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How to increase consumer intention to use Chatbots? An empirical analysis of hedonic and utilitarian motivations on social presence and the moderating effects of fear across generations

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Abstract

As chatbots become more advanced and popular, marketing research has paid enormous attention to the antecedents of consumer adoption of chatbots. This has become increasingly relevant because chatbots can help mitigate the fear and loneliness caused by the global pandemic. Therefore, unlike previous work that focused on design factors, we theorize that social presence serves a mediating role between consumer motivations (i.e., hedonic and utilitarian) and intention to use a chatbot service based on self-determination theory. Our results from a structural equation model ($n = 377$) indicate that hedonic (but not utilitarian) motivation significantly affects chatbots' social presence, ultimately influencing intention to use the chatbot service. We also found that fear of COVID-19 amplifies the effect of social presence on intention to use the chatbot service. In this dynamic, we found an additional moderated moderation effect of generational cohorts (i.e., baby boomers and Generations X, Y, and Z) in experiencing different levels of fear of COVID-19. Overall, our findings emphasize the importance of motivation-matching features for consumer adoption of chatbot services. Our findings also indicate that marketers may utilize the fear element to increase adoption of chatbot services, especially when targeting the young generations (e.g., Generation Z).

Keywords Chatbot · Social presence · Motivation · Artificial intelligence · Global pandemic · COVID-19 · Fear · Generation cohort · Robot-human interaction

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1 Introduction

During the COVID-19 pandemic, worldwide precautions such as social distancing and quarantining have restricted direct human-to-human interaction [1, 72] and, in turn, heightened our desire for social interaction [29]. As a result, consumers have felt more socially isolated and lonely during (vs. before) the pandemic [32, 114]. As artificial intelligence (AI) chatbots can stimulate human-like conversations anywhere and anytime [43, 74], this paper aims to address the following question: Can chatbots replace human warmth and fulfill social presence, especially in the global pandemic?

Addressing the above question is timely because as technologies advance, AI chatbots can now respond to almost any text-based or voice-based requests in a less robotic, more natural, and intelligent manner [77]. Not surprisingly, chatbot services are rapidly entering various business sectors to help reduce human labor cost and increase operational efficiencies [108]. Indeed, experts have projected that the chatbot market will grow steadily from $17.17 billion in 2020 to $102.29 billion by 2026 [122]. However, literature related to consumer adoption of chatbot services is relatively scant and predominantly features chatbots' external design (e.g., appearances) and anthropomorphic elements (e.g., gender identity) [4, 9, 43, 55, 64]. Despite the continuous growth and wide popularity of chatbots, unfortunately, little is known about the motivational drivers of how and why consumers engage with chatbots.

This paper aims to fill these gaps in the literature by revealing the underlying mechanism of chatbot adoption based on self-determination theory (SDT) [26, 104]. According to SDT, consumer behavior is driven either by *hedonic (or intrinsic) motivation*, which pursues fun, pleasure, and/or satisfaction, or by *utilitarian (or extrinsic) motivation*, which seeks to attain resources and/or reduce of (the risk of) punishment. We argue that these two types of motivation differently shape consumer adoption of chatbot services. Furthermore, this paper aims to reveal an underlying mechanism by highlighting the role of social presence, which is defined as the perceived presence of another social being, characterized by human warmth and personal touch, via a technological medium [8, 107]. This paper also examines the fear of the pandemic as a moderator between social presence and intention to use chatbot services. Additionally, this paper shows that generational cohort further moderates the effect of fear. The overall conceptual model is presented in Fig. 1.

Our research offers the following contributions. First, it extends the literature on SDT and consumer-chatbot interaction by illustrating the effects of consumers' motivation on the pursuit of social presence from chatbots. Second, it contributes to the literature on emotions by showing fear's positive role in facilitating consumers' adoption of chatbots. Third, it offers new insights by comparing the levels of fear felt during pandemics across different generations to further examine the relationship between social presence and chatbot adoption. Altogether, this paper advances current theoretical and managerial understandings of AI-based chatbots by examining an emerging dynamic of the consumer-chatbot relationship.

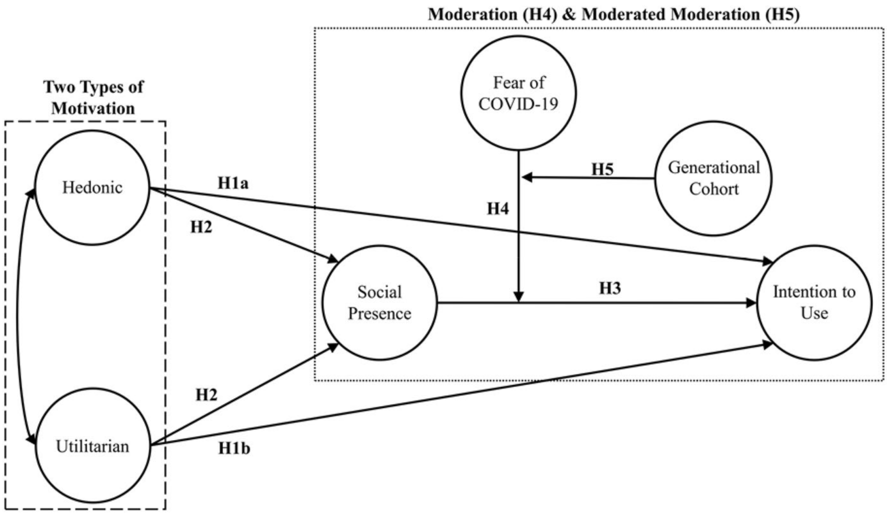

Fig. 1 Conceptual model

2 Literature review and hypotheses

2.1 Chatbots

A *chatbot*, or *bot* or *conversational agent*, is a computer program that uses automated algorithm-based technologies, such as natural language processing, machine learning, and AI, to mimic conversational interactions with humans [22]. Researchers have classified chatbots based on their form of existence (physical or virtual and embodied or disembodied), type of communication (text-based or voice-based), and abilities (mechanical chatbots for routine tasks vs. thinking chatbots for idiosyncratic tasks) [4, 52, 106]. At base, the primary function of a chatbot is to quickly generate relevant responses by mimicking human-to-human conversation processes. However, recent technologies have also allowed chatbots to provide instant, convenient, personalized, round-the-clock customer services [43], and in parallel, the adoption of chatbots has grown rapidly [37, 119].

In response to the hype, marketing scholars have begun investigating factors that influence consumers' attitudes and behaviors toward chatbots. As shown in Table 1, prior research has primarily focused on chatbots' design cues, particularly anthropomorphic cues, including communication style [64], visual appearance [43], and gender identity [9]. Scholars have argued that people not only are motivated to detect such cues in non-human entities like chatbots [31], but also rely on those cues as perceivable heuristics to form judgments about chatbots [3]. Other scholars have also adopted the technology acceptance model or use and gratification theory to examine how consumers employ chatbots to achieve utilitarian (e.g., informativeness and

Table 1 Review of previous empirical research on chatbots and the present study

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Qiu and Benbasat [99]	Embodied and disembodied, text-based and voice-based	Experiment	Humanoid embodiment (avatar vs. none), output modality (human voice vs. text-to-speech vs. text)	Social presence, trusting beliefs, perceived usefulness, enjoyment, usage intention	Humanoid embodiment (avatar vs. none)	Social agency theory	Chatbots with (vs. without) humanoid embodiment are perceived to have greater social presence. Among the three output modalities, chatbots with voice elicit the highest perceived social presence whereas chatbots with text output are perceived to have the least social presence. Social presence predicts trusting beliefs and perceived enjoyment, and both trusting beliefs and perceived usefulness are determinants of usage intention.
Li and Mao [71]	Embodied, text-based	Survey, experiment, interviews	Similarity of communication style	Hedonic perceptions (perceived transparency, engagement, and enjoyment), utilitarian perceptions (informativeness and credibility), social presence, reuse intention	None	SAP, theories of human communications, theory of hedonic vs. utilitarian information systems	Similarity between the communication style of virtual advisory systems and consumers increases hedonic and utilitarian perceptions. Only perceived engagement and perceived enjoyment predict social presence. Perceived transparency, perceived engagement, perceived enjoyment, informativeness, and social presence positively influence reuse intention.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Mimoun and Pocin [86]	Embodied, text-based	Survey	Decision quality, playfulness, social presence	Utilitarian value, hedonic value, satisfaction, behavioral intention	None	SPT, CASA	Decision quality influences behavioral intention via utilitarian value. Hedonic value mediates the impact of playfulness and social presence on satisfaction and behavioral intention.
Etemad-Sajadi [33]	Embodied	Survey	Social presence	Trust, emotional appeal, online real-time interactivity, patronage intention	None	Not specified	Online real-time interactivity determines the intention to patronize avatars. Trust impacts interactivity more than emotional appeal does. Avatar's social presence positively affects trust and emotional appeal.
Araujo [4]	Disembodied, text-based	Experiment	Anthropomorphic design cues (language style and name), intelligent agency framing	Perceived anthropomorphism (mindful and mindless), social presence, perceptions of the company (attitude, satisfaction, and emotional connection)	None	CASA	Anthropomorphic design cues prompt consumers to perceive chatbots as being human-like and to develop emotional connections with companies that introduce such chatbots.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Go and Sundar [43]	Embodied and disembodied, text-based	Experiment	Anthropomorphic visual cues, identity cues, message interactivity	Social presence, perceived homophily, perceived contingency, perceived dialogue, perceived expertise, perceived friendliness, website attitude, intention to revisit the website	None	MAIN, SPT	As the message interactivity of chatbots increases, consumers are likely to perceive higher levels of chatbots' social presence, homophily, and dialogue, which in turn increase the chatbots' perceived expertise and friendliness as well as consumers' attitudes toward websites and their behavioral intention. Consumers' attitude is affected by the interactions between visual and identity cues as well as between identity cues and message interactivity. Conversely, intention was influenced only by the interaction between visual and identity cues.
Luo et al. [78]	Disembodied, voice-based	Field experiment	Disclosure of chatbot's identity	Purchase likelihood	None	Not specified	When consumers discover that their conversational partners are chatbots, not humans, they make fewer purchases due to perceiving chatbots as being less knowledgeable than humans and lacking in empathy.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
McLean and Osei-Frimpong [83]	Embodied, voice-based	Survey	Utilitarian benefits, hedonic benefits, symbolic benefits, social presence, social attraction	Intention to use	Perceived privacy risk	Uses and gratification theory, SPT, MAIN, TAM, UTAUT	Except for hedonic benefits, all independent variables positively influence the usage intention of in-home voice assistants. Although perceived privacy risks enhance the impact of utilitarian benefits, social presence, and social attraction on intention, they weaken the impact of hedonic benefits and symbolic benefits.
Chung et al. [17]	Disembodied, text-based	Survey	Chatbot's marketing effort (interaction, entertainment, trendiness, customization, and problem-solving)	Quality of communication (accuracy, credibility, and competence), satisfaction	None	Not specified	Chatbots' marketing effort positively influences their communication accuracy and credibility. Communication accuracy and credibility positively influence customers' satisfaction.
De Cicco et al. [24]	Embodied and disembodied, text-based	Experiment	Interaction style, presence of avatar	Social presence, trust, perceived enjoyment, attitude toward the chatbot	None	SPT, CASA	Interaction style determines a chatbot's social presence, which in turn influences trust, perceived enjoyment, and, subsequently, attitude.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Sheehan et al. [106]	Embodied, text-based	Experiment	Chatbot's miscommunication (error-free vs. clarification vs. error)	Anthropomorphism, intention to adopt	Need for human interaction	Anthropomorphism theory	Consumers perceive error-free chatbots and clarification chatbots (vs. error chatbots) as being more human-like and are more likely to adopt them. Anthropomorphism significantly mediates the miscommunication–intention relationship, while the need for human interaction strengthens the anthropomorphism–intention relationship.
Borau et al. [9]	Embodied	Experiment	Chatbot's gender identity	Perceived humanness, perceived uniqueness of treatment from bot, attitude toward the bots, trust, perceived credibility	None	Anthropomorphism theory	Consumers prefer female bots over male bots due to perceiving female bots as being more human-like and more likely to cater to special needs.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Fernandes and Oliveira [35]	Voice-based	Survey	Perceived ease of use, usefulness, subjective social norms, perceived humanness, social interactivity, social presence, trust, rapport	Intention to accept	User experience, need for human interaction	Service robot acceptance model	Of all factors, only perceived usefulness, perceived social presence, trust, and rapport positively influence Millennials' intention to accept digital voice assistants.
Hildebrand and Bergner [48]	Disembodied, text-based	Experiment	Presence of conversational social cues	Affective trust toward the chatbot, benevolence attribution toward the company, recommendation acceptance	None	Not specified	Conversational (vs. non-conversational) advisory chatbots increase consumers' affective trust toward the chatbots, which in turn positively affects their perceptions of the company and willingness to accept recommendations from chatbots.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Jin and Youn [56]	Embodied, text-based	Experiment	Chatbot anthropomorphism, chatbot–consumer personality matching	Chatbot-related outcomes (continuance usage intention and willingness to recommend), brand-related outcomes (attitude and purchase intention)	Social phobia	Anthropomorphism theory, SCM, warmth–competence framework, SAP	Social phobia moderates the impact of chatbots' anthropomorphism on brand-related outcomes, albeit only for a low level of social phobia, and chatbot-related outcomes. Social phobia moderates the impact of consumer–chatbot personality matching on the outcome variables for competent chatbots only.
Moriuchi [91]	Embodied, voice-based	Survey	Performance expectation, effort expectation, perceived risk, social influence	Chatbot usage experience, anthropomorphism, engagement, intention to reuse, actual use	Internet usage experience	Realism maximization theory, anthropomorphism theory, UTAUT, social influence theory, theory of reasoned action, ECT	Performance expectation, effort expectation, perceived risk, and social influence significantly determine experience with using chatbots, which in turn positively influences reuse intention via the mediating effects of anthropomorphism and engagement. Experience with using the Internet moderates that serial mediation effect while intention determines actual use.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Pitardi and Marriott [97]	Voice-based	Survey, in-depth interviews	Perceived ease of use, usefulness, enjoyment, social presence, social cognition, consumers' privacy concern	Attitude, trust, intention to use	None	TAM, UTAUT 2, social response theory, extended privacy calculus model	Attitude is positively influenced by perceived usefulness, ease of use, enjoyment, social presence, and social cognition, but negatively influenced by privacy concern. Ease of use, social presence, and social cognition are antecedents of trust. Trust positively influences attitude. Attitude determines intention.
Roy and Naidoo [102]	Embodied, text-based	Experiment	Anthropomorphic conversational style (warm vs. competent)	Social perception of brand (warm vs. competent), brand attitude, brand purchase intention	Time orientation (present vs. future)	Anthropomorphism theory, SCM	Present (vs. future)-oriented individuals evaluate brand more favorably and are more likely to purchase the brand when they converse with a warm (vs. competent) chatbot. Such effect is mediated by social perception of brand.
Crolic et al. [22]	Embodied and disembodied, text-based	Field data analysis, experiment	Chatbot's anthropomorphism	Heightened expectations of chatbot's efficacy, customer's satisfaction, evaluation of company, purchase intention	Customer's anger	Anthropomorphism theory, ECT, emotion theories	Chatbots' anthropomorphism can harm purchase intention for angry (vs. not angry) customers due to an expectation that the chatbots' efficacy will be disconfirmed or violated after interacting with the chatbots.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Guha et al. [44]	Embodied, voice-based	Content analysis, survey	Natural speech, social cues, task range, accuracy	Artificiality, intelligence, evaluation (continued use intentions)	Verbalizer, tech-savviness, perceived sacrifice (time, finance, effort), length of relationship, age, gender	Signaling theory	Voice assistant's (VA) artificiality is negatively associated with consumers' evaluation. Such association is weaker among older users. VA's intelligence is negatively associated with consumers' evaluation. Such association is stronger among users who perceive to make more sacrifice. However, such association is weaker among older users and among users who have owned VA for a longer period of time. VA's natural speech is negatively associated with its artificiality. VA's social cues are negatively associated with its artificiality. VA's task range is positively associated with its intelligence. VA's accuracy is positively associated with its intelligence. Artificiality mediates the impact of natural speech and social cues on continued use. Intelligence mediates the impact of accuracy and task range on continued use.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Fotheringham and Wiles [37]	Embodied and disembodied, text-based and voice-based	Event study, experiment	Industry chatbot launches, business settings for chatbot (B2B vs. B2C), level of chatbot's anthropomorphism	Abnormal stock returns for the chatbot launch	Level of chatbot's anthropomorphism	Anthropomorphism theory	Launching AI chatbots positively influences firms' abnormal stock returns. Abnormal returns are higher from launching AI chatbots targeted at B2B (vs. B2C) customers. However, such effect will weaken as the chatbot becomes more human-like.
Jiang et al. [55]	Embodied, text-based	Survey, experiment	Social presence	Experiential innovativeness, perceived intimacy, sense of empowerment, continued usage intention, purchase intention	Communication styles (cute vs. formal)	SPT, innovativeness theory, customer engagement theory, anthropomorphism theory, uncanny valley theory	Social presence determines experiential innovativeness and intimacy, which in turn increases usage continuance intention and purchase intention. Moreover, a cute (vs. formal) communication style strengthens the impact of chatbots' social presence on customers' perception of intimacy.
Klein and Martinez [64]	Embodied, text-based	Experiment	Anthropomorphic design cues	Perceived enjoyment, attitude, trust, customer satisfaction	None	Anthropomorphism theory	Anthropomorphic design cues positively influence consumers' satisfaction toward the chatbot via the mediating role of perceived enjoyment, attitude, and trust.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
Lee and Park [70]	Not specified	Survey	Parasocial relationship	Communication accuracy, communication credibility, communication competence, satisfaction, continuance usage intention	None	Parasocial theory	Parasocial relationship determines all three communication qualities. Communication accuracy and competence are antecedents of satisfaction. Satisfaction significantly determines intention.
Mishra et al. [87]	Voice-based	Survey	Playfulness, escapism, anthropomorphism, visual appeal, social presence	Hedonic attitude, utilitarian attitude, word-of-mouth intention, actual use	Prestige	UTAUT	Playfulness, escapism, and anthropomorphism positively influence hedonic attitude whereas visual appeal and social presence determine utilitarian attitude. Both hedonic and utilitarian attitude also lead to word-of-mouth intention and actual use. Prestige moderates the relationship between playfulness and hedonic attitude, and between escapism and hedonic attitude.

Table 1 (continued)

Study	Chatbot type	Research methods	Independent variables	Dependent variables	Moderators	Theoretical foundations	Major findings
The present study	Disembodied, text-based	Survey	Hedonic motivation, utilitarian motivation	Social presence, intention to use	Fear of COVID-19, generational cohort	SDT, SPT, social support theory, generational cohort theory	Hedonic motivation determines social presence, but utilitarian motivation does not. Both types of motivation, along with social presence, positively influence intention. The social presence–intention relationship is moderated by fear of COVID-19 and further by generational cohort.

The cited works are presented in chronological order by year of publication and, within the same year, in alphabetical order. CASA = Computers–are–social–actors paradigm, ECT = Expectancy (dis)confirmation theory, MAIN = Modality–agency–interactivity–navigability model, SAP = Similarity–attraction paradigm, SCM = Stereotype content model, SDT = Self-determination theory, SPT = Social presence theory, TAM = Technology acceptance model, UTAUT = Unified theory of acceptance and use of technology.

usefulness), hedonic (e.g., escapism and playfulness), symbolic (e.g., trendiness), or social (e.g., social attraction) benefits [15, 17, 71, 83, 87, 91, 97]. Despite those benefits, consumers may still be hesitant about using chatbots due to potential security and privacy risks [15, 83, 91, 100, 116]. Additionally, chatbot studies have also examined the role of user-related elements such as age and gender [83], technology anxiety [100], social phobias [56], anger [22], or even time orientation [102].

2.2 Hedonic and utilitarian motivation

SDT is a metatheory encompassing six mini-theories, each of which explains a collection of motivational occurrences [104]. Within the scope of SDT, cognitive evaluation theory, organismic integration theory, and goal contents theory define and distinguish two fundamental human motivations (i.e., intrinsic and extrinsic) based on the reasons and goals that drive our actions [27, 104]. As a result, marketing literature has adopted SDT to argue that consumers search for, purchase, and consume products and services for either hedonic or utilitarian reasons [5, 7, 10, 121].

On the one hand, cognitive evaluation theory [26] defines hedonic motivation (or intrinsic motivation) as the driver of a behavior related to achieving the satisfactions inherent in performing that behavior. For reasons of amusement, escapism, excitement, enjoyment, and fantasy fulfillment, performing such behavior often gives rise to experiential, multisensory, and/or emotional satisfaction [5, 121]. Hedonic motivation has an internal locus of causality [10], meaning that consumers endorse and willingly engage in the behaviors [27]. On the other hand, organismic integration theory [104] defines utilitarian motivation (or extrinsic motivation) as the driver of behavior that aims to attain instrumental values such as external rewards or social approval. Prior research often considers utilitarian behavior as a means to an end that allows individuals to execute tasks successfully, efficiently, and on time in order to attain external goals [5, 121]. Utilitarian motivation has an external locus of causality [10]. As a result, the literature usually describes hedonic motivation in terms of "fun" and utilitarian motivation in terms of "work" [5].

According to SDT [103], consumers engage in an activity with either hedonic motivation (i.e., out of pure interest) or utilitarian motivation (i.e., for external rewards). In either case, motivation is a powerful force that activates behavioral intentions. In this research, we expected that hedonic motivation would increase intention to use chatbots. This is because chatbots can converse with consumers in an automatic and interactive manner (e.g., telling jokes) whereas older one-way technologies such as websites cannot. As a result, consumers can achieve a true sense of joy, entertainment, playfulness, and escapism when interacting with chatbots [17, 87, 97]. Similarly, we also expected that consumers' utilitarian motivation would increase their intention to use chatbot services, but for different reasons: because chatbots are informative [15, 71] and easy to use [97]. Hence, chatbots help consumers make the right decisions [86], solve their problems [17], and accomplish their desired goals [116]. In that regard, research has shown that hedonic and utilitarian aspects such as benefits [83], values [86], and attitudes [87] positively influence consumers' intention to use and patronize chatbots. Thus, we first hypothesized the following:

H1a Consumers' hedonic motivation positively influences their intention to use a chatbot service.

H1b Consumers' utilitarian motivation positively influences their intention to use a chatbot service.

2.3 Chatbots' social presence

Whereas prior consumer research has focused on humans' actual social presence (i.e., the physical presence of other human beings in the same environment) [23], our research focuses on technology-mediated social presence. In technology-mediated settings, social presence refers to the extent to which a medium allows individuals to feel as if others are psychologically present [8, 107]. According to social presence theory [107], technology with high social presence is often characterized as being warm, personal, sensitive, and sociable. Because those characteristics are often valued in interpersonal relationships, communication technology with high social presence (e.g., video and voice calls) are preferred for tasks involving interpersonal engagement [107]. In contrast, technology with low social presence (e.g., email and fax) are preferred for efficiency-focused tasks that require less interaction [113]. According to Biocca et al. [8], social presence is often examined in the human–computer domain because it explains why design cues facilitate favorable attitudinal or behavioral responses [24, 43, 83].

Chatbots are, by definition, artificial representations of human-like intelligence with the ability to mimic human-to-human conversations [22]. Therefore, social presence is prevalent in research on human–chatbot interaction because it describes "sense of being with another… either a human or artificial intelligence" [8] (p. 456). Prior research has indicated that a chatbot's social presence increases when it has a socially oriented interactive style [24], a cute communication style [55], or a humanoid avatar or human voice [99]. Meanwhile, other antecedents of chatbots' social presence have remained unexplored. To the best of our knowledge, only Li and Mao [71] have examined antecedents of chatbots' social presence other than design cues. They found that chatbots' hedonic values (e.g., perceived engagement and perceived enjoyment) positively influence their social presence whereas utilitarian values (e.g., informativeness and credibility) do not. The present study differs from theirs in two ways. First, although both examined hedonic and utilitarian antecedents of chatbots' social presence, Li and Mao [71] focused on value-based aspects (i.e., what consumers can obtain from using chatbots). In contrast, because consumers' motivations shape their perceptions [80, 121, 124], we focused on motivation-based aspects (i.e., why people use chatbots). That distinction is congruent with the taxonomy in Ling et al. [74], in which they considered benefits as usage-related factors and motivations as user-related factors. Second, whereas Li and Mao [71] did not explain why utilitarian benefits do not impact social presence, this paper adopts SDT to explain that phenomenon.

SDT [26, 103] posits that our fundamental need for relatedness emerges at birth, as evidenced by the fact that infants feel most secure when staying close to their parents. In addition, although relatedness can provide extrinsic benefits (e.g., admiration from peers), humans have evolved to be intrinsically motivated to find, establish, and maintain high-quality (i.e., close, open, and trusting) relationships with others [104]. As mentioned, social presence is characterized by humans' warmth, personal touch, sensitivity, and sociability [107]. Those are common characteristics of high-quality interpersonal relationships [12, 25]. Therefore, we argue that when consumers are hedonically motivated, they expect to form high-quality relationships with other social beings [28], which is more likely with chatbots possessing high social presence. By contrast, SDT also postulates that utilitarian motivation makes people focus more on instrumental outcomes such as financial resources, fame, power, or outward attractiveness [104]. In such case, people tend to perceive their relationship partners as instruments for achieving utilitarian goals, rather than as mutually respected or supported partners [28, 61]. Research has shown that in peer-to-peer accommodation settings, when the guests have utilitarian motivations, social interaction with the host can be regarded as a burden rather than a reward [42]. Thus, we argue that when consumers focus on utilitarian motivations, a chatbot's warmth or sociability contributes little to their usage goals. As a result, such consumers are unlikely to seek a sense of social presence from chatbots. Based on those arguments and findings, we hypothesized that:

H2 The positive impact of consumers' hedonic motivation on chatbots' social presence is stronger than the impact of utilitarian motivation on chatbots' social presence.

The computer-as-social-actors paradigm suggests that although people fully acknowledge chatbots' non-human nature, they still tend to treat chatbots with social presence as if they were human [69, 101]. In such situations, because people's mental schema about chatbots is congruent with their preexisting schema about humans, they are likely to treat chatbots more favorably [3]. Moreover, people have a basic need for social relatedness [104], and chatbots with high social presence possess characteristics (e.g., warmth and sociability) required to facilitate high-quality relationships [12, 25]. Thus, chatbots' social presence can satisfy people's need for relatedness, motivating them to accept and use chatbots. Likewise, past research has shown that social presence is positively associated with chatbot adoption [35, 43, 71, 83]. Based on the preceding arguments and findings, we also hypothesized that:

H3 A chatbot's social presence positively affects consumers' intentions to use the chatbot service.

2.4 The moderating effect of COVID-19 fear

Fear, a negatively valanced emotion activated in response to present or potential dangers, can prompt a defensive reaction for self-protection [67]. During the COVID-19 pandemic, people have often felt fear because the virus is highly contagious [65] and deadly [109]. Furthermore, the lack of face-to-face interactions resulting from social distancing policies has also increased loneliness in the general population [32]. Since loneliness negatively affects mental well-being [54, 112], people have also been afraid of being lonely during the pandemic [60]. Therefore, we positioned fear of COVID-19 as a context-specific moderator of the relationship between chatbots' social presence and consumers' intention to use chatbot services.

Chatbot research has found that the relationship between social presence and consumers' adoption is moderated by factors such as design cues [55], perceived privacy risk [83], and usage frequency or preference for technology over humans [35]. However, the moderating role of the psychological consequences of exogenous events (e.g., fear of a pandemic) in that relationship remains unknown. This factor is critical because people have been afraid of the pandemic [109], causing them to rely more on virtual technologies [16]. Therefore, this research aims to explain the moderating role of COVID-19 fear based on social support theory.

According to the stress-buffering hypothesis (or social support theory) [18, 20], social support is an effective resource that can buffer the pathogenic and psychological impacts of stressful events. Particularly, social support helps to modify the appraisal of stress, reduce adverse effects of stress, and facilitate adaptive coping against stress [94]. Therefore, social support from all sources can help mitigate the psychological consequences of the COVID-19 pandemic.

We expect that as consumers' fear of COVID-19 increases, the impact of chatbots' social presence on intention to use chatbots will be more pronounced. This is because as consumers become more fearful of the pandemic, they feel more distressed and need more psychological resources to cope with it [18, 20]. Under such circumstances, a chatbot with high social presence can offer consumers a sense of warmth, human touch, sensitivity, and sociability [107]. Furthermore, all those characteristics foster high-quality interpersonal relationships [12, 25]. Because using chatbots allows consumers to maintain social interactions, it also helps to promote their social well-being [34] which in turn helps them to cope with the psychological stress resulting from their fears [21]. Conversely, individuals who are less fearful of the pandemic require fewer psychological resources to cope and are thus less likely to use chatbots to obtain those resources. In line with our argument, [29] found that for consumers with a high (vs. low) level of fear of COVID-19, perceived human presence in shared houses increases their sense of social connectedness, making them more likely to stay in shared houses. Therefore, we hypothesized that:

H4 Fear of COVID-19 amplifies the impact of a chatbot's social presence on consumers' intentions to use the chatbot service.

2.5 The moderated moderating effect of generational cohort

According to generational cohort theory, individuals' thoughts and behaviors are often shaped by the socio-historical events that occurred during their youth [30]. Because individuals born during the same period often experience the same socio-historical events, they share similar values, beliefs, and expectations that later define their generational identity [14]. Considering that dynamic, prior studies have found that consumers' behaviors vary across different generations in contexts such as tourism [14], automobiles [89], and retailing [30].

In our study, we expected that the moderating effect of fear on the relationship between social presence and intention to use would be further moderated by generational cohort for three reasons. First, different generations fear the pandemic to varying extents. As humans age, negative life events and chronic life conditions accumulate [96]. Also, older generations have already lived through several pandemics, including the Asian flu (1957–1958), the Hong Kong flu (1968–1970), HIV/AIDS (1981–present), SARS (2002–2003), and swine flu (2009–2010) [105]. Thus, older generations tend to be more psychologically resilient against such stressful events [96] and to have a higher threshold for loneliness than younger generations [50]. Second, compared to the older generation, younger generations have exhibited greater levels of loneliness [114], anxiety [11], and stress and depression [59], as well as lower levels of resilience, during the COVID-19 pandemic [45]. Third, as digital natives, younger generations (e.g., Generation Z) tend to have easier and more frequent access to new technologies, as well as a greater capability to learn how to use them [85]. This makes younger generations more willing to interact with chatbots than older generations [13]. Thus, when experiencing fear of COVID-19, younger generations are more likely to interact with chatbots as surrogates for human warmth than the older generation. Accordingly, we hypothesized that:

H5 Generational cohort moderates the moderating effect of COVID-19 fear on the relationship between chatbots' social presence and intention to use chatbot services, such that as the generation cohort becomes younger, an increase in the level of COVID-19 fear will strengthen the positive impact of chatbots' social presence on their intention to use chatbot services.

3 Method

3.1 Data collection and sampling

We collected data via an online survey on Amazon Mechanical Turk. The survey included four sections. First, we provided them with general instructions on how to complete the survey. Second, we provided our definition of chatbot and an illustration of a wealth management app powered by a chatbot (see Appendix A). This aimed to ensure that all participants shared a similar understanding of the chatbot service. Third, we asked participants to answer questions relevant to the investigated constructs. Lastly, we collected their demographic information.

To determine the required sample size, we conducted an a priori power analysis, which requires the desired effect size, power levels, statistical probability levels, and the degrees of freedom of the model [120]. The degrees of freedom was calculated using the number of latent constructs and observed items [57]. As a rule of thumb, we considered 0.30 as the desired effect size, 0.90 as the desired power level, and 0.05 as the desired probability level [19, 110]. The minimum sample size was calculated to be 188 [110].

Although 400 questionnaires were distributed, only 377 valid responses were obtained after unqualified participants were screened by attention-checking questions. Our sample was proportionately distributed in terms of gender (men: 65%; women: 35%), age (20–29 years old: 19%; 30–39 years old: 36%; 40 years old and older: 45%), level of education (less than a bachelor's degree: 21%; bachelor's degree: 60%; master's degree and higher: 29%), employment status (full-time: 69%; part-time: 16%; self-employed: 7%; unemployed: 3%; student: 3%; retired: 2%), and annual household income (<US $50,000: 48%; $50,000–$100,000: 38%; >$100,000: 14%).

3.2 Measurements

We measured utilitarian motivation with a three-item scale and hedonic motivation with a five-item scale adapted from [5]. The scale for social presence contained four items adapted from [41]. The scale for intention to use contained three items adapted from [115]. Fear of COVID-19 was measured with six items adapted from [123]. We used a 7-point scale (1 = *not at all*, 7 = *extremely*) for fear and a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) for the other constructs. Appendix B provides the measurement items for our constructs.

4 Results

4.1 Common method biases

Following Podsakoff et al. [98], we ensured our participants that their anonymity would be protected, that there were no right or wrong answers, and that their responses would be used for academic purposes only. Beyond that, we conducted a pre-test with 40 participants to ensure that the survey was free of ambiguity and complex syntax [79]. Nonetheless, because we simultaneously collected data for the dependent and independent variables in the same self-administered survey, there was a risk of common method biases (CMBs) [98]. Therefore, we conducted a series of procedures to assess the potential presence of CMBs.

First, the results of Harman's single-factor test in our exploratory factor analysis [98] revealed that the first principal component accounted for less than 50% of the

Table 2 Reliability and convergent validity

Construct	Items	Mean	SD	Loading	Cronbach's Alpha (α)	CR	AVE
Utilitarian motivation	UM_1	3.812	0.878	0.789	0.831	0.832	0.622
	UM_2	3.968	0.853	0.802			
	UM_3	3.886	0.905	0.775			
Hedonic motivation	HM_1	3.536	1.103	0.746	0.891	0.892	0.623
	HM_2	3.371	1.209	0.830			
	HM_3	3.316	1.256	0.793			
	HM_4	3.324	1.195	0.761			
	HM_5	3.302	1.248	0.815			
Social presence	SP_1	3.308	1.154	0.837	0.917	0.912	0.723
	SP_2	3.271	1.227	0.847			
	SP_3	3.382	1.159	0.817			
	SP_4	3.178	1.310	0.898			
Fear of COVID-19	FC_1	4.255	1.849	0.844	0.945	0.946	0.745
	FC_2	4.355	1.819	0.914			
	FC_3	4.408	1.915	0.915			
	FC_4	4.427	1.902	0.907			
	FC_5	4.430	1.860	0.825			
	FC_6	3.668	2.119	0.763			
Intention to use a chatbot service	IU_1	3.650	1.041	0.856	0.864	0.866	0.684
	IU_2	3.599	1.017	0.846			
	IU_3	3.655	1.048	0.776			

SD = standard deviation, CR = composite reliability, AVE = average variance extracted

total variance (i.e., 39.08%). Therefore, no single factor explained most of the variance. Second, we conducted a confirmatory factor analysis to examine if a single-factor model (i.e., with all indicators loaded onto one factor) fit the data [98]. As expected, the single-factor model did not fit the data ($\chi^2(189) = 3{,}118.569$, $p < 0.001$; TLI = 0.453; CFI = 0.508; RMSEA = 0.203). Finally, using a common latent factor (CLF) approach [98], we constrained all indicators' paths to the CLF to be equal and the CLF's variance to be 1 [68]. The results showed that the variance explained by the CLF (i.e., the squared unstandardized loading of items linked to the CLF) was 44.89%, which was below the threshold of 50% [68]. Considering those results, we concluded that CMBs were not problematic in our study.

4.2 Measurement model

As shown in Table 2, because Cronbach's alphas and composite reliabilities of all constructs exceeded the threshold of 0.70 [6], they all demonstrated internal consistency reliability. Next, because all factor loadings exceeded 0.65 [93] and all values

Table 3 Correlation matrices and discriminant validity ($n = 377$)

	UM	HM	SP	FC	IU
Utilitarian motivation (UM)	*0.789*				
Hedonic motivation (HM)	0.532	***0.790***			
Social presence (SP)	0.339	0.706	***0.850***		
Fear of COVID-19 (FC)	0.158	0.440	0.376	***0.863***	
Intention to use (IU)	0.523	0.731	0.589	0.239	***0.827***
Mean	3.889	3.370	3.285	4.257	3.635
SD	0.759	1.004	1.086	1.689	0.918

Values in bold italics are the square root of average variance extracted

Table 4 Result of heterotrait-monotrait (HTMT) ratio analysis ($N = 377$)

	UM	HM	SP	FC	IU
Utilitarian motivation (UM)					
Hedonic motivation (HM)	0.536				
Social presence (SP)	0.349	0.689			
Fear of COVID-19 (FC)	0.160	0.465	0.394		
Intention to use (IU)	0.530	0.746	0.590	0.272	

of average variance extracted (AVE) exceeded 0.50 [81], our convergent validity was established.

Next, we adopted two criteria to examine discriminant validity [117]. First, we used the Fornell–Larcker criterion [36], which holds that the square root of AVE has to exceed the inter-construct correlations to obtain support for discriminant validity. Our results in Table 3 indicate that such requirement was satisfied.

Second, we conducted the heterotrait-monotrait (HTMT) test [47] to check the "ratio of the average correlations between constructs to the geometric mean of the average correlations within items of the same constructs" [117] (p. 124). We calculated the HTMT ratio using a plugin in Amos [40]. According to the result in Table 4, we obtained support for discriminant validity because the HTMT ratios of all inter-constructs were below 0.85 [47].

4.3 Structural model

We used Amos 24.0 to run structural equation modeling. Because both hedonic and utilitarian motivations point to the same consumer motivation, a covariance was drawn between the two constructs. Also, demographic profiles (i.e., age, gender, level of education, and household income) were treated as control variables [53]. According to Hu and Bentler [51], all indices indicated that our data fit relatively well with the model ($\chi^2(143) = 340.042$, $p < 0.001$, GFI = 0.916, AGFI = 0.888, NFI = 0.913, IFI = 0.948, TLI = 0.937, CFI = 0.947, RMSEA = 0.061, and SRMR = 0.068). Figure 2 shows the results of the structural analysis.

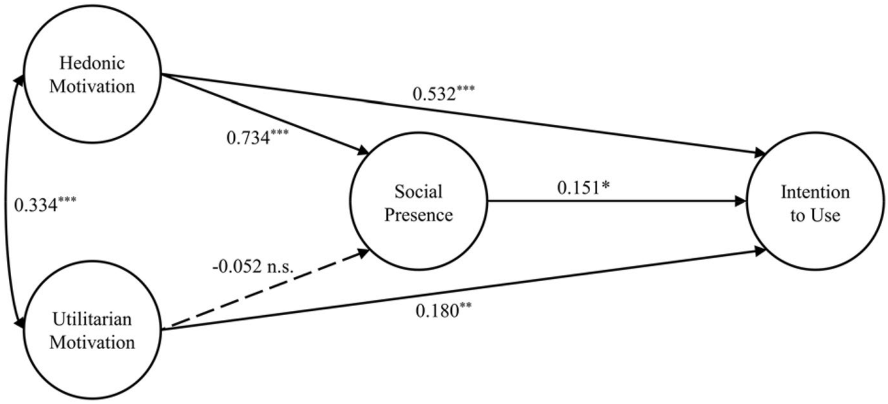

Fig. 2 Structural model ($N=377$). Note: All values are standardized coefficients; n.s. = non-significant. * $p<0.05$. ** $p<0.01$. *** $p<0.001$.

None of the control variables significantly influenced intention to use: age ($\beta=0.033$, $t=0.829$, $p>0.05$), gender (β = −0.020, $t=-0.487$, $p>0.05$), level of education ($\beta=0.023$, $t=0.579$, $p>0.05$), and household income ($\beta=0.045$, $t=1.105$, $p>0.05$). This suggests that the overall pattern of the results does not depend on the presence or absence of the control variables.

Regarding our hypotheses, both hedonic motivation ($\beta=0.532$, $t=9.470$, $p<0.001$) and utilitarian motivation ($\beta=0.180$, $t=3.198$, $p<0.010$) significantly influenced intention to use. Additionally, we conducted another test by excluding social presence in our model to obtain the total effect between the two motivations and intention to use. The significant impact of hedonic motivation ($\beta_{total\ effect}=0.642$, $t=9.806$, $p<0.001$) and utilitarian motivation ($\beta_{total\ effect}=0.170$, $t=2.992$, $p<0.010$) on intention to use remained the same. Altogether, both H1a and H1b were supported.

Furthermore, hedonic motivation positively influenced social presence ($\beta=0.734$, $t=10.502$, $p<0.001$) whereas utilitarian motivation did not (β = −0.052, $t=-0.910$, $p>0.05$), supporting H2.

Last, social presence had a significant positive impact on intention to use ($\beta=0.151$, $t=2.279$, $p<0.05$), supporting H3.

4.4 Moderation analysis

To test the moderating effect of fear on the relationship between social presence and intention to use (H4), we used Model 1 of the PROCESS macro for SPSS [46] with a 10,000-bootstrapping method and a 95% confidence interval (CI). We maintained the aforementioned control variables; however, none were significant, suggesting that the overall results do not depend on these control variables. Our results show

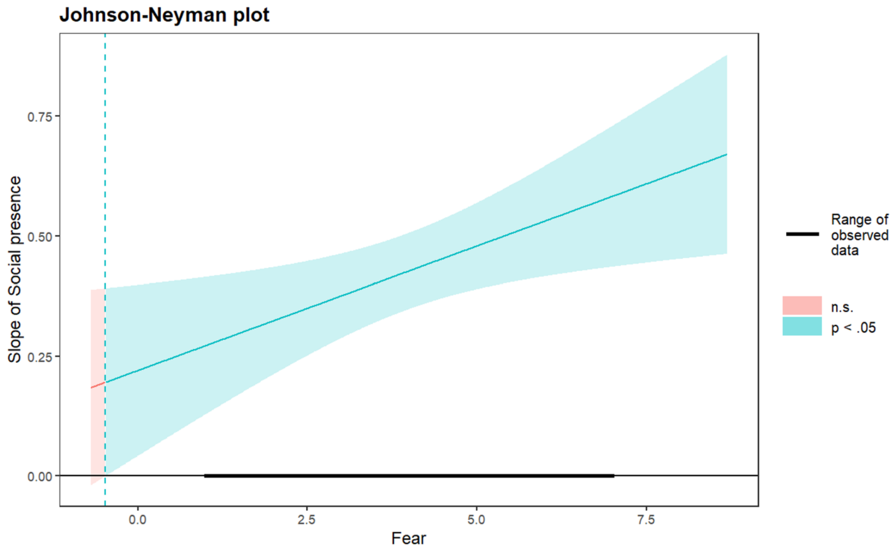

Fig. 3 Johnson-Neyman plot for the moderating effect of COVID-19 fear on the relationship between social presence and intention to use

that the overall model was significant (F (7, 369) = 23.149, $p < 0.001$) and explained 30.5% of the variance. More importantly, as expected, the interaction term was significant and positive ($\beta = 0.052$, $t = 2.520$, $p < 0.05$, 95% CI = [0.011, 0.092]), supporting H4.

Moreover, we plotted the above moderation results using the Johnson-Neyman technique [58] in RStudio [73]. As shown in Fig. 3, the impact of social presence on intention to use chatbot was significant and positive at all levels of COVID-19 fear.

4.5 Moderated moderation analysis

We conducted a moderated moderation analysis using Model 3 in PROCESS macro [46] to examine how the three-way interaction between social presence, fear, and generational cohort impacts intention to use (H5). This analysis was performed using a 10,000-bootstrapping method with a 95% CI [46]. First, we divided our sample into three generational cohorts[1]: young generation (Generation Y and Generation Z, born 1980–2010, $n = 220$), middle generation (Generation X, born 1960–1979, $n = 132$), and senior generation (baby boomers, born 1940–1959, $n = 25$). Second, we coded generational cohort as a ternary variable (1 = senior generation, 2 = middle generation, and 3 = young generation). Thus, the obtained results relevant to generational cohort would be interpreted in relation to the senior generation. Next,

[1] The generational cohort was divided following McKinsey & Company's segmentation method [38].

we specified generational cohort as a multicategorical variable with three categories in the PROCESS macro. In addition, we maintained the aforementioned control variables (except age), but none were significant. The overall model was significant ($F(14, 362) = 13.056$, $p < 0.001$) and explained 33.6% of the variance.

Our results (part I of Appendix C) revealed that the three-way interaction between social presence, fear, and generational cohort was significant for the middle generation ($\beta = 0.158$, $p < 0.05$, 95% CI = [0.018, 0.298]) when compared with the senior generation. Also, the three-way interaction was significant for the young generation ($\beta = 0.185$, $p < 0.01$, 95% CI = [0.046, 0.324]) when compared with the senior generation.

In addition, our results were interpreted from another angle by recoding the generation cohort variable to change our reference group (i.e., 1 = *middle generation*, 2 = *young generation*, and 3 = *senior generation*). Repeating the above procedures, the obtained results relevant to generational cohort would be interpreted in relation to the middle generation, which is reported in part II of Appendix C. Specifically, the three-way interaction was insignificant for the young generation ($\beta = 0.026$, $p > 0.05$, 95% CI = [–0.058, 0.111]) when compared with the middle generation.

To further examine the results, we looked at the conditional effect of social presence on intention to use at different levels of fear and generation (see part III of Appendix C for more information). For the senior generation, social presence only predicted behavioral intention for participants with a low level of fear, and the strength of the association decreased as the level of fear increased ($\beta_{low\ fear} = 0.415$, $p < 0.05$; $\beta_{moderate\ fear} = 0.230$, $p > 0.05$; high fear: $\beta_{high\ fear} = 0.045$, $p > 0.05$). However, for the middle generation, social presence positively influenced behavioral intention, and the strength of the association increased as the level of fear increased ($\beta_{low\ fear} = 0.435$, $p < 0.001$; $\beta_{moderate\ fear} = 0.517$, $p < 0.001$; $\beta_{high\ fear} = 0.600$, $p < 0.001$). Similarly, for the young generation, social presence also positively influenced behavioral intention, and the strength of the association also increased as the level of fear increased ($\beta_{low\ fear} = 0.302$, $p < 0.05$; $\beta_{moderate\ fear} = 0.429$, $p < 0.001$; $\beta_{high\ fear} = 0.556$, $p < 0.001$).

The overall moderated moderation results are summarized in Fig. 4 using the Johnson-Neyman plot. Altogether, H5 was partially supported because there was a distinctive pattern with the senior generation while the other two generations shared a similar pattern.

5 Conclusions

5.1 Summary and discussion

In summary, our study yielded the following findings. First, both hedonic and utilitarian motivation exerted positive impact on consumers' intention to use the chatbot service in question (i.e., on a mobile app). Second, hedonic motivation prompted a

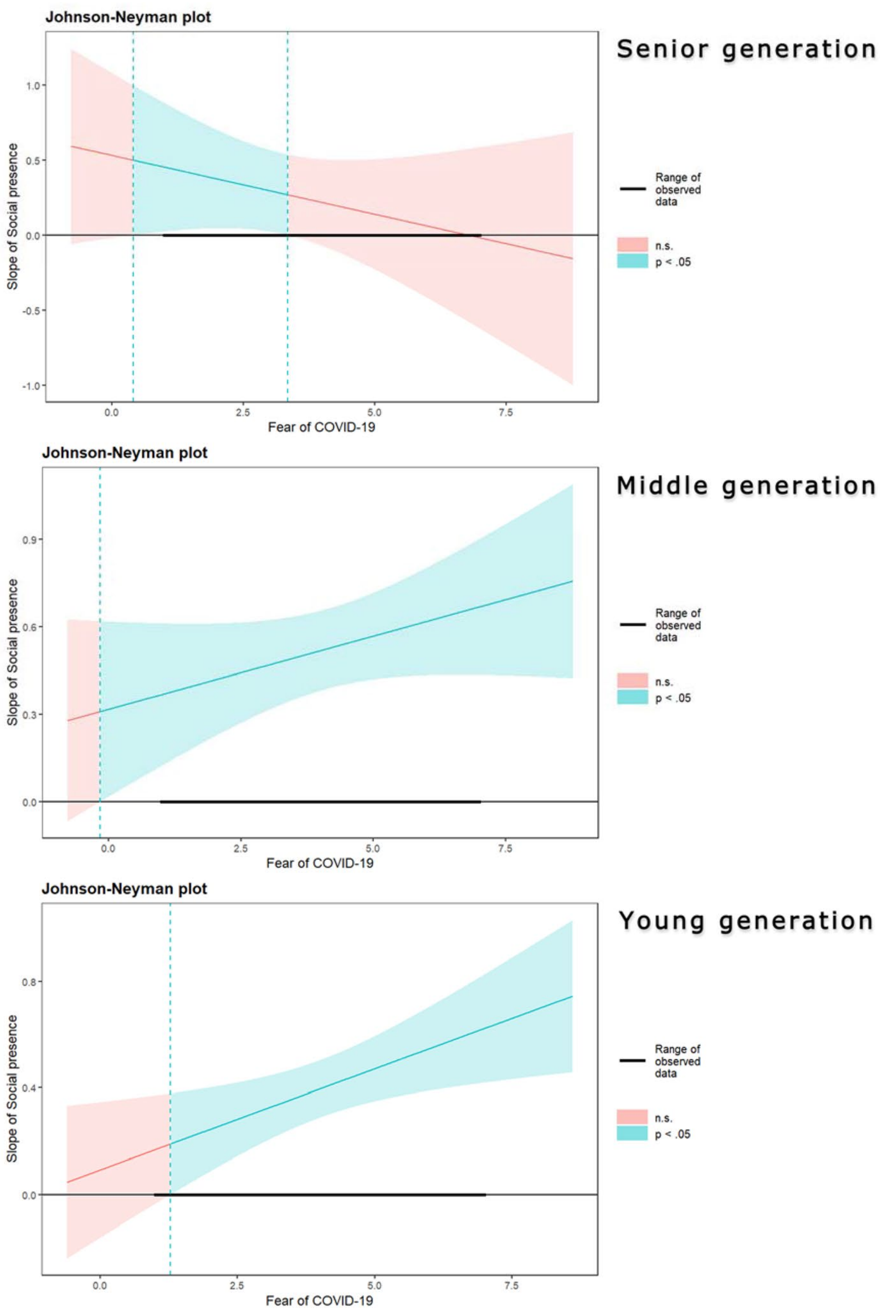

Fig. 4 Johnson-Neyman plots for the three-way interaction between generation cohort, fear of COVID-19, and social presence on intention to use

Table 5 Summary of the research results

Hypothesis	Description		β	*p*-value	95% CI	Conclusion
H1a	HM → IU		0.532	< 0.001	----	Supported
H1b	UM → IU		0.180	< 0.01	----	Supported
H2	HM → SC		0.734	< 0.001	----	Supported
	UM → SC		–0.052	> 0.05	----	
H3	SC → IU		0.151	< 0.05	----	Supported
H4	FC×SC → IU		0.052	< 0.05	[0.011, 0.092]	Supported
H5	GC×FC×SC → IU, such that:					Partially support
	For MG (vs. SG):	FC×SC → IU	0.158	< 0.05	[0.018, 0.298]	
	For YG (vs. SG):	FC×SC → IU	0.185	< 0.01	[0.046, 0.324]	
	For YG (vs. MG):	FC×SC → IU	0.026	> 0.05	[–0.058, 0.111]	

CI = confidence interval, FC = fear of COVID-19, GC = generational cohort, HM = hedonic motivation, IU = intention to use, MG = middle generation, SC = social presence, SG = senior generation, UM = utilitarian motivation, YG = young generation

higher expectation for the chatbot's social presence whereas the impact of utilitarian motivation was insignificant. Third, fear of COVID-19 strengthened the influence of social presence on consumers' intention to use the chatbot. Last, generational cohort partially moderated the moderating effect of fear on the relationship between the chatbot's social presence and consumers' intention to use it. These results are summarized in Table 5.

Regarding H5, the result was partially supported. We account for this result due to an indifference across the young generations (i.e., X, Y, and Z) compared to the senior generation (i.e., baby boomers). Additionally, results from the post-hoc independent *t*-tests showed no significant differences in the mean value of COVID-19 fear (M_{young} = 4.378, M_{middle} = 4.198, $t(350) = 0.977$, $p > 0.05$) between the young and middle generations. This proves that these two generations are quite similar in terms of feeling fear, resulting in no significant difference in its moderation effect between social presence and intention to use the chatbot.

5.2 Theoretical contributions

First, prior studies have adopted different theoretical accounts to investigate how and why consumers adopt chatbots (Table 1). For instance, using the theory of anthropomorphism [31], Borau et al. [9] found that by imbuing chatbots with female (vs. male) identity, people perceive chatbots as more human-like and thus are more likely to favor and accept female (vs. male) chatbots. This is because female (vs. male) humans are perceived to be more likely to recognize and consider the unique needs of others in real life. However, most chatbot-related research that adopts anthropomorphism theory [9, 102], the similarity–attraction paradigm [56, 71], or the computers–are–social–actors paradigm [4, 24] has often started from the design side [4, 43, 55], rather than from the consumers' state-of-mind side (e.g., motivations). Therefore, our research contributes to the literature by examining consumers' inner psychological drivers based on SDT [26, 104].

Moreover, our theoretical framework is not grounded in one of the most popular frameworks in this area, called uses and gratifications theory (UGT) [62, 63], for the following reasons. First, UGT was originally developed to explain how using mass media can satisfy our needs [62], making UGT medium-oriented. Second, the categorization of media-related needs in UGT was the result of speculative searches in the literature on mass media [63]. In contrast, the categorization of needs and motivation in SDT resulted from logical deductions and systematic reviews of prior need-related theories and empirical research in psychology [26, 104]. Third, UGT considers media-related needs to originate from both external (e.g., politics, family, religion) and internal sources [63]. However, SDT considers humans' needs and motivations to originate from within the self [26]. As the primary objective of this research was to examine how consumers' innate psychological motivations influence their perception and behavioral intention, our theoretical account is grounded in SDT.

Our literature review identified two studies that examined seemingly similar antecedents as ours: Li & Mao [71] and McLean and Osei-Frimpong [83]. However, McLean and Osei-Frimpong [83] investigated hedonic, utilitarian, social, and symbol benefits of chatbots using UGT. Also, their research examined usage-related antecedents whereas ours examined user-related antecedents [74]. Similarly, although Li & Mao [71] investigated hedonic and utilitarian factors, those antecedents were also usage-related but not user-related [74]. Moreover, they did not explain why utilitarian factors failed to impact social presence. Thus, our findings contribute to research on consumer–chatbot interaction by explaining why consumers' hedonic but not utilitarian motivations increase their expectation of chatbots' social presence based on social presence theory [8, 107] and SDT [104].

Furthermore, our findings contribute to the literature on social presence and social support. In particular, socially present chatbots may serve as surrogates for human warmth and thus can be regarded as a means to gain social support [21, 34]. Therefore, our findings suggest that people who feel fear during the pandemic tend to use chatbots with a high level of social presence to cope with such a crisis.

Moreover, our findings contribute to the literature on emotions. Relevant findings indicate that negative emotions are likely to generate negative consumer responses based on mood congruency effect [82]. For example, negative emotions from COVID-19 adversely impact humans' well-being due to a high level of anxiety, depression, stress, loneliness, and/or insomnia [29, 109]. However, our results show the positive role of COVID-19 fear as a driver that facilitates consumer–chatbot interaction. Thus, our findings contribute to the marketing literature on consumers' emotions by showing that negative emotions can positively affect consumers' adoption of chatbot services.

Our findings also contribute to the literature on young consumers (e.g., Generation Z). Although a few scholars have suggested generational differences [2, 13, 75], empirical validation has not been tested in consumer–chatbot interactions during the global pandemic. Our findings fill this gap by comparing baby boomers with younger generations (i.e., Generations X, Y, and Z). Our study found that younger generations were more fearful of the pandemic, thus increasing the impact of chatbots' social presence on consumers' intention to use the chatbot. Conversely, the senior generation was found to be less fearful of the pandemic due to higher psychological resilience against such external shocks [50, 96]. To the best of our knowledge, our study provides initial evidence on how different generational cohorts use a chatbot service.

Finally, although we examined consumers' adoption of chatbots during the pandemic, our findings may still be relevant in the post-pandemic era. Research has shown that people are generally less happy and more depressed after (vs. before) the COVID-19 pandemic [39, 92, 118]. In other words, the psychological consequences of the pandemic may be long-lasting. Furthermore, consumers' technology use preferences formed during the pandemic could persist even after it has ended [76, 84]. Therefore, to cope with the persisting consequences of the pandemic [18, 20], consumers are likely to continue seeking psychological resources through interacting with socially present chatbots.

5.3 Managerial implications

First, marketers can design motivation-matching features when they launch chatbot services to their consumers. For example, if individuals are prone to build a human connection, then marketers should emphasize the hedonic rather than utilitarian motivation of using a chatbot service to increase consumer intention to use chatbots. Moreover, increased chatbot usage can translate into increased revenue (e.g., from in-app purchases and advertisements), as well as more consumer behavioral data.

Second, our results regarding fear of COVID-19 can be extended to other types of global crises, including pandemics, wars, and natural disasters. Therefore, our findings suggest that such fear-inducing events can be a good time for managers to launch their chatbot services to facilitate awareness and promote wider consumer adoption.

Third, our results suggest that different generations fear the pandemic to varying extents. This indicates that age matters in tailoring promotional messages as part of a targeting strategy during pandemics. For example, when the promotional messages for chatbot services target younger generations, firms should emphasize social benefits such as emotional comfort (e.g., "using chatbots is like having a friend by your side").

5.4 Limitations and directions for further research

First, this study analyzes cross-sectional survey data, which limits interpretations by making them correlational. Thus, future research could build on the present study by designing experiments that involve real human-chatbot interactions to investigate causality, for example by having participants communicate with a real chatbot.

Second, the sample size for the senior generation (i.e., baby boomers) was relatively small, and the number of participants was not balanced among three generational cohorts. It is true that the senior generation often constituted a small proportion of the collected samples in prior research [2, 13, 75]. Still, it would be beneficial for future research to use a systematic sampling approach to collect a more balanced sample.

Third, we measured a general fear of COVID-19. Future research could decompose such fear into different sources, such as fear related to economic state and fear related to health concerns [30]. Perhaps older generations are more susceptible to feel fear from health and economic instability whereas young generations might feel fear mainly because of economic reasons. Therefore, future research could compare different sources of fear and examine how each is linked to chatbot adoption.

Fourth, individuals with social anxiety disorder tend to avoid interacting with other people due to fear of being socially scrutinized [88, 125]. Since AI chatbots are becoming more human-like, one would expect that social phobia would nullify the role of social presence. Yet research has found that because bots (vs. humans) do not judge [49], talking to chatbots may help alleviate social anxiety [95], in turn facilitating chatbot adoption [56]. Thus, we call for future research to examine examine how individuals' anxiety levels interact with social presence and chatbot adoption.

Fifth, our research only examines consumers' intention to use chatbot services. However, intention does not always lead to actual behaviors [90]. The intention-behavior gap is a fruitful avenue for future research to examine actual behaviors of consumers in using chatbots. We suggest conducting a field experiment to increase the external validity of our findings and to provide corroborating evidence by showing actual behaviors. Moreover, it would be beneficial for future research to examine how anxiety might delay actual behavior of using chatbots, even when intention to use still exists [66, 111].

Lastly, individuals can form virtual connections using more immersive technologies such as augmented reality, virtual reality, or virtual influencers. Based on our initial findings, we suggest that future scholars investigate how consumers' need for social connectedness can be satisfied through artificially induced human warmth offered by those immersive technologies.

Appendix A

Illustration and definition of "chatbot" provided to the participants at the beginning of the survey

The following picture provides an example of a financial service on a wealth management app using a chatbot.

A chatbot is a computer program that simulates human conversation through voice commands, text chats, or both.

Appendix B

Measurement items used in our survey

Fear (of COVID-19)

"Faced with the Covid-19 situation, please rate how you feel according to the following adjectives." (1 = *not at all*, 7 = *extremely much*).

FC_1: Frightened.
FC_2: Tense.
FC_3: Nervous.

FC_4: Anxious.
FC_5: Uncomfortable.
FC_6: Nauseous.

Social presence (of chatbots)

"To what extent do you agree with the following statements?" (1 = strongly disagree, 5 = strongly agree).

PH_1: Interacting with the chatbot service of a wealth management app provides a sense of human contact.
PH_2: Interacting with the chatbot service offered by a wealth management app provides the sense of a personal touch.
PH_3: Interacting with the chatbot service offered by a wealth management app provides a sense of sociability.
PH_4: Interacting with the chatbot service of a wealth management app provides a sense of human warmth.

Utilitarian motivation (in using a chatbot-powered mobile app)

"To what extent do you agree with the following statements?" (1 = strongly disagree, 5 = strongly agree).

UM_1: I often accomplish exactly what I want to when I engage with mobile apps.
UM_2: I often feel that my use of mobile apps is successful.
UM_3: In general, using mobile apps is a good experience because the functions work very quickly.

Hedonic motivation (in using a chatbot-powered mobile app)

"To what extent do you agree with the following statements?" (1 = strongly disagree, 5 = strongly agree).

HM_1: Compared to other things I could have been doing, time spent using mobile apps is typically enjoyable for me.
HM_2: When I engage with mobile apps, I often feel the excitement of the hunt.
HM_3: Engagement with mobile apps truly feels like an escape from reality.
HM_4: I enjoy using mobile apps for their own sake, not just for the benefits I might receive.
HM_5: While using mobile apps, I often feel a sense of adventure.

Intention to use (a chatbot-powered mobile financial app)

"To what extent do you agree with the following statements?" (1 = strongly disagree, 5 = strongly agree).

BI_1: I will use a wealth management app on a regular basis in the future.
BI_2: I will frequently use a wealth management app in the future.
BI_3: I will recommend using a wealth management app to others.

The following picture provides an example of a financial service on a wealth management app using a chatbot.

Appendix C

Results of the moderated moderation analysis

Part I. Dependent variable: Intention to use (Senior generation serves as the reference group for results relevant to generation cohort)					
		β	SE	t-value	95% CI
(Constant)		0.387	0.841	0.460	[–1.267, 2.040]
Social presence		0.695	0.261	2.666^{**}	[0.183, 1.208]
Fear		0.518	0.222	2.331^{*}	[0.081, 0.955]
Social presence × Fear		–0.109	0.064	–1.700	[–0.236, 0.017]
Middle generation		1.448	0.934	1.551	[–0.389, 3.285]
Young generation		2.548	0.895	2.845^{**}	[0.786, 4.309]
Social presence × Middle generation		–0.387	0.298	–1.298	[–0.972, 0.199]
Social presence × Young generation		–0.586	0.292	$–2.005^{*}$	[–1.161, – 0.011]
Fear × Middle generation		–0.621	0.250	$–2.490^{*}$	[–1.112, – 0.131]
Fear × Young generation		–0.784	0.244	$–3.209^{**}$	[–1.264, – 0.030]
Social presence × Fear × Middle generation		0.158	0.071	2.223^{*}	[0.018, 0.298]
Social presence × Fear × Young generation		0.185	0.071	2.611^{**}	[0.046, 0.324]
Gender		–0.010	0.084	–0.121	[–0.175, 0.154]
Education		0.063	0.060	1.038	[–0.056, 0.182]
Income		0.092	0.047	1.947	[–0.001, 0.185]
Part II. Dependent variable: Intention to use (Middle generation serves as the reference group for result relevant to generation cohort)					
		β	SE	t-value	95% CI
Social presence × Fear × Young generation		0.026	0.043	0.609	[–0.058, 0.111]
Part III. Conditional effect of social presence on intention to use at different values of fear and generation					
Generation	Fear	β	SE	t-value	95% CI
Senior generation	Low (Mean – 1SD)	0.415	0.143	2.904^{**}	[0.134, 0.695]
Senior generation	Moderate (Mean)	0.230	0.137	1.677	[–0.040, 0.499]
Senior generation	High (Mean + 1SD)	0.045	0.202	0.224	[–0.352, 0.442]
Middle generation	Low (Mean – 1SD)	0.435	0.082	5.287^{***}	[0.273, 0.596]
Middle generation	Moderate (Mean)	0.517	0.066	7.821^{***}	[0.387, 0.647]

Part I. Dependent variable: Intention to use (Senior generation serves as the reference group for results relevant to generation cohort)					
Middle generation	High (Mean + 1SD)	0.600	0.087	6.889^{***}	[0.429, 0.771]
Young generation	Low (Mean – 1SD)	0.302	0.069	4.361^{**}	[0.166, 0.439]
Young generation	Moderate (Mean)	0.429	0.055	7.746^{***}	[0.320, 0.538]
Young generation	High (Mean + 1SD)	0.556	0.080	6.975^{***}	[0.400, 0.713]

Note. *SE* = standard error; CI = confidence interval. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

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