RESEARCH ARTICLE

Role of cognitive absorption in building user trust and experience

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Abstract

The growth of artificial intelligence (AI) and its applications in business has proliferated in recent years. Businesses have started adopting various technology practices relevant to automation and AI, and research investigating this phenomenon is becoming increasingly important. Taking this as a cue, the present research investigates the effect of human-to-machine interaction and human-to-human interaction towards cognitive absorption and its subsequent effect on trust, experience, and continuation intention in the context of services. The study built a 3 × 3 factorial design with automated chatbots (machine interaction) and service executives (human interaction) used as a stimulus in the experiment. Data collected from 410 respondents were analyzed using structural equation modeling to test the proposed hypotheses. The findings indicated that human-to-machine interaction influences cognitive absorption more positively compared to human-to-human interactions. The study results also provide evidence for the role of the trust, experience, and technology continuation intention in a technology background rooted in human-machine interactions. The present study adds a valuable contribution to the existing literature relevant to human-to-machine interaction, cognitive absorption, trust, experience, and continuation intention. The study also provides valuable inputs to technology and marketing managers.

KEYWORDS
artificial intelligence, chatbots, cognitive absorption, continuation intention, services marketing, technology, trust

1 | INTRODUCTION

Technologies like the internet of things and artificial intelligence (AI) have impacted various interfaces related to marketing and other business disciplines (Duan et al., 2019; Dwivedi et al., 2020, 2021). The functions of AI are already having a massive impact on automated customer-based interactions (Hopkinson et al., 2018; Moriuchi, 2019). Businesses have started operating 24/7 automated services to optimize their performance and to build a sustainable relationship.

Data collected from customers has become crucial for enhancing the satisfaction level and automating services with efficiency (Mariani et al., 2018, 2019). Such service mechanism predominantly involves natural language processing chatbots and other machine-learning tools. A study by vxchange.com says that 77% of global customers are already interacting with AI-powered technology using different means (Seal, 2019). The study also confirms that the use of automated chatbots is to increase by 136% by 2021 (Seal, 2019). In their article, Davenport and Ronanki (2018) termed these interactions as

"Cognitive Engagement". Kumar et al. (2016) have supported the idea that the impact of intelligent technology in marketing will be huge in the coming years. Unlike human interaction, chatbots optimize themselves based on the queries of customers. The immersion and cognitive interaction with chatbots may vary compared to human interaction. So it is important to see how customers equip themselves for long-term association with chatbots. In other words, it is vital to know the factors that motivate users to continue using this technology. Existing studies have investigated service continuation intention (Hansen et al., 2003), but not specific to the AI chatbot level. Given the complications and other issues that AI faces (Salanova et al., 2013), it is challenging and vital to understand the continuing intention of AI technology among customers.

As addressed above, the level of immersion and cognitive engagement vary with human-to-machine interaction and human-to-machine interaction. Presently, service interactions in marketing are mostly reliant on human interaction, but the future can be more reliant on the machine interaction. Literature in services marketing has addressed the fact that cognitive and immersive interaction is necessary to uplift service quality (Choi et al., 2020; Edvardsson, 2005). However, it remains unknown whether there is a difference between human-to-human and human-to-machine interaction in creating this cognitive immersion. Luo et al. (2019), in their article's future research direction, emphasized that it is vital to investigate the difference of two-way communication between human-to-human and human-to-machine interaction. Immensely, understanding this communication difference in the service industry will help the practitioners optimize the communication accordingly. In his book, Hoffman (2014) supports the idea that the users positioning towards AI usage should be tested from a cognitive psychology perspective. Previous research related to technology models (Bhattacherjee & Barfar, 2011), web applications (Susanto et al., 2016; Vatanasombut et al., 2008; Wu et al., 2014), and cognitive psychological theories (Roca & Gagné, 2008; Swar et al., 2017) have received proper attention from studies related to continuation intention. Nevertheless, the same is not streamlined in the perspective of human-to-human and human-to-machine interactions. Notably, Agarwal and Karahanna (2000) supported the use of cognitive absorption theory to understand the immersion process in information systems and intelligence research. Assimilating from the above discussion, we propose using cognitive absorption theory to investigate its impact on technology continuation intention in a human versus machine environment. By investigating the impact of human-to-machine and human-to-human interaction on cognitive absorption, the results will open a new theoretical lens which would benefit the existing models and benefit the service practitioners. Building from the gap mentioned above, this research investigates the direct effect of human versus machine interaction on cognitive absorption and the intervening effect of cognitive absorption in the relationship between human versus machine interaction and continuation intention.

Subsequently, two significant factors are specifically identified to play an important role in AI communications: trust (Araujo et al., 2020) and experience (Sands et al., 2020). The service industry acknowledges trust as the most crucial attribute that enhances human service

interactions (Bahadur et al., 2020), but the role of trust in an automated service environment remains minimally explored. Similarly, the experience is a significant variable in a technology-mediated environment (Oh et al., 2009; Van Doorn et al., 2017). Also, the experience derived from automated service interaction can vary from human service interactions. More specifically, the service experience is an important criterion for building a positive service environment and enhancing the employee-customer relationship (Bueno et al., 2019). Given the dynamic changes in automated service interactions and the level of immersion involved in it, there is a demand to investigate the impact of this advancement on trust and experience. Previous literature has addressed the idea that trust (Dimitriadis & Kyrezis, 2010; Johnson et al., 2008; Oh et al., 2009; Slade et al., 2015) and experience (Van Doorn et al., 2017) will play a crucial role in the growing technology paradigm.

Similarly, previous studies have addressed that experience and trust are crucial elements of AI technology adoption (Siau & Wang, 2018). But its direct and indirect involvement with cognitive absorption and technology continuation intention remains unexplored. From the above-mentioned gaps, this research investigates the direct and intervening effect of trust and experience in the relationship between cognitive absorption and technology continuation intention.

Assimilating from the above discussion, we propose the following research questions.

- *RQ1a*: How does human-machine interaction establish its relationship with cognitive absorption?
- *RQ1b*: How does human-human interaction establish its relationship with cognitive absorption?
- *RQ2*: What is the subsequent effect of cognitive absorption on user trust, user experience, and technology continuation intention?
- *RQ3*: What is the direct and intervening effect of cognitive absorption in the relationship of human-to-machine interaction and human-to-human interaction on continuation intention?

Overall, the study will contribute in the following ways: (1) research in human-to-machine interaction is becoming increasingly important in the service industry. The results of the study can contribute to the existing knowledge available that is specific to service interaction. Besides, this study as a whole has the potential to unpack further discussions related to chatbots in the service sector. A framework that contrasts human-machine interaction and human-human interaction is a longstanding gap (Luo et al., 2019) and this research fills that void. More specifically, the model serves insightful opinions for the service sector; (2) the proposed model is built by inferring from different psychology theories, namely flow theory, social cognitive theory (SCT), and absorption theory, and thus the findings can contribute to these theories accordingly; (3) the concept of continuation intention is positioned based on the tenets of expectation confirmation theory (ECT; Bhattacherjee, 2001a), the hypothesis between cognitive absorption and continuation intention will be a great addition to the existing knowledge on ECT and services marketing literature; (4) by employing cognitive absorption in

this framework as a direct and intervening variable in the model, the study results add more valuable knowledge to literature related to services marketing interaction and human vs machine frameworks; (5) the role of trust and experience in an automated service environment will extend the previous knowledge available in literature in services marketing, trust, and experience. Besides the above-mentioned theoretical contribution, the study results open up new insights for managers of the service industry to optimize their chatbots accordingly.

The remaining section of the paper is organized in the following manner; First, the paper proposes the theoretical model after explaining the variables' theoretical background, and the hypotheses are then explained. Second, the paper discusses the methodology and analysis used in this study. The study used a 3 × 3 factorial experimental design is used in this study by employing 410 samples to analyze the hypotheses. Automated chatbot with three interaction levels to set stimuli for human-machine interactions and three systemized service interactions were used to set stimuli for human-human interactions. Third, the results concerning the hypotheses are presented. Finally, the discussion of the results with a clear emphasis on the theoretical contributions and practical implications are given.

2 | THEORETICAL BACKGROUND

2.1 | Human-machine interaction

Many authors have used different terminologies to address this phenomenon, namely human-machine interaction, human-computer interaction, human-robot interaction, and human-system interaction. However, "human-machine interaction" is a broader meaning which covers all growing technologies like AI, machine learning, and data analytics (Dix et al., 2003). Though the idea of human-AI interaction or interactivity has been in the limelight for the last decade, the concept has been in existence since the 1980s. Notably, Norman (1984) explains human-machine interaction as a preliminary stage of machine invasion. Further subsequent studies provided various nuances associated with human-machine interactions. For example, Ntuen et al. (1995) state that human-machine interaction begins from mechanical tool interaction and is later oriented towards human-computer interactions, human-robotic interactions, and finally moving towards autonomous systems. The fundamental process of human-machine interaction is built to facilitate cognitive engagement among users (Ko et al., 2019; Wiltshire & Fiore, 2014; Woods, 1985). To date, existing works related to human-machine interactions have been mostly addressed under different cognitive functions such as cognitive systems (Ko et al., 2019), cognitive engineering and technology (Takada et al., 2017; Woods, 1985), sustainable cognitive computing (Haldorai et al., 2019) and cognitive work analysis (Pereira et al., 2018).

Human-machine interaction is a multidisciplinary field, and its applications are many folds and can contribute to any discipline where humans and machines can coexist together (Clabaugh & Matarić, 2018). Consequentially, research on human-machine interaction has been

increasing in recent times, with its outcome benefiting different industries like agriculture (Vasconez et al., 2019), medicine (Topol, 2019), automobiles (Randell, 2017), construction (Luo et al., 2018), aviation (Wilson et al., 2019), etc. The applications of human-to-machine interactions are fast becoming omnipresent across all business functions (Garbuio & Lin, 2019; Metcalf et al., 2019). Although human-machine interaction is expanding its boundaries across every business function, its role in the services industry through chatbots is a notable aspect (Kunz et al., 2019; Sands et al., 2020). Previous literature has addressed various aspects associated with automated services marketing like self-service technologies (Kaushik & Rahman, 2015), self-service kiosks (Collier et al., 2017), self-checkouts (Collier et al., 2017), service robots (van Pinxteren et al., 2019; Złotowski et al., 2017), and self-scanning devices (Kaushik & Rahman, 2015). Notably, chatbots using AI synchronization is a recent uprising in the last 5 years in the service industry. Kaczorowska-Spychalska (2019) has supported the notion that chatbots can control many marketing functions through a human-machine interface.

A chatbot is a computer program that conducts a conversation in natural language and sends a response based on business rules and data tuned by the organization (Kaczorowska-Spychalska, 2019). This technology facilitates customers to chat with AI-commanded chatbots to answer queries regarding various pre-tuned levels. Despite the growth of this phenomenon in services, research that investigates the human-to-machine interaction is scant. Various theories have been connected in relevance to human-to-machine interactions like activity theories (Engestrom, 2000) and human performance (Wickens et al., 2015). But there are no theories that have connected or compared the consequence of cognitive absorption as an outcome from human-machine interactions or human-human interactions. This research builds the framework based on this, which would yield an extensive contribution to the area of human-machine interaction in psychological and marketing studies.

2.2 | Cognitive absorption theory

Agarwal and Karahanna (2000) refer to cognitive absorption theory as a "state of deep involvement with software." In a similar sense, Guo and Ro (2008) defined cognitive absorption as the state of a user's involvement and engagement during the use of new technology. Deci and Ryan (1985) represented cognitive absorption as a form of intrinsic motivation that emerges to experience pleasure and satisfaction. The base of cognitive absorption is built based on the concept of cognitive engagement (Webster & Ho, 1997) and the theory of flow (Csikszentmihalyi, 1997). The idea of cognitive engagement is derived from the tenets of the theory of absorption. In their study, Tellegen and Atkinson (1974) define absorption as traits and dispositions, which lead to total attention and later consume the individual's resources. The term absorption was then extended with the concept of cognitive engagement to derive a broader meaning. Cognitive engagement is more concerned with the human-machine interaction and the subjective experience that the user derives from the same (Webster & Ho, 1997). Cognitive engagement comprises three distinct dimensions: curiosity,

attention focus, and intrinsic interest (Webster & Hackley, 1997). Alongside cognitive engagement, the theoretical explanation of flow (Csikszentmihalyi, 1990) brings an experiential understanding of cognitive absorption theory. Csikszentmihalyi (1990) described flow as a sensation felt by an individual when they act with full involvement. The flow construct is explained through four major inherent dimensions: intense concentration, feeling of control, loss of consciousness, and temporal transformation (Csikszentmihalyi, 1990). The flow theory has received prolific attention from information systems studies, which have mainly been routed to understand user behavior and user experience.

Agarwal and Karahanna (2000) introduced five dimensions of cognitive absorption, namely (1) temporal dissociation (an engaged interaction without noticing the passage of time), (2) focused immersion (an immersed engagement when other important attentions are ignored), (3) heightened enjoyment (an enjoyable interaction), (4) control (the user's perceived charge or control that they own during the interaction), (5) curiosity (the user's expectation and cognitive curiosity to explore more in the interaction). Notably, cognitive absorption literature has received considerable attention and has been applied fruitfully in the areas related to technology. Previous studies have supported the hypothesis that cognitive absorption can induce technology adoption behavior (Agarwal & Karahanna, 2000; Agarwal et al., 1997). Recent studies have encouraged the investigation of users' cognitive absorption perceptions to build strong technology adoption (Ghasemaghaei, 2019). Extending upon the above discussion, the present study attempts to understand cognitive absorption's effect on technology continuation intention.

2.3 | User experience

User experience ("UX") is an important variable to be investigated in the process of human-machine interactions (Hassenzahl & Tractinsky, 2006). Hassenzahl and Tractinsky (2006) explain user experience as an intersection of enjoyment, affection, and experiential facets. User experience is one of the major drivers which enhances technology interaction. To support this view, previous studies have found that users tend to have a more enjoyable experience during human-computer interaction compared to human-human interaction (Mandryk et al., 2006). Hoffman and Novak (1996) defined the experience flow state using three characterizations: (1) user response for machine–computer interactivity, (2) intrinsic enjoyment, (3) loss of self-consciousness, and (4) self-reinforcement. Similarly, Rodriguez-Sanchez et al. (2008) proposed three characterizations of flow experience specific to information and communication technology, namely (1) enjoyment, (2) intrinsic interest, and (3) absorption. A plethora of studies have investigated different aspects of experience in connection with technology behavior. For example, Thüring and Mahlke (2007), in their study, investigated the role of usability, aesthetics, and emotional experience in technology acceptance. Similarly, O'Brien (2010) explains the utilitarian and hedonic motivations behind user experience in a technology interface.

In their study, Hornbæk and Hertzum (2017) supported the idea that the uprising of and dynamism in the technology interface warrant more investigation in understanding user experience. A series of studies have investigated the relationship between experience and various technology-related variables. Still, the relationship between cognitive absorption level and user experience remains unknown. Hassenzahl (2018), in his recent study, explains the relationship between cognition and user experience as "cognitive and beauty." The theory of cognitive absorption is raised from the theoretical background of flow experience, which further explains the relationship between cognitive absorption and user experience. Though recent studies have investigated user experience in connection with technology adoption (Wang, 2020), the relationship between user experience and technology continuation remains the least explored. This study focuses on building the theoretical framework based on this missing link.

2.4 | User trust

Trust is a multidimensional construct that holds a broad definition across the disciplines. Amidst various definitions available, the one proposed by Mayer et al. (1995) is accepted across multiple disciplines. They defined trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995; p. 712). Lankton et al. (2015) contrasted the difference between human-like trusting beliefs and system-like trusting beliefs based on a comprehensive literature review. Earlier, Johnson (2007) also proposed a similar view that trust towards technology and a firm will differ based on the inherent components. This difference can be explained by comparing the study by Mayer et al. (1995) and Mcknight et al. (2011). Mayer et al. (1995) explained that human-like trusting components are composed of three dimensions: ability, benevolence, and integrity. Mcknight et al. (2011) explained that system-like trusting components consist of three components: reliability, functionality, and helpfulness. This research has built the concept of trust based on system-like beliefs. Mcknight et al. (2011) also explain that trust in technology depends on the positive technology attributes and the user-specific expectations. Besides, this series of research has represented trust with attributes of the technology. For example, Muir and Moray (1996) explain user trust in terms of user knowledge and perception of the capabilities of technology.

Though the perspective of trust is measured through various modes in technology-oriented researches, the root of trust grows from social psychology theories (Cook, 2005). Previous studies have explained the orientation of trust both in cognitive and behavioral aspects (Yousafzai et al., 2005). Researches have supported the idea that trust in technology is enhanced by social influence and expectation. To support this view, Lippert and Davis (2006) posit two kinds of trust that play an essential role in the technology adoption process, namely interpersonal trust and technology trust. The role of

technology in the service sector has grown considerably, and so does the scope to study the trust aspects on the same. Johnson et al. (2008), in their research, stated that trust towards technology-related services is mainly determined through satisfaction with the services. A recent study by Hegner et al. (2019) suggested that the role of trust will be crucial in growing automated technology phenomena. In their research, Nordheim et al. (2019) recommended studying the role of trust in service chatbots specifically. Although trust has been adequately examined for various technology platforms, its role in technology continuation intention with specific reference to service chatbots is yet to be investigated.

2.5 | Technology continuation intention

The technology continuation originally derived from expectation disconfirmation theory (EDT; Oliver, 1980). EDT describes the outcomes of consumer satisfaction in terms of product repurchase and service retention concepts. Building from this theory, later technology-related studies have started emphasizing technology retention models and technology continuation intention. Bhattacherjee (2001a) applied the EDT model to understand the information systems continuation intention. Likewise, various studies have used this construct (continuation intention) for examining various technologies, including mobile internet services (Thong et al., 2006), web-based learning systems (Liao et al., 2009), mobile banking (Zhou et al., 2010), e-procurement systems (Chang et al., 2008), wireless technology (Yen et al., 2010) and

knowledge management systems (Lin & Huang, 2008). Most of the studies have identified user satisfaction as the critical determinant of technology continuation intention (Deng et al., 2010; Stone & Baker-Eveleth, 2013). However, very few studies have tried to understand technology continuation intention from a psychological perspective. Moreover, the use of technology interfaces like chatbots in the services industry is growing, and it is vital to frame strategies to find a way to make users continue the technology. To fill this gap in the literature, the framework proposed in this study has attempted to connect cognitive absorption theory with technology continuation intention.

3 | CONCEPTUAL FRAMEWORK AND HYPOTHESES

From the discussion from the theoretical background, it is evident that six streams of studies contribute to answering our proposed research questions and thus framing the conceptual model utilized in this study. The conceptual model and its hypothetical arguments are posited based on the studies related to the human-machine interaction, the theory of cognitive absorption, the studies related to user experience, the studies related to user trust, the studies related to technology continuation intention, and notably, the background of service interactions in the marketing domain. The proposed conceptual framework is given in Figure 1, and the corresponding hypotheses about the model are discussed and outlined as follows.
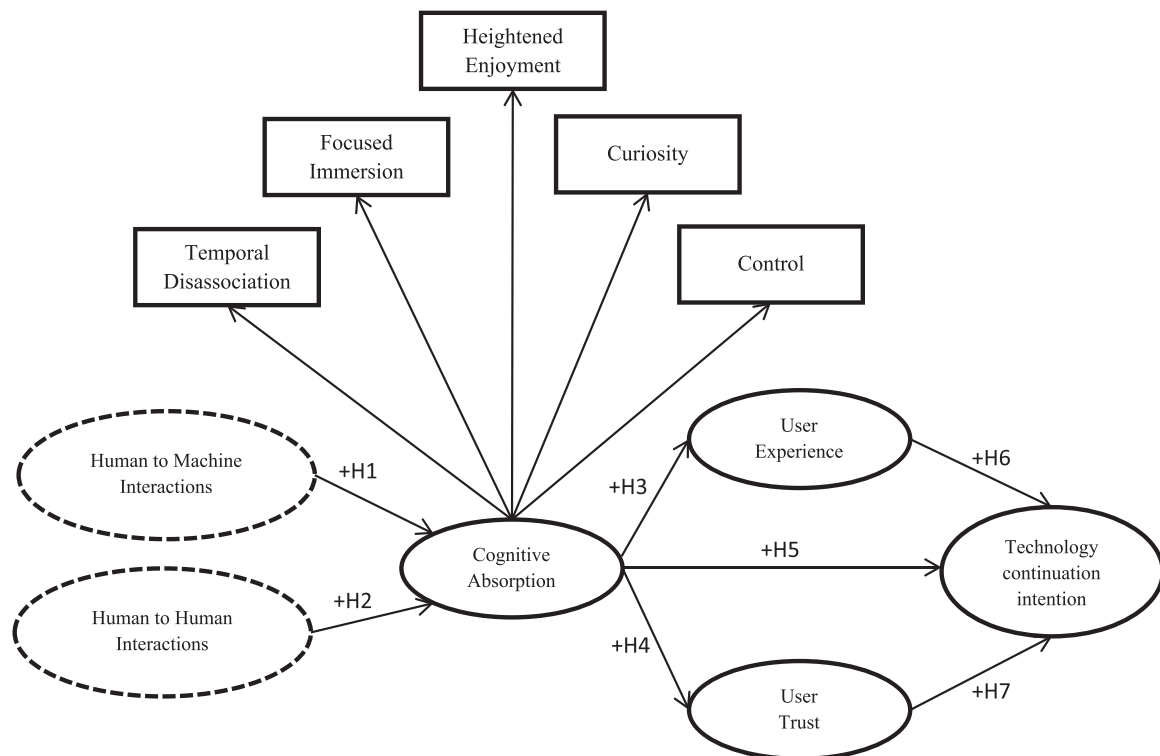

FIGURE 1   Theoretical model of the study

3.1 | The effect of human-to-machine interactions and human-to-human interactions on cognitive absorption

As discussed above, research related to human-to-machine interactions has existed since the 1980s. One of the significant outcomes of human-to-machine interaction is cognitive engagement (Chi & Wylie, 2014). Similarly, other studies have supported the idea that human-to-machine interactions can impart higher cognitive engagement, which can induce solution-based results (Shukor et al., 2012). Besides, during cognitive engagement, users develop intrinsic motivation and derive pleasure from interacting with machines (Szalma, 2014; Webster et al., 1993). According to literature-based on social psychology, intrinsic motivation enhances experiential involvement (Wild et al., 1995). Extending upon this, Wild et al. (1997), in their experimental study, found that intrinsic motivations can result in more absorption in the diffusion of knowledge and enjoyment. Such diffusion with the help of intrinsic motivation can enhance the user's cognitive ability to process complex information and, as a result, can create an experience (Ryan & Deci, 2000). During experiencing cognitive absorption in an IT platform, users tend to exercise both control and enjoyment during interactions (Reychav & Wu, 2015). As explained above, cognitive absorption is a deep involvement that energizes a high level of motivation towards any interaction (Shang et al., 2005). The diffusion of cognition between humans and machines can create more intrinsic motivation to continue or pursue the interaction again (Shang et al., 2005). Similarly, Lin (2009) found that cognitive absorption can result in high technology-oriented behaviors. In-depth interactions can build significant cognitive absorption (Ghasemaghaei, 2019). Assimilating from the above arguments, it is clear that human-to-machine interactions can enhance deep cognitive interactions. The same understanding can be extended by identifying the role of human-to-machine interaction to cognitive absorption specific to marketing service interactions. Thus we propose the following hypothesis:

Hypothesis 1: *Human-to-machine interaction will have a significant positive effect on cognitive absorption.*

Human-to-human interaction is a natural process followed in services marketing. While one section of research argues that human-to-machine interaction will be the future of marketing (Kumar et al., 2016), another research section states that the human touch cannot be replaced by machine interaction (Czepiel, 1990). SCT states that social interactions can heighten cognitive assessment capacity among humans through the cognitive learning process (Bandura, 2001). Building from SCT, studies have suggested that human-to-human interactions in the workplace can create innovative behavior and improve cognitive representation (Ng & Lucianetti, 2016). Besides SCT, studies have found that human-to-human interaction has emotional and cognitive dimensions (Frith & Frith, 2012; Nikolinakou & King, 2018; Saad & Gill, 2000; Soscia, 2007). Roche and McConkey (1990) identified three properties stating the nature of absorption, namely (a) hypnosis and hypnotizability, (b) imagery, daydreaming, and consciousness, and (c) attentional processing of psychophysiological responses. According to absorption

theory, hypnosis explains the change in experiential and cognitive behavior due to social interaction. The attributes mentioned above, concerned with interaction, also apply to the service interactions specific to human-to-human. Notably, Solnet et al. (2019), in their research, specified that the human touch in service interactions is much more essential even in this era where automated interactions are becoming increasingly viable. Following from the above discussion on SCT and absorption theory, it can be understood that emotions and cognitions can enhance deep involvement in human interaction. Building from the above arguments, it can be assumed that human-to-human interaction can also lead to cognitive absorption. Thus we propose the following hypothesis.

Hypothesis 2: *Human-to-human interaction will have a significant positive effect on cognitive absorption.*

3.2 | The effect of cognitive absorption on user experience and trust

Cognitive absorption theory mainly deals with user motivations and involvement in technology. Deng et al. (2010) represented cognitive absorption as a substitute to measure optimal user experience. But other studies have indicated that cognitive absorption indicates a deep involvement within the cognitive circumference, and experience can be one of its outcomes (Agarwal & Karahanna, 2000). Similarly, a pool of literature has supported the notion that cognitive and social-cognitive developments can enhance the flow experience (Dietrich, 2004; Guizzo & Cadinu, 2017; Klasen et al., 2012). It is essential to understand the impact of cognitive absorption on user experience, rather than synonymously representing cognitive absorption with user experience (Mpinganjira, 2019). Though cognitive absorption theory connects with flow theory, it involves a broader meaning than merely focusing on user experience (Zhu & Morosan, 2014). To support this argument, Visinescu et al. (2015) found that cognitive absorption and user experience are different constructs. Moreover, the research showed that website dimensionality on cognitive absorption is positively moderated by user experience. Despite considerable knowledge being available in the literature that has associated cognitive absorption with user experience, no study has tried to investigate its direct relationship. Given the deep involvement state of cognitive absorption, the involvement state can enhance the perceived experience during the service. Previous studies have suggested that involvement can accelerate experience (Zatori et al., 2018). The following hypothesis is proposed accordingly:

Hypothesis 3: *Cognitive absorption will have a significant positive effect on user experience.*

With rising security issues in emerging technology systems, trust has become a focal construct in information systems research (Li et al., 2008). Moreover, trust plays a vital role in AI technology adoption (Siau & Wang, 2018). Past research has supported the idea that cognitive absorption will positively build user trust in a virtual environment (Chandra et al., 2012), learning performance

(Trouche, 2004), and online learning environment (Leong, 2011). Creating trust in a technology-oriented environment requires paramount attention (Bruneel et al., 2017). Though the construct trust is utilized predominantly in information systems research, its roots have grown from psychology literature. Rousseau et al. (1998) define trust as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (p. 395). Notably, many studies have built the functioning of trust within the scope of social psychology (Cook, 2005; Halevy et al., 2019). Studies have revealed that both cognitive and affective states can enhance trust (Colquitt et al., 2012; Schaubroeck et al., 2011). Notably, Martín et al. (2011) found that cognitive signals can build more substantial involvement and trust than peripheral signals.

Similarly, Sorrentino et al. (1995) have supported the idea that trust can be altered based on the cognitive processing styles. Given that cognitive absorption refers to the deep involvement state, there is a strong possibility that it can build user trust. Literature has also stated that user involvement creates the strong trust (Johnson et al., 2008). As both cognitive disposition and involvement can enhance trust, we propose that cognitive absorption positively creates user trust. Though the relationship between cognitive absorption and user trust has been given little attention in the literature (Chandra et al., 2012; Leong, 2011; Trouche, 2004), the same is not examined in contrast with human-to-machine interactions. Exploring such assumptions will add significant value to literature relevant to trust in social psychology and information systems. Also, given the nature of the dimensions (temporal disassociation, focused immersion, heightened enjoyment, curiosity, and control) of the cognitive absorption construct, trust can be positively influenced by the construct. Studies have supported the effect of enjoyment on trust (Wu & Liu, 2007), control on trust (Van der Heijden et al., 2003), and immersion on trust (Montague et al., 2010). From this perspective, it would be appropriate and interesting to extend the results in a human-to-machine interaction context. Hence, we propose the following hypothesis:

Hypothesis 4: *Cognitive absorption will have a significant positive effect on user trust.*

3.3 | The effect of cognitive absorption on technology continuation intention

Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975) posits that behavioral intention is mainly derived from attitude and social influences. Emerging from a social psychology background, TRA is the basis for most technology-oriented theories like the theory of planned behavior (Ajzen, 1991) and technology acceptance model (Davis, 1989). Besides a social psychology background, the perspectives of technology adoption are also drawn from the cognitive psychology area (Abraham et al., 2013). Various factors attribute to technology-oriented behaviors, among which technology involvement and cognitive developments have received considerable

attention. Walsh et al. (2010) supported the notion that involvement and cognition can influence high-technology-oriented product usage. Given that absorption is intrinsic by nature, Davis et al. (1992) supported the view that intrinsic motivation can enhance technology adoption. While technology adoption has received massive attention in the literature, technology continuation intention is another term that has started receiving good attention in technology adoption research.

Most studies have used satisfaction as a significant precursor for technology continuation intention (Amoroso & Lim, 2017; Bhattacherjee et al., 2008; Deng et al., 2010; Lin, 2012; Oghuma et al., 2016; Stone & Baker-Eveleth, 2013). Other studies have used attitude (Amoroso & Lim, 2017), ease of use (Wangpipatwong et al., 2008), enjoyment (Oghuma et al., 2016), usefulness (Oghuma et al., 2016; Stone & Baker-Eveleth, 2013; Wangpipatwong et al., 2008), perceived fit (Lin, 2012), technology readiness (Chen et al., 2009), and behavioral control (Chen et al., 2009), hedonic value (Hong et al., 2017), utilitarian value (Hong et al., 2017), self-efficacy (Wangpipatwong et al., 2008), and habit (Amoroso & Lim, 2017) as influential independent variables for technology continuation intention. Deng et al. (2010) investigated cognitive absorption and technology continuation intention in the same model, but the study did not establish any direct relationship between the two constructs. Given that cognitive absorption theory relates to flow theory, previous literature has shown that flow can influence continuation intention (Chang & Zhu, 2012). Both cognitive and affective actions can control technology adoption, but the same is not extended with the model relevant to technology continuation intention. Though there is no direct model available to support the relationship between cognitive absorption and continuation intention, researchers have found that user involvement can positively induce technology continuation intention (Shiau & Luo, 2013). Provided that cognitive absorption involves deep involvement, cognitive absorption can append positive continuation intention. Based on this discussion, the following hypothesis is proposed:

Hypothesis 5: *Cognitive absorption will have a significant positive effect on technology continuation intention.*

3.4 | The effect of user experience and trust towards technology continuation intention

User experience has become an important factor that creates sustainable technology adoption (Hornbæk & Hertzum, 2017; McCarthy & Wright, 2004). Hoffman and Novak (1996) and Rodriguez-Sanchez et al. (2008) have emphasized the role of intrinsic enjoyment and absorption as an important component of flow experience in the technology-related environment. To support this view, previous studies have found that absorption can result in higher flow experience and technology immersion (Shin & Kim, 2008). Notably, Zhou (2013), in their study on mobile payment services, found flow experience to have a significant impact on continuation intention, and Chou and Ting (2003) found that flow experience can increase

repetitive behavior in a cyber-game platform. As stated above, the experience is an absorption state that can develop feelings in our mind, enhancing the intimate relationship with human or technology. Intimacy is possible both in human interactions and machine interactions. Given the positive intimate relationship with the technology, there is a possibility that perceived intimacy can encourage users to continue the technology. Lee and Kwon (2011) supported this view by finding that intimate relationships with technology can enhance technology continuation intention. Besides, Beetles and Harris (2010), in their research, explained that intimacy in service interactions is important to build an effective service mechanism. The arguments lay an indirect foundation for the hypothesis between experience and technology continuation intention. However, no study has yet examined or demonstrated the direct relationship between the experience and technology continuation intention in the context of services. In light of the above arguments, this study proposes that user experience can build positive intention towards technology continuation. This hypothesis will bring a new perspective to studies related to human-machine interactions and value addition to flow theory.

Hypothesis 6: *User experience will have a significant positive effect on technology continuation intention.*

Many studies have emphasized the importance of trust to create a sustainable technology platform for users (Dimitriadis & Kyrezis, 2010; Johnson et al., 2008) and businesses (Ryssel et al., 2004). Bhattacherjee (2001a) explained that satisfaction would have a more substantial influence to use the system again. Similarly, trust is vital to building higher satisfaction. Although numerous studies have investigated whether trust can enhance technology adoption, the same is not extended in nonhuman technology interactions. A recent study by Waytz et al. (2014) found that trust also plays a significant role in nonhuman technology interactions through anthropomorphic characteristics. Though Susanto (2016) identified trust as a significant predictor of technology continuation intention, there is a lack of a strong theoretical basis to support this hypothesis. Building from social psychology, Pfattheicher and Böhm (2018) added that trust is mainly driven by social expectations.

Interestingly, Turner (2015) observed that most of the advancing technology adoptions are triggered by social interest. Like this, Dwyer et al. (2018) have supported the belief that social interactions have increased virtual technology usage. Given that social psychology has started importing most of its ideology for understanding technology behavior, trust is one such composition of an individual and social phenomenon that can play a more influential role in technology continuation intention. By connecting these relationships and setting the base from social psychology studies, the study hypothesizes that the greater the trust in human-to-machine interaction, the more likely it is that a positive intention to continue using technology can be built. The following hypothesis is proposed based on the above discussion:

Hypothesis 7: *User trust will have a significant positive effect on technology continuation intention.*

4 | RESEARCH METHODOLOGY

4.1 | Study design and experimental conditions

This study uses 3×3 factorial designs to investigate the proposed model. The two experimental variables employed in this study are "Human-to-Machine Interaction (high automated interactive annotations × medium automated interactive annotations × low automated interactive annotations)" and "Human-to-Human Interaction (personal direct interaction × personal telephone interaction × personal live chat)." To conduct this experiment, we used an ongoing business of a real estate agent to create a website with necessary chatbot interactions. The study used the website and the service executives to represent the experimental variables accordingly. Table 1 shows the explanation about the two variables and the explanation for corresponding conditions. Given the experimental conditions, the data is collected in nine waves, with each wave representing each block of the design. Data was collected from 454 customers/clients of the business, of which 410 eligible responses were used. The socio-demographic information about the study participants is available in Table 2. Also, it can be seen from the table that all the participants have at least one past interaction experience with AI chatbots.

An automated chatbot was created on the website to operationalize the first variable (human-to-machine interaction), using an available plugin. An automated chatbot will work based on the pre-tuned questions and answers any number of queries by empowering AI algorithms. To understand the queries' strength, a pilot study was tested with 40 customers to understand the maximum and the minimum number of queries they investigate in a chatbot. The results indicated that a customer travels up to a maximum of nine queries and a minimum of one query (mean = 4.05; SD = 1.92). Based on the pilot study results, the high automated interactive annotations were confined to nine query parameters, the medium automated interactive annotations are fixed to have six query parameters, and the low automated interactive annotations are fixed to have three query parameters. The business executives decided the query parameters based on the most searched queries. Some of the example keywords used in the programming are product offerings, service offerings, prices, available locations, land registrations, contact, etc. The second independent variable (human-to-human interaction) is also operationalized using three conditions, personal direct interaction was set to have high-effect stimuli, personal telephone interaction is set to have medium-level stimuli, and low live chat interaction is set to have low-level stimuli. The stimuli levels are decided based on an in-depth interview with 48 service executives to understand the effectiveness of the service interaction. The explanation for all the conditions is given in Table 1.

4.2 | Experiment procedure and manipulations

The experiment was conducted in nine waves, in which each wave represents the nine blocks (3×3). The detailed manipulations about

TABLE 1 Conditions of the two experimental variables

Human-to-machine interaction (This variable deals with service response through automated chatbots with the chat facility available in the website)	
High (coded as 3)	In the high conditions, chatbots are designed to have a response with different questioning parameters. This questioning parameter gives a highly optimized, automated chatbot interaction.
Medium (coded as 2)	In medium conditions, chatbots are designed to have a response with 6 different questioning parameters. This questioning parameter gives good automated chatbot interaction.
Low (coded as 1)	The low conditions occur in a way that chatbots are optimized to have response queries with 3 different question parameters. However, the design involves automated interaction but is still not as optimized as the high and medium condition.
Human-to-human interaction (This variable deals with service response by personal interaction, telecall and through the chat facility available in the website)	
High (coded as 3)	In high conditions, the service executives scheduled a direct visit with the clients to explain the business offerings.
Medium (coded as 2)	The medium conditions is designed in a way that users can register their details in the website to which they receive a voice telecall from the service executive.
Low (codes as 1)	The low conditions are designed in a way that users can interact with service executives live through a chat facility, which is integrated the service executive mobile phones.

TABLE 2 Social demographic information about the study participants

Socio-demographic		Frequency	
Variables	Characteristics	N = 410	Percentage (%)
Gender	Male	224	54.63
	Female	186	45.37
Age	Under 30 years	188	45.85
	31–40 years	126	30.73
	41–50 years	58	14.15
	Above 50 years	38	9.27
Occupation	Business	112	27.32
	Private sector employee	214	52.20
	Public sector employee	56	13.66
	Others	28	6.83
Education	Higher secondary	65	15.85
	Under-graduation	186	45.37
	Postgraduation	131	31.95
	PhD	28	6.83
Prior experience and interactions with AI chatbots	1–3 interactions	122	29.76
	4–6 interactions	102	24.88
	7–9 interactions	99	24.15
	More than 9 interactions	87	21.22

Abbreviation: AI, artificial intelligence.

the nine waves and blocks are given in Appendix A. Each wave was pretuned to nine respective experimental blocks with the factoring of both the experimental variables. The experiment and data collection for the first three waves were completed in an average of 8 days, and the remaining six waves were completed in an average of 5 days. In the first three waves, the service executives personally met the clients based on the existing leads, and further to it, they requested that the clients interact with the website's automated chatbot for more information and learn more about the offers. The screenshots of the website and automated chatbots are provided in Appendix B. For Wave 1, 2, and 3, the automated chatbot was tuned to provide more information on incentives, rules, regulations, discounts, daily offers, etc. Of the 326 leads (Wave 1 = 112, Wave 2 = 106, Wave 3 = 108) met personally by the executives, it was identified that 209 clients (Wave 1 = 68, Wave 2 = 76; Wave 3 = 65) interacted in the automated chatbot. Fifty highly responsive clients were randomly selected from each wave to collect data on the study model. Finally, 137 eligible data (Wave 1 = 45; Wave 2 = 46; Wave 3 = 46) were used in the study pertaining to Waves 1–3.

For the remaining six waves, online advertising campaigns were conducted for the real estate business with the landing page set to the business website with the automated chat facility made available. This process enables the clients/users/customers who click the advertisements to be redirected to the website. The campaign ran for a month, after which all six remaining waves of the experiment were completed. For Waves 4–9, the automated chatbot was tuned first to ask for contact information registration. It provided levels of

interaction based on the wave in which the experiment is conducted. There were a total of 1628 redirects to the website during the month, of which 726 people provided their contact information and used the automated chatbot facility (Wave 4 = 116; Wave 5 = 122; Wave 6 = 131; Wave 7 = 107; Wave 8 = 137; Wave 9 = 113). In the follow-up to their registration and automated chat facility, during Waves 4–6, a service executive will make a telephone call to explain more about products and services. Based on the registered information during Waves 7–9, the service executives will follow up with the clients with a live chat session to explain more about products and services. A total of 50 highly responsive customers from each wave were randomly chosen to collect data. Finally, 273 (Wave 4 = 43; Wave 5 = 44; Wave 6 = 43; Wave 7 = 48; Wave 8 = 47; Wave 9 = 48) were found to be eligible and the same were used for further analysis in the research. Malhotra and Birks (2006) recommended that randomization can reduce the selection bias error during experimental research, so by randomly assigning the participants to blocks, we tried to control the effect of selection bias.

4.3 | Experiment validations

The study conducted manipulation checks to confirm whether the conditions and blocks correspond to the assumption. Two validation exercises were carried out; the first validation exercise was employed to check the variance among the proposed conditions for human-to-machine interaction and human-to-human interaction. The second validation was conducted to test the difference between the blocks.

4.3.1 | Experiment condition validations

The 90 working professionals who expressed their definite plans to purchase an asset in the near future were used in the experiment validations. The same conditions defined above for the two experimental variables are tested here.

The conditions of the first variable (human-to-machine interaction) were tested using 45 samples. The variable was mainly divided based on interaction. Fifteen subjects were allotted for each condition (high automated interactive annotations/medium automated interactive annotations/low automated interactive annotations), with each condition represented by the following respective stimuli (nine levels automated chatbot/six level automated chatbot/three level automated chatbot). After their interaction with the chatbots (minimum = 10 min; maximum = 18 min), we circulated a questionnaire with three questions measured on a 5-point scale with 5 being Strongly Agree and 1 being Strongly Disagree. The scale is mainly adapted from Liu's (2003) interactive scale. The responses were tested using analysis of variance (ANOVA) to understand the differences in mean value. The results showed that nine levels of automated chatbot had high mean values in all three questions, and there is a significant difference in mean scores among the conditions. The results are as follows: I felt I had active control during the

automated interaction (mean = 3.333; $F = 11.541$ ($df = 42,2$); $p < 0.001$), I enjoyed the two-way communication in the automated interaction (mean = 3.04; $F = 11.062$ ($df = 42,2$); $p < 0.001$); and there was great synchronization with the query and responses during the automated interaction (mean = 3.26; $F = 25.305$ ($df = 42,2$); $p < 0.001$).

Further, the conditions of the second variable (human-to-human interaction) were tested with 45 sample customers, who were prospective leads for the business. Fifteen customers were assigned to the three conditions (personal direct interaction/personal telephone interaction/personal live chat). In the first condition, 15 customers were met by the service executive personally based on the leads. In the second condition, 15 customers were assigned to receive a telephone call from the service executive once they entered their contact details in the chatbox. In the third condition, 15 samples were assigned to the webpage chatbot in which there was a live chat facility available. After the interaction (minimum = 12 min; maximum = 53 min), we used a questionnaire with a similar scale and measurements to understand the effectiveness of the conditions. The results showed that service executives' personal visit is more effective in human interaction than a telephonic conversation or live chat, with a significant mean difference. The results were as follows: I felt I had active control during the interaction (mean = 3.488; $F = 26.395$; $df = 42,2$; $p < 0.001$); I enjoyed the two-way communication and queries were answered (mean = 3.244; $F = 23.233$; $df = 42,2$; $p < 0.001$); there was great synchronization with the query and responses during the interaction (mean = 3.216; $F = 32.241$; $df = 42,2$; $p < 0.001$).

4.3.2 | Experiment block validations

Next to the experimental condition validation, the manipulated validation was checked using a separate sample of 90 participants. The nature of the block and its detailed description is given in Appendix A. Ten samples were assigned to each block. The preexperiment was completed in 9 days representing the nine blocks. After every experiment, the customers were approached, and they were asked to fill a questionnaire which had eight questions measured on a 5-point scale with 5 being Strongly Agree and 1 being Strongly Disagree. Five questions were selected from the scale of cognitive absorption (Agarwal & Karahanna, 2000), and three questions were asked about trust, experience, and technology continuation. This validation is performed to confirm whether blocks respond to the framework provided. We used ANOVA to check on the mean differences. It was found that all questions showed a significant difference in the mean scores. The results were as follows: time flies when I use this service interaction ($F = 7.050$; $df = 8,81$; sig = 0.000); during the interaction, my attention does not get diverted very easily ($F = 6.092$; $df = 8,81$; sig = 0.000); I have fun interacting in the portal and speaking with the executive ($F = 7.369$; $df = 8,81$; sig = 0.000); while interacting, I feel in control ($F = 11.079$; $df = 8,81$; sig = 0.000); this interaction enhances my curiosity ($F = 3.401$; $df = 8,81$; sig = 0.002); overall it is a great experience interacting in the portal and with the executive

($F = 4.458$; $df = 8,81$; sig = 0.000); overall I trust the services offered by this business ($F = 9.318$; $df = 8,81$; sig = 0.000); and I would be happy to interact using this chat technology in future ($F = 17.885$; $df = 8,81$; sig = 0.000). The block validation for the main sample is given in Appendix D.

The clients were found to have interacted using automated chatbots concerning the respective blocks. For example, the participants of Wave 1 on an average, engaged up to 8.11 levels of the questioning parameter in the chatbot. Likewise the participants' engagement with chatbot changed with respect to the blocks (the means of questioning parameter engagement levels in automated chatbots; Wave 1 = 8.11 level; Wave 2 = 5.56 level; Wave 3 = 2.83 level, Wave 4 = 7.95 level, Wave 5 = 5.06 level, Wave 6 = 2.79 level, Wave 7 = 8.27 level, Wave 8 = 5.47 level, Wave 9 = 2.75 level). The above engagement shows that the automated chatbot interactions are well represented with the blocks presented in the design (Appendix A).

4.4 | Questionnaire and measurement

The study used scales adapted from previous studies (Agarwal & Karahanna, 2000; Chen et al., 2009; Lin, 2009; Morgan-Thomas & Veloutsou, 2013; Nel & Boshoff, 2017). The scales are slightly modified to fit in with the context of this study. The questionnaire went through three iterations of corrections from 10 experts belonging to the area relevant to the study to check whether the items represented the construct and investigated the proposed hypotheses. The scale for the cognitive absorption construct is derived from Lin (2009), which was found to be consistent with its original work by Agarwal and Karahanna (2000). As discussed above, cognitive absorption is a latent construct, which consists of five dimensions, namely temporal dissociation (three items), focused immersion (three items), heightened enjoyment (three items), curiosity (three items), and control (two items). The scale for user experience is derived from the study by Morgan-Thomas and Veloutsou (2013), which consists of six items. The scale for user trust is derived from Nel and Boshoff (2017). The scale for technology continuation intention is derived from previous studies (Bhattacherjee et al., 2008; Bhattacherjee, 2001b; Chen et al., 2009). All the scale items are measured in a 5-point Likert scale format, with 5 representing Strongly Agree and 1 representing Strongly Disagree. The detailed information on the questionnaire and scale is given in Appendix F.

The experimental variables: machine-to-human interactions and human-to-human interactions are measured using dummy variable coding. The three conditions of the machine-to-human interactions are coded as 3 to 1 based on the condition level (high automated interactive annotations as "3," medium automated interactive annotations as "2," low automated interactive annotations as "1"). Similarly, the conditions of human-to-human interaction are coded accordingly (personal direct interaction as "3," personal telephone interaction as "2," personal live chat as "1"). Previous studies have

used a similar measurement methodology for experimental variables (Balakrishnan et al., 2020; Edwards et al., 2002; Jöreskog & Sörbom, 1989).

4.5 | Analysis

This study employed structural equation modeling (SEM) as an analysis technique. Initially, the first-order confirmatory factor analysis was conducted to evaluate the content, convergent, and discriminant validity requirements, followed by the second-order confirmatory factor analysis. Besides this, the study also tested for common method bias (CMB). Previous studies have suggested that SEM can be effectively used for hypothesis testing (Fornell & Larcker, 1981; Gefen et al., 2000; MacCallum & Austin, 2000). The study also tested for mediation effect to understand any significant indirect effect present in the model. Models 2, 3, 4, and 5 provided in Appendix C and D present the investigated mediation paths. The maximum likelihood estimation method was used in the structural equation model to analyze the model. All the analyzes were used using Microsoft Excel, SPSS 21.0, and AMOS. Besides SEM, the study also employed multivariate analysis of variance (MANOVA) and ANOVA to test the statistical difference among the variables across the experimental conditions and with the interaction between the experimental variables.

5 | RESULTS

5.1 | Measurement model

The results of the first order and the second-order measurement model are provided in Table 3. As shown in the table, the construct's factor loadings are higher than 0.60, which confirms the content validity requirements for both first-order and second-order measurement models. The table also shows the Cronbach's alpha values, which is more than the required threshold value of 0.750. The values of average variance extracted (AVE) and composite reliability are presented in Table 4. It can be observed that the values of AVE are above 0.50; this satisfies the requirement for convergent validity. The diagonal values in Table 4 represent the square root of AVE, which is above the intercorrelation values of the respective constructs. This procedure confirms the discriminant validity requirements. Overall, the measurement model results satisfy the requirements for the content, convergent, and discriminant validity. The model fit indices for the measurement and structural models are provided in Table 5, demonstrating an excellent fit for both models.

5.2 | Common method bias

Podsakoff et al. (2003) stated in their research that social science researches that administer survey methods should confirm the

TABLE 3 Measurement model

First/second order	Constructs	No. of Items	Mean range	Standardized factor loadings (range)	Cronbach alpha
First-order constructs	Temporal disassociation	3	3.38–3.41	0.681***–0.827***	0.801
	Focused immersion	3	3.31–3.39	0.732***–0.810***	0.819
	Heightened enjoyment	3	3.37–3.42	0.750***–0.841***	0.842
	Curiosity	3	3.41–3.53	0.741***–0.851***	0.834
	Control	2	3.37–3.38	0.807***–0.824***	0.797
	User trust	3	3.31–3.36	0.746***–0.826***	0.825
	User experience	6	3.23–3.45	0.668***–0.895***	0.909
	Technology continuation intention	4	3.35–3.41	0.767***–0.822***	0.872
Second-order constructs	Cognitive absorption	5	3.06–3.42	0.708***–0.955***	0.941
	User trust	3	3.31–3.36	0.744***–0.823***	0.825
	User experience	6	3.23–3.45	0.669***–0.895***	0.909
	Technology continuation intention	4	3.35–3.41	0.765***–0.822***	0.872

absence of CMB analysis. "To test the CMB, we used common latent factor (CLF) approach to measure the common variance of the observed variables present in the model" (Podsakoff et al., 2003). The comparison of standardized regression between the CLF versus non-CLF model will give a comprehensive view of the CLF. During the CLF analysis, it was observed that the difference of standardized regression weights between the CLF and non-CLF model is well below 0.05. Since "the CLF model is well in control" (MacKenzie &

Podsakoff, 2012), it can be concluded that the items and measurement are unlikely to suffer from CMB.

5.3 | Structural model results

The structural path results are provided in Figure 2, and the fit indices of the structural model are given in Table 5. The fit indices of

TABLE 4 Inter-construct correlations and AVE values

First-order constructs	CR	AVE	1	2	3	4	5	6	7	8
1. User trust	0.826	0.614	**0.783**							
2. Temporal dissociation	0.810	0.588	0.202	**0.767**						
3. Focused immersion	0.820	0.603	0.260	0.723	**0.777**					
4. Heightened enjoyment	0.845	0.646	0.219	0.766	0.758	**0.804**				
5. Curiosity	0.839	0.635	0.244	0.673	0.692	0.737	**0.797**			
6. Control	0.799	0.665	0.316	0.575	0.530	0.532	0.713	**0.816**		
7. User experience	0.908	0.625	0.291	0.321	0.270	0.293	0.311	0.232	**0.791**	
8. Tech continuation intention	0.873	0.633	0.439	0.457	0.412	0.438	0.524	0.511	0.426	**0.796**

Second-order constructs	CR	AVE	1	2	3	4
1. Tech continuation intention	0.873	0.633	**0.796**			
2. User experience	0.908	0.625	0.425	**0.790**		
3. User trust	0.827	0.614	0.439	0.291	**0.784**	
4. Cognitive absorption	0.941	0.763	0.521	0.344	0.272	**0.874**

Notes: 1. AVE represents average variance extracted; 2. CR represents composite reliability; 3. Tech continuation intention represents technology continuation intention; 4. Square root of AVEs are presented in the diagonal for each construct in bold format; 5. All values in the correlation matrix are significant at 99% confidence level.

TABLE 5 Fit indices of the measurement and structure model

Fit indices	Measurement model (first order)	Measurement model (second order)	Structural model	Recommended value	Reference
χ^2	666.464	314.543	362.463	Not applicable	
df	296	126	153	Not applicable	
χ^2/df	2.252	2.496	2.369	≤3.00	Bentler (1990)
GFI	0.889	0.922	0.924	≥.900	Bentler (1990)
NFI	0.901	0.944	0.938	≥.900	Bentler (1990)
CFI	0.942	0.966	0.963	≥.900	Bentler (1990)
RMR	0.042	0.043	0.058	≤.100	Hu and Bentler (1988)
RMSEA	0.055	0.060	0.058	≤.080	Bentler (1990)

the structural model showed an excellent fit. Also, the r^2 values of cognitive absorption (0.274), user experience (0.220), user trust (0.234), and technology continuation intention (0.396) showed reasonable variance explained. All the hypotheses were supported at $p < 0.001$ level, of which the relationship of cognitive absorption with user experience (0.346***) is observed to be higher than its relationship with user trust (0.271***). Among all the hypotheses, the relationship between cognitive absorption and technology continuation intention is highly significant (0.373***). Most importantly, human-to-machine interaction is found to have a higher coefficient

value with cognitive absorption (0.247***) than the relationship between human-to-human interaction and cognitive absorption (0.171***). Overall, all the hypotheses were found to be positively significant.

Table 6 shows the mediation results of Models 2, 3, 4, and 5. The figures for Models 2, 3, 4, and 5 are given in Appendix C. The mediation analysis results pertaining to Models 2 and 3 showed that both user experience and user trust indirectly mediate the relationship between cognitive absorption and technology continuation intention. Zhao et al. (2010) explain this mediation as complementary
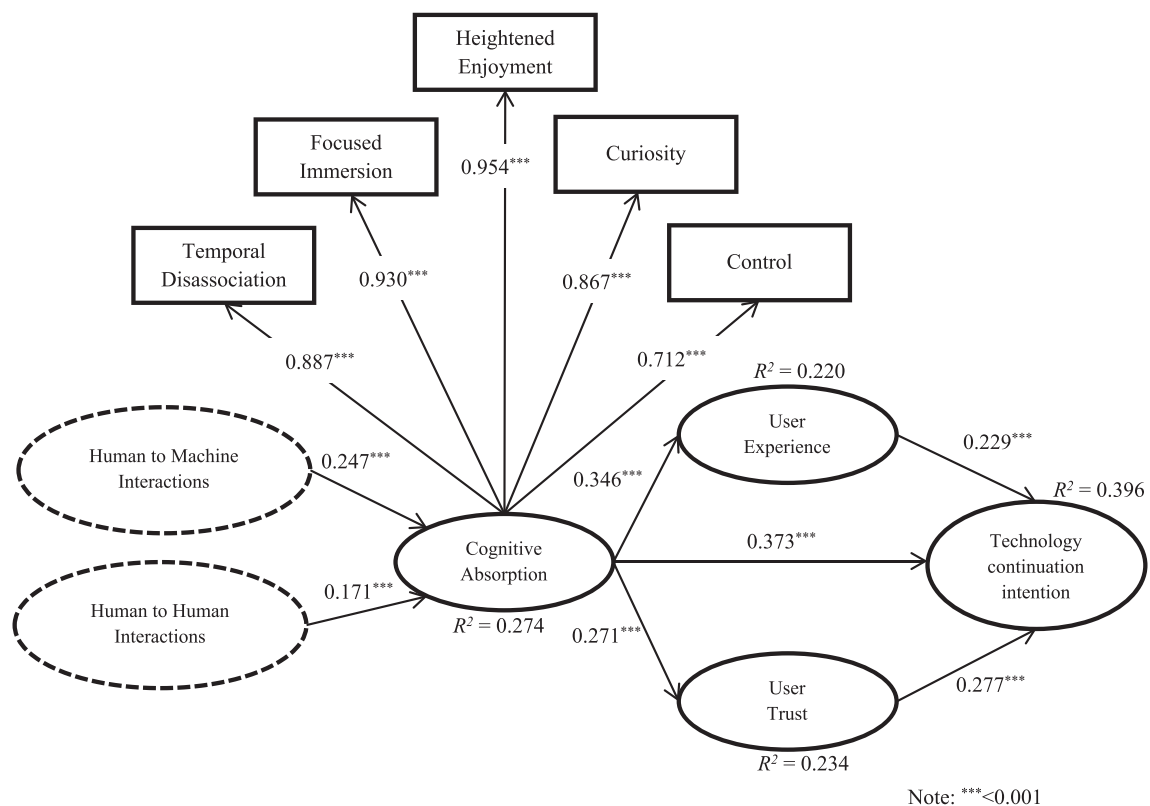

FIGURE 2 Standardized estimates and r^2 values of the hypothetical model

TABLE 6 Multiple mediation effects present in the structural model

Effects	Model 2 standardized estimates	Model 3 standardized estimates	Model 4 standardized estimates	Model 5 standardized estimates
Effect a	0.522***	0.510***	0.099[ns]	0.130***
(SE, lower bound, upper bound)	(0.061, 0.393, 0.634)	(0.059, 0.377, 0.615)	(0.055, -0.014, 0.205)	(0.054, 0.025, 0.232)
Effect b	0.426***	0.436***	−0.032[ns]	0.043[ns]
(SE, lower bound, upper bound)	(0.068, 0.218, 0.557)	(0.060, 0.180, 0.554)	(0.050, −0.131, 0.067)	(0.048, -0.052, 0.139)
Effect c	0.096***	0.074***	0.131***	0.087***
(SE, lower bound, upper bound)	(0.029, 0.048, 0.165)	(0.026, 0.043, 0.151)	(0.029, 0.079, 0.191)	(0.026, 0.039, 0.143)

Note:

1. Effects a, b, c denotes the total, direct and indirect effects, respectively. All the estimates are standardized and significant at the 95% level. $n = 410$, bootstrap iterations = 5000 through bias-corrected percentile bootstrap method.

2. Models 2 and 3 investigates the effect of cognitive absorption on technology continuation intention mediating through user experience and user trust respectively.

3. Models 4 and 5 investigate the effect of human-to-machine interactions (Model 4) and human-to-human interactions (Model 5) on technology continuation intention mediating through cognitive absorption.

mediation, in which both direct and indirect effects are significant. Next, Models 4 and 5 examined the intervening effect of cognitive absorption on the relationship of human-to-machine and human-to-human interactions towards technology continuation intention. Though it was found that total and direct effects are insignificant, the indirect effects were found to be significant. Zhao et al. (2010) term this kind of mediation effect as indirect-only mediation.

Table 7 provides the results of MANOVA, which investigated the significant difference of the variables across the experimental variable conditions. The results indicated that the cognitive absorption, user experience, user trust, and technology continuation intention together differ across both the conditions of experimental variables individually and during the interaction. The partial eta squared values of MANOVA indicated that the investigated variables significantly differ more with human-to-machine interaction than human-to-human interaction. Table 8 provides the results of ANOVA. The results indicated that cognitive absorption scores are significantly different across the conditions of both human-to-machine and human-to-human interaction. However, the partial eta squared

values for cognitive absorption indicated that the difference is highest with human-to-machine interaction. User experience failed to significantly differ across both human-to-machine and human-to-human interactions. The scores of user trust are significantly different across the conditions of human-to-machine interactions but insignificant across the conditions of human-to-human interactions. In contrast, the scores of continuation intention are significantly different across the human-to-human interaction but insignificant across the conditions of human-to-machine interaction. A detailed discussion of the results is presented in the next section.

6 | DISCUSSION AND IMPLICATIONS

The present study introduced a framework incorporating machine-to-human interaction and human-to-human interaction and analyzed its effect on cognitive absorption. Subsequently, the effect of cognitive absorption on user experience, user trust, and technology continuation intention is also analyzed. The study followed a 3 × 3

TABLE 7 MANOVA results

Effects	Wilks' lambda	df	F-statistic	Partial η²
Main effects				
Human-to-machine interaction	0.834	8, 796	9.449***	0.087
Human-to-human interaction	0.932	8, 796	3.549***	0.034
Interaction effects				
Machine-to-human interaction × human-to-human interaction	0.837	16, 1216	4.555***	0.043

Note: ***Represents values significant at 99% confidence level. Partial η2 represents partial eta squared.

Abbreviation: MANOVA, multivariate analysis of variance.

TABLE 8 ANOVA results

Effects	Cognitive absorption		User experience		User trust		Technology continuation intention	
	F-statistic	partial η^2	F-statistic	partial η^2	F-statistic	partial η^2	F-statistic	Partial η^2
Main effects								
Human-to-machine Interaction	13.612***	0.064	2.415[ns]	0.012	9.907***	0.047	2.139[ns]	0.011
Human-to-human Interaction	5.914***	0.029	0.202[ns]	0.001	0.104 [ns]	0.001	5.472***	0.027
Interaction effects								
Machine-to-human interaction × human-to-human interaction	5.885***	0.055	2.235[ns]	0.022	2.730**	0.027	4.117***	0.039

Note: ***Represents values significant at 99% confidence level; **represents values significant at 95% confidence level; "ns" represents values not significant. Partial η2 represents partial eta squared.

Abbreviation: ANOVA, analysis of variance.

factorial research design and analyzed the model using SEM. The results are discussed in the following sections. The merits of the proposed model and research results in terms of theoretical contribution and practical implications are discussed in the subsequent subsections.

6.1 | Discussion of results

The study RQ1 investigated Hypotheses 1 and 2; the results imply that both human-to-machine interaction and human-to-human interaction is significantly associated with cognitive absorption. In relation to Hypotheses 1 and 2, the interaction between humans and machines was found to positively affect human-to-human interaction. The partial eta squared of ANOVA and MANOVA showed that the scores of cognitive absorption differ more significantly across the human-to-machine interactions. This result complements and strengthens the results found related to Hypotheses 1 and 2. Though no study has directly investigated Hypotheses 1 and 2, the results are inconsistent with existing knowledge, which says cognitive absorption is positively associated with technology interfaces (Agarwal & Karahanna, 2000; Hsu & Lin, 2017; Lin, 2009; Saadé & Bahli, 2005).

Moreover, by comparing the human-machine interaction and human-human interaction variables in the same model, the study enabled the literature to compare the results of the two experimental variables. The results also opened a new avenue of discussion from a theoretical and practical perspective. RQ2 investigated Hypotheses 3, 4, 5, 6, and 7. The results of Hypothesis 3 (cognitive absorption towards user experience) showed a significant positive effect. Most of the studies have addressed cognitive absorption as a process of flow theory (Agarwal & Karahanna, 2000) and have substituted the cognitive absorption in place of user experience. This study opened a new theoretical knowledge that cognitive absorption is different from user experience, but still, they are significantly related to each other. More specifically, the results of Hypothesis 3 will be additional information to the literature related to service interaction.

Hypothesis 4 investigated the relationship between cognitive absorption and user trust. The results indicated that cognitive absorption builds positive user trust. However, the results are consistent with research that has investigated hypotheses related to the virtual environment (Chandra et al., 2012), technology learning performance (Trouche, 2004), and online learning environment (Leong, 2011). Still, there is no direct comparison between cognitive absorption and user trust in human-machine interaction in the service's context. These results will be a valuable contribution to the theories that have connected trust in the services marketing context. Hypothesis 5 investigated the relationship between cognitive absorption and technology continuation intention. However, there is no direct link available to support the results, given the connection of flow theory with cognitive absorption. The results are consistent with the results from the literature that suggests that flow could influence continuation intention (Roca et al., 2006; Chang & Zhu, 2012).

Moreover, this hypothesis brings more identity to the experience regarding service interactions, which were not investigated comprehensively before. Hypothesis 6 investigated the relationship between user experience and technology continuation intention. The results showed a significant positive relationship between the two variables. While most of the studies have investigated and found a significant relationship between experience and technology adoption (Zhou, 2013), the present study extended the theoretical understanding by finding that experience can significantly influence technology continuation intention. Hypothesis 7 investigated the relationship between user trust and technology continuation intention. The results showed a significant positive relationship between the variables. With the growing importance of trust in information systems research and services marketing research, the hypothesis's result will add value to the literature related to these domains.

To investigate RQ3, the indirect effect of cognitive absorption in the relationship of human-to-machine interaction (Model 4) and human-to-human interaction (Model 5) towards technology continuation intention is calculated. The results indicated only indirect effect, but no direct effect was found. This finding is new since no

previous study has attempted to investigate the intervening effect of cognitive absorption in service interactions. Besides, the results of mediation analysis showed that both user experience and user trust could induce an indirect effect between cognitive absorption and technology continuation intention.

6.2 | Theoretical contributions and implications

The proposed model and its results contribute to the literature in the following ways. First, the studies investigating human-machine interaction are becoming increasingly important in service interaction, and the results of this study add value to the existing models and provide a pathway to future research. The study compares human-machine interaction with human-human interaction in a service setup. Given the growth of technology automation and AI function in the service sector, the study results will provide a greater understanding of the theoretical models in SST, chatbots, and AI-powered relationship management tools. Second, the study results contribute to flow theory, SCT, and absorption theory. Third, the results concerned with technology continuation intention extend the existing knowledge in ECT, with specific reference to human-to-machine interaction in the service industry. Fourth is the intervening role of cognitive absorption and its impact on the service interaction. Fifth, the role of experience and trust in a human-machine interaction was clearly explained through the model's results. Sixth, this study provides a holistic model for explaining the human-machine interaction.

The studies concerning human-machine interaction are limited. Literature is flooded with terminologies concerning human-computer interaction, human-robotic interaction, and human-system interaction. However, most of the existing studies have investigated different phenomena happening on the surface of human-machine interaction. Our study adds value by creating an experimental variable named human-machine interaction. Hence, the results and proposed hypotheses relating to human-machine interaction variables have made a unique contribution to existing human-machine theories. These theories have previously been applied in different contexts, including student learning (Chen & Macredie, 2004; Koedinger et al., 2012), services (Curran & Meuter, 2005), online buying (Close & Kukar-Kinney, 2010), operational interaction (Bader & Kaiser, 2019), medical improvements (Herbert et al., 2018), road safety (Oviedo-Trespalacios et al., 2018), and automated assistants (Guzman, 2019).

Our study has provided empirical evidence to support some of the crucial assumptions and arguments made in the existing literature on this topic. For example, Woods (1985) proposed that human-machine interaction creates a cognitive system. Minimal research has been undertaken to explain this proposition conceptually or examine it empirically. Our study extended and contributed to Woods' (1985) argument by testing it empirically. Similarly, Sheridan (2016) and Sahaï et al. (2017) pointed out that human-to-machine involvement can be challenging compared with human-to-human interaction. The results of this study provide a comparative result, which can offer a

greater understanding of the results provided by Sheridan (2016) and Sahaï et al. (2017). The study compared the effect of cognitive absorption between human-machine interaction and human-human interaction. This result is a worthwhile contribution to theories related to services and marketing. This research's findings add value to existing technology service models since it was found that human-to-machine interaction significantly improves cognitive absorption more than human-to-human interaction. Also, the results will benefit the existing theories related to self-service technology (Curran & Meuter, 2005; Lee & Lyu, 2016), kiosks (Vakulenko et al., 2018), chatbots (Nordheim et al., 2019), and other technology-oriented services. Besides the service implications, the model results also add valuable inputs to other existing marketing literature.

Second, besides adding value to the literature in human-computer interactions, the results of this study also extend and contribute to psychological literature. The results concerned with user experience have added valuable context to flow theory (Csikszentmihalyi, 1990). Specifically, the hypothesis of user experience and technology continuation intention has shown that flow can also append sustainable technology adoption. Also, most of the studies have investigated the function of cognitive absorption as an outcome of a technology-mediated interaction. This research has extended this path by comparing human-to-human interaction with human-to-machine interaction, which is an added contribution to SCT and absorption theory. SCT majorly supports human-to-human interaction and cognitive outcome. By comparing human-to-machine interaction and human-to-human interaction, this study enables the researchers to understand the cognitive architecture prevalent in both the mechanism. In the case of absorption theory, literature has stated that a more profound involvement is possible both in human and machine interactions.

Third, by identifying cognitive absorption as a significant predictor for technology continuation intention, this study brings a new perspective to EDT regarding human versus machine interactions. Most of the studies in information systems have used satisfaction and attitude as significant predictors of technology continuation intention (Bhattacherjee, 2001a). While most of the literature has addressed the existing relationship between cognitive absorption and technology adoption (Amoroso & Lim, 2017; Oghuma et al., 2016; Stone & Baker-Eveleth, 2013), this research extends this knowledge to technology continuation intention. The results can be extended to information system researches involving EDT. Moreover, the results between cognitive absorption and technology continuation justify the importance of immersive level dialogues necessary for the service sector. Previous studies have argued that service interactions contribute to customer-employee relationships' value creation (Ballantyne & Varey, 2006). The results have emphasized that the immersion level present in the technology-level interactions in the services sector can enhance customers' intention to continue with the technology.

Fifth, the results of user trust and user experience extend the understanding of flow and cognitive absorption theories. The positive relationship between cognitive absorption and user experience

will bring a new perspective for flow theory (Csikszentmihalyi, 1997) by separating involvement from experience since some of the literature has used cognitive absorption as a substitute for flow experience, and other sets of studies have used flow experience as a substitute for user experience. These studies metaphorically have represented the intersections as the whole circle. Thus, by proposing cognitive absorption and user experience as different constructs, this study has added further insights to the existing literature on this body of work, which has implications for future research. User trust is found to influence a significant indirect effect between cognitive absorption and technology continuation intention, which is an additional contribution to the literature. Also, the study has examined a holistic model by including both human-to-computer interaction and human-to-human interaction variables. Overall, the model has added comprehensive inputs to existing theories related to cognitive absorption (Agarwal & Karahanna, 2000), continuation intention (Bhattacherjee, 2001a), user trust (Dimitriadis & Kyrezis, 2010), user experience (Hassenzahl & Tractinsky, 2006) and literature on human and machine interaction.

6.3 | Managerial implications

The present study opens a discussion for business managers with specific reference to services marketing executives. The result comparing human-to-machine interaction and human-to-human interaction should motivate the service industry to use advanced artificial response system to answer customer queries. By using the chatbot as a study stimulus, the study offers lucrative marketing strategies to marketers regarding the usage of an automated query system and its effectiveness. The application of AI technology has become omnipresent across the customer journey. Technologies like voice assistant, personalization mechanism, automated query management, automated sales force, and AI advertising campaign management tools have started adding value to the different marketing functions. The affair between AI and marketing will increase in the coming years; the same also induces more human-machine interaction. The study model provides valuable suggestions based on the model. From a holistic perspective, the study recommends marketers and business executives to create strong involvement using AI functions.

The involvement of customers is crucial to create strong engagement with brands and technology. The results concerned with cognitive absorption confirm that AI technologies can append strong involvement. This result is a significant finding that can guide service interactions. Previous studies have mostly investigated various variables that can uplift service quality and service standards. This study has emphasized that creating an immersive discussion is also essential to derive positive service outcomes. Also, both user experience and trust play a vital role in creating such an intention. Creating an experience is necessary to uphold positive attention to the technology. Experience and trust are two sides of a technology coin. Marketers and technology managers should try to create

experience transparently and ethically. This process can enable users to perceive a positive experience without affecting trust.

7 | CONCLUSION AND LIMITATIONS

The study investigated and compared cognitive absorption in a human versus machine environment through a conceptual model. The study performed a 3×3 factorial experiment with prevalidated conditions and manipulations. It used chatbots and business service executives as the central stimulus in the study to compare human-to-machine interaction and human-to-human interaction. The CMB analysis showed that the data is free from instrument bias. The authors were cautious about selecting a sample with pre-experience in using chatbots, so the knowledge regarding chatbots was not considered as a major hindrance during the experiment. Despite the fact that the participants are randomly assigned to the blocks, the effect of selection bias may still prevail because of the low sampling frame size for each block. The study used only AI-powered chatbots to represent human-to-machine interaction. The proposed hypothetical model found that human-machine interaction contributes more to cognitive absorption compared to human-human interaction. Moreover, the model gives an outline to create technology continuation intention with trust and experience as significant drivers of the relationship.

Overall, the model provides valuable insights to the marketing and technology managers, and the study results add value to the existing literature concerning human-machine interaction, cognitive absorption, continuation intention, trust, and experience. The validated experimental design and conditions used in the study can also benefit future researchers by enabling them to adopt and extend similar models using technology interfaces. Future research can focus more on investigating the experience and trust variables with respect to other AI-powered technologies such as voice assistants, digital assistants, campaign management, and data analytics. The present research has also conceptualized trust as system-based beliefs, and future studies can compare the system-like trusting beliefs and human-like trusting beliefs in a chatbot environment. Minimal research has identified or investigated the AI-related factors such as perceived anthropomorphism, perceived animacy, and perceived intelligence integrated with technology-related theories. The proposed framework in this study can be extended using AI factors to check how these relate to cognitive absorption state. Exploring these areas will benefit marketers and technology practitioners.

DATA AVAILABILITY STATEMENT
Data available on request from the authors.

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APPENDIX A: Factorial manipulations

Blocks	Human-to-machine interaction	Human-to-human interaction	Explanation
Block 1 (Wave 1)	High (9 levels automated chat)	High (Personal direct visit)	This block represents the clients who were personally visited by the service executives and subsequently those who engage with the 9-level high interactive automated chatbots were taken as a representative experimental sample.
Block 2 (Wave 2)	Medium (6 levels automated chat)	High (Personal direct visit)	This block represents the clients who were personally visited by the service executives and subsequently those who engage with the 6-level high interactive automated chatbots were taken as a representative experimental sample.
Block 3 (Wave 3)	Low (3 levels automated chat)	High (Personal direct visit)	This block represents the clients who were personally visited by the service executives and subsequently those who engage with the 3-level high interactive automated chatbots were taken as a representative experimental sample.
Block 4 (Wave 4)	High (9 levels automated chat)	Medium (Personal tele-call)	This block represents the clients who have interacted with 9-level high interactive automated chatbots and subsequently those who were followed by the clients through telephone conversations were taken as a representative sample.
Block 5 (Wave 5)	Medium (6 levels automated chat)	Medium (Personal tele-call)	This block represents the clients who have interacted with 6-level high interactive automated chatbots and subsequently those who were followed by the clients through telephone conversations were taken as a representative sample.
Block 6 (Wave 6)	Low (3 levels automated chat)	Medium (Personal tele-call)	This block represents the clients who have interacted with 3-level high interactive automated chatbots and subsequently those who were followed by the clients through telephone conversations were taken as a representative sample.
Block 7 (Wave 7)	High (9 levels automated chat)	Low (Live Chat)	This block represents the clients who have interacted with 9-level high interactive automated chatbots and subsequently those who were followed by the clients through telephone conversations were taken as a representative sample.
Block 8 (Wave 8)	Medium (6 levels automated chat)	Low (Live Chat)	This block represents the clients who have interacted with 6-level high interactive automated chatbots and subsequently those who were followed by the clients through live chat sessions were taken as a representative sample.
Block 9 (Wave 9)	Low (3 levels automated chat)	Low (Live Chat)	This block represents the clients who have interacted with 3-level high interactive automated chatbots and subsequently those who were followed by the clients through live chat sessions were taken as representative sample.

Note: Time duration for experiment and data collection (Wave 1 = 8 days; Wave 2 = 9 days; Wave 3 = 7 days; Wave 4 = 5 days; Wave 5 = 6 days; Wave 6 = 4 days; Wave 7 = 5 days; Wave 8 = 5 days; Wave 9 = 5 days.

APPENDIX B: Sample screenshots of the website for experiment and manipulation checks
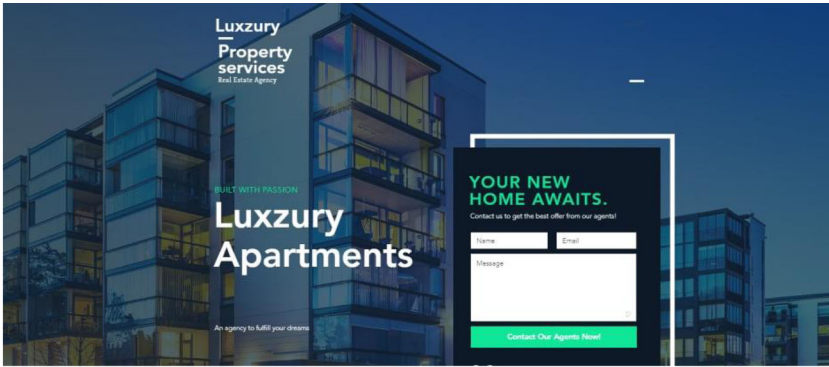
Appendix B[1]: The screenshot of the website with user registration portal

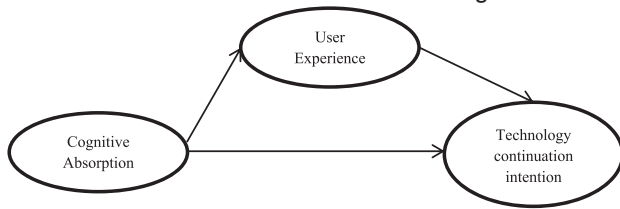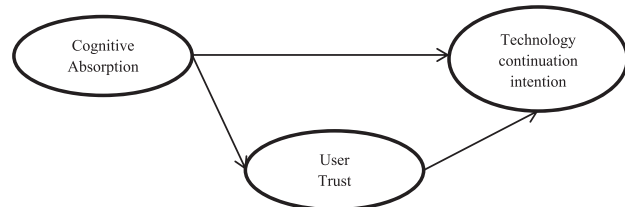**Appendix B[2]:** The screenshot of the website with manual chat portal

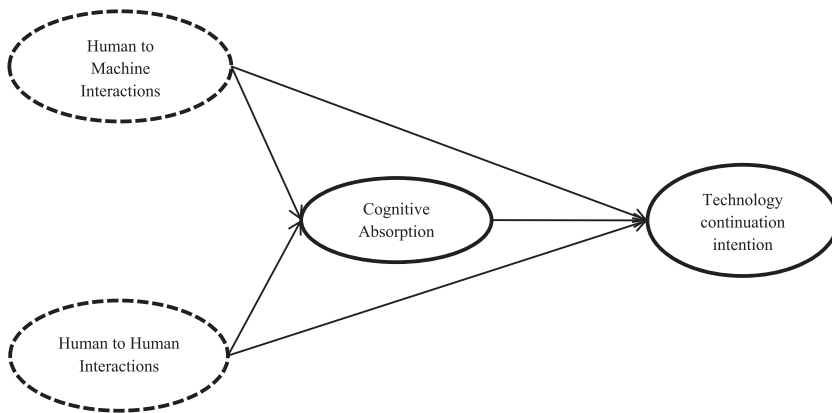**Appendix B[3]:** The screenshot of the website with automated messages

Appendix B[4]: The screenshot of the website with AI Chat

APPENDIX C: Models 2 and 3 exhibiting the mediation path given in Figure 1

Appendix C[1]: Model 2 representing user experience as mediator

Appendix C[2]: Model 3 representing user trust as mediator

APPENDIX D: Model 4 investigating RQ2a and RQ2b

APPENDIX E: Block validation with the study sample

Blocks	Mean values of the factors							
	TD	FI	HE	Curiosity	Control	UE	UT	TCI
Block 1	3.7739	3.5972	3.4764	3.9719	3.5568	2.8017	3.0978	4.5166
Block 2	3.5847	3.3095	3.2930	3.7136	3.1752	2.8633	2.8485	4.1075
Block 3	3.3729	3.2012	3.1269	3.4447	3.0376	2.7706	2.8642	3.7925
Block 4	3.2708	3.1333	3.0804	3.4179	3.0222	2.7767	2.8195	3.9667
Block 5	3.0611	2.9562	2.8630	3.1143	2.8128	2.5528	2.6644	3.5557
Block 6	3.5135	3.3350	3.2465	3.5754	3.2061	2.6972	2.7722	3.8594
Block 7	3.4281	3.2275	3.1410	3.5263	3.2720	2.6222	2.8980	4.0108
Block 8	3.2646	3.1120	3.0095	3.2448	2.9501	2.5389	2.8986	3.7931
Block 9	2.8986	2.7241	2.6470	2.8314	2.5671	2.0620	2.4151	3.1062
F Values	7.295***	6.510***	6.785***	11.989***	8.777***	7.551***	5.995***	12.375***

Note: TD represents Temporal Disassociation; FI represents Focused Immersion; HE represents Heightened Enjoyment; UE represents User Experience; UT represents User Trust; TCI represents Technology Continuation Intention.

The mean values reported above represent the mean of the factor scores.

APPENDIX F: Details of the scale and CFA—factor loadings for each item

Construct	Scale	Factor loadings
Temporal Disassociation	Time appears to go by very quickly during the service interaction.	0.827
	Sometimes I lose track of time when I interact during service queries.	0.681
	I wish to spend more time on service interactions than I intended.	0.786
Focused Immersion	While involved in the service interaction, I am absorbed in what I am doing.	0.786
	During the service interaction, I am immersed in the task I am performing.	0.732
	During service interaction, I get distracted by other attentions very easily. (reversed)	0.810
Heightened Enjoyment	I have fun during the service interaction.	0.817
	The interaction provides me with a lot of enjoyment.	0.750
	I enjoy interacting during the service queries.	0.841
Curiosity	The service interaction excites my curiosity.	0.851
	The service interaction makes me curious.	0.741
	The service interaction arouses my imagination.	0.795
Control	I feel that I have no control during my interactions. (reversed)	0.824
	The queries allow me to control my interaction.	0.807
User Experience	The interaction through chatbots is more appealing.	0.793
	It is easy to navigate through chatbots during interactions.	0.737
	The query results are returned promptly.	0.876
	The interaction is more personalized.	0.751
	The query results are always up to date.	0.895
	The query results are always accurate.	0.668
User Trust	The service interaction through chatbots is reliable	0.746
	The service interaction through chatbots is trustworthy	0.776
	The service interaction through chatbots is dependable	0.826
Technology Continuation Intention	I want to continue using my chatbots for service queries	0.775
	My intentions are to continue using my chatbots for service queries rather than any alternative means.	0.822
	I intend to continue using chatbots for processing more queries in future	0.767
	If I could, I would like to discontinue using chatbots for service queries. (measured in reverse scale)	0.817

Note: All items are measured in the 5-point Likert scale (5: being Strongly Agree and 1: being Strongly Disagree).