Technology*, 1–18.

Zhu, W., Mou, J., & Benyoucef, M. (2019). Exploring purchase intention in cross-border E-commerce: A three stage model. *Journal of Retailing and Consumer Services, 51*, 320–330.

Złotowski, J., Strasser, E., & Bartneck, C. (2014, March). Dimensions of anthropomorphism: from humanness to humanlikeness. In *2014 9th ACM/IEEE international conference on human–robot interaction (HRI)* (pp. 66–73). IEEE.