Artificial intelligent chatbots as brand promoters: a two-stage structural equation modeling-artificial neural network approach

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Abstract

Purpose – This study investigates the determinants of effective human and artificial intelligence (AI) relationship-building strategies for brands. It explores the antecedents and consequences of consumers' interactant satisfaction with communication and identifies ways to enhance consumer purchase intention via AI chatbot promotion.
Design/methodology/approach – Microsoft Xiaoice served as the focal AI chatbot, and 331 valid samples were obtained. A two-stage structural equation modeling-artificial neural network approach was adopted to verify the proposed theoretical model.
Findings – Regarding the IQ (intelligence quotient) and EQ (emotional quotient) of AI chatbots, the multi-dimensional social support model helps explain consumers' interactant satisfaction with communication, which facilitates affective attachment and purchase intention. The results also show that chatbots should emphasize emotional and esteem social support more than informational support.
Practical implications – Brands should focus more on AI chatbots' emotional and empathetic responses than functional aspects when designing dialogue content for human–AI interactions. Well-designed AI chatbots can help marketers develop effective brand promotion strategies.
Originality/value – This research enriches the human–AI interaction literature by adopting a multi-dimensional social support theoretical lens that can enhance the interactant satisfaction with communication, affective attachment and purchase intention of AI chatbot users.

Keywords AI chatbot, Human–AI interaction, Social support, Interactant satisfaction with communication, Affective attachment, Purchase intention
Paper type Research paper

1. Introduction

User: I have bad skin.

Xiaoice: Generally speaking, clear skin indicates a good skin condition.

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User: What should I do? For oily skin?

Xiaoice: Oily skin? Do you have many pimples?

User: Do you have any idea?

Xiaoice: The Body Shop's tea tree oil may be an excellent choice. (Conversation between user and Xiaoice)

Artificial intelligence (AI) chatbots are tailored for multi-turn conversations based on natural language understanding, multimodal intelligence (i.e. text, voice or images), speech recognition, problem solving, empathetic conversational systems and machine learning (Kietzmann *et al.*, 2018; Shum *et al.*, 2018). Practitioners are increasingly paying attention to chat-oriented systems, such as Xiaoice, Rinna and Zo. In particular, Xiaoice, developed by Microsoft, is popular in Chinese social media. Xiaoice had more than 660 million users in 2018 and more than 5.3 million followers on Weibo. Moreover, 25% of users have said "I love you" to Xiaoice (Hornigold, 2019). Unlike traditional systems, which can only respond to action commands, such as turning on lights, booking tickets or processing product orders, AI chatbots are also equipped with chat-oriented systems (e.g. chatting with users, cheering them up, giving compliments) that can satisfy users' needs for emotional support and succeed in maintaining a continuous chat flow (Shum *et al.*, 2018).

Brand recommendations by AI chatbots are considered more effective than official advertisements or traditional celebrity endorsements in altering consumers' attitudes toward a brand, which in turn encourages their brand engagement and purchase intention (Jiménez-Castillo and Sánchez-Fernández, 2019; Packard and Berger, 2017; Roma and Aloini, 2019; Thomas and Fowler, 2021). Research has proved that by incorporating multiple AI benefits (i.e. mechanical, thinking and feeling intelligence), AI chatbots can easily understand consumers' preferences and attitudes, and they may exhibit better human-like interactions with consumers (Huang and Rust, 2021; Kim *et al.*, 2021). Thus, questions arise about how best to implement AI chatbots to facilitate brand promotion and how to make users unconsciously adopt such recommendations.

While prior studies have emphasized the functional aspects of AI chatbots (Brill *et al.*, 2019; Kilian *et al.*, 2019; Liew and Tan, 2018; Mimoun *et al.*, 2017; Van den Broeck *et al.*, 2019), few studies have focused on the social aspects (Chattaraman *et al.*, 2019; Sands *et al.*, 2021). Thus, research integrating the social aspects is still required. AI chatbots are designed to recognize emotions and learn from historical conversations to understand human intentions (Hoffman and Novak, 2018) and provide more human-like responses to promote intimacy, emotional engagement, connection and social engagement (Huang and Rust, 2021; Kim *et al.*, 2021). Such interactions imply that social support is exchanged between users and AI chatbots.

We propose a theory of social support (Cohen and Wills, 1985) rooted in the context of AI chatbots to address this gap. As scholars have recognized that multi-dimensional social support is frequently exchanged in online communities (Chiu *et al.*, 2015; Zhao *et al.*, 2014), we investigate the role of social support in fostering human–AI interactions. The objective of this research is to propose a theoretical framework that explores how social support fosters interactions between AI chatbots and consumers and then encourages affective attachment and purchase intention, which is important for promoting human–AI interactions.

Together, this study adopts social support theoretical perspectives (Cohen and Wills, 1985) and explores multi-dimensional social support (i.e. emotional, informational and esteem support) of AI chatbots. Each facet of social support offers insights for practitioners and can help build human–AI interactions. This study also aims to provide empirical verification to supplement previous research on AI chatbots by adopting a two-stage structural equation modeling-artificial neural network (SEM-ANN) approach. Therefore, we focus on the crucial factors that can benefit social interactions and long-term brand relationship building.

The contribution of this research is threefold. First, it contributes to the marketing literature, as previous studies have not considered how the social aspects of AI chatbots affect users' psychological and behavioral outcomes. Because AI chatbots are dialogue-based and socially oriented (Huang and Rust, 2021; Kim *et al.*, 2021), examining the social aspects of AI chatbots is important. Thus, our study includes socially related factors, such as social support and interactant satisfaction with communication (social attraction and emotional credibility), to elucidate the social nature of AI chatbots. Second, this study extends existing knowledge on social support to the field of human–AI interaction by investigating how different types of social support (i.e. emotional, informational and esteem support) affect interactant satisfaction with communication and subsequent outcomes. Third, this study uses the SEM-ANN method to analyze the predictive effect of social support on affective attachment and purchase intention in the context of AI chatbots. Therefore, this study contributes to the literature by addressing whether brand recommendation through AI chatbots and their user-generated content can be useful for brands.

In the next sections of this study, we review the literature related to AI chatbots and social support theory as a theoretical basis and then develop the hypotheses. Next, we describe the research methods and discuss the results of the SEM-ANN. After that, we provide insights for both theory and practice. Finally, we discuss the study's limitations and provide directions for further research.

2. Literature review

2.1 AI chatbots

As a virtual companion to users, AI chatbots are "created to establish emotional attachment to users and have skill sets for user assistance" (Shum *et al.*, 2018, p. 13). AI chatbots include both IQ (intelligence quotient) and EQ (emotional quotient) capacities. For IQ capacities, AI chatbots are designed for more efficient, accessible, relevant and updated information retrieval. IQ capacities based on computer vision, information retrieval and active and adaptive learning allow for immediate feedback and both reactive and proactive services (Shum *et al.*, 2018). Previous research has shown that AI chatbots can provide active customer service, such as collecting information from users' past queries, preferences and shopping habits; analyzing product features and online reviews and providing personalized recommendations, notifications and more flexible customer service (Huang and Rust, 2021; Kim *et al.*, 2021). For EQ capacities, AI chatbots are designed to create empathetic conversation systems that mimic human–human communication (Shum *et al.*, 2018). For example, Xiaoice is endowed with speech recognition and synthesis that can support personalized multi-turn conversation as opposed to single-turn conversation. Xiaoice has natural language understanding and multimodal intelligence, which enables it to communicate with users through voice, texts, images and emojis, displaying language variety and multiple cues (Shum *et al.*, 2018).

Our review of the literature suggests that there are functional and social aspects to exploring AI chatbot adoption. The *functional aspects* draw from the technology acceptance model (Ashfaq *et al.*, 2020; McLean and Osei-Frimpong, 2019; Rietz *et al.*, 2019; Zarouali *et al.*, 2018), the information system (IS) success model (Trivedi, 2019) and expectancy confirmation theory (McLean and Osei-Frimpong, 2019) as theoretical lenses. For example, research has shown that the system quality, information quality and service quality of customer service chatbots positively affect the customer experience and generate brand love (Trivedi, 2019). The functional and form design of AI chatbots can increase perceived usefulness, ease of use and enjoyment, which in turn can facilitate behavioral intention (Rietz *et al.*, 2019). Moreover, customer expectations and the perceived performance of virtual assistants such as Siri and

Alexa can affect customer satisfaction through the mechanism of expectation confirmation (Brill *et al.*, 2019). Chung *et al.* (2020) found that the perceived marketing effort (perceived interaction, entertainment, trendiness, customization and problem solving) of the Burberry chatbot affects communication quality (accuracy, credibility and competence) and brand satisfaction. Research has also shown that the attention-guiding behaviors of chatbots affect perceptions of the agent's communicative abilities in the context of completing calendar tasks (Rosenthal-von der Pütten *et al.*, 2019). In addition, the perceived intrusiveness of a customer-service chatbot for a movie theater can facilitate message acceptance and patronage intention (Van den Broeck *et al.*, 2019).

Another stream of research includes more *social aspects*. For example, Chattaraman *et al.* (2019) found that interaction style and user-exchange modality can affect perceived trust and perceived synchronous interactivity with digital shopping assistants. The majority of research has focused on functional aspects and has primarily assessed the general usage intention toward and satisfaction with AI chatbots. However, given that different characteristics of AI chatbots serve different purposes, Shum *et al.* (2018) elucidated the opportunities and challenges related to AI chatbots and highlighted the importance of examining their social aspects. Despite research on the functional aspects of AI chatbots, empirical research on the social determinants of AI chatbot usage is insufficient. Thus, this study adopts the lens of social support to provide a more comprehensive investigation of the relationships between users and AI chatbots. Table 1 summarizes the different aspects of prior research on AI chatbots.

2.2 Theory of social support

Social support refers to "an individual's perceptions of general support or specific supportive behaviors from others in their social network, which enhance their functioning or may buffer them from adverse outcomes" (Malecki and Demaray, 2003, p. 232). The theory of social support was initially proposed in the research domains of psychological and physical health in the context of offline environments (Cohen and Wills, 1985).

With computer-mediated communication on the rise, many empirical studies have used social support theory to interpret virtual social support in the online sphere. Sharma and Khadka (2019) characterized emotional, esteem and network support as nurturing support and informational and tangible support as action-facilitating support; they found that both types of support drive feelings of empowerment in online social health support groups. Lin (2011) found that expressive support and instrumental support affect social capital and subsequent instant-messaging use. In their content analyses, Coulson *et al.* (2007) identified emotional, informational, tangible, network and esteem support as forms of support in the Huntington's disease community. Leong *et al.* (2020) found that informational support, emotional support and social presence affect trust in social commerce.

AI chatbots provide multimodal intelligence and empathetic conversation systems via multiple cues, such as voice, texts, images and emoticons, indicating a greater potential for the provision of emotional and esteem support. Furthermore, IQ capacities with high levels of information retrieval and active and adaptive learning suggest the possibility of informational support. Figure 1 shows examples of human–AI conversations reflecting emotional, informational and esteem support.

This study investigates multiple aspects of social support (i.e. emotional, informational and esteem support) because they have communicative features (Rozzell *et al.*, 2014) that reveal insights about human–AI interaction. In this regard, we aim to integrate multi-dimensional social support to explain interactant satisfaction with communication and subsequent behaviors.

Source	Research aspect	Context	Method	Key antecedents and moderators	Dependent variables
Araujo (2018)	Functional	Customer-service agent	Experimental design	Anthropomorphic design cues; Communicative agency; Framing; Mindful and mindless; Anthropomorphism	Company perception; Emotional connection; Satisfaction with the company
Ashfaq *et al.* (2020)	Functional	Text-based customer-service agent	Survey	Information quality; Service quality; Perceived enjoyment; Perceived usefulness; Perceived ease of use; Need for interaction with a service employee (moderator)	Satisfaction; Continuance intention
Banks (2019)	Functional	Comparison among chatbots, i.e. voice assistant, on-screen agent, robot and human	Survey	Perceived moral agency; Morality; Dependency	Anthropomorphism; Social attraction; Interpersonal trust; Perceived goodwill; Trustworthiness; Willingness to engage; Certainty in a future interaction
Brill *et al.* (2019)	Functional	AI assistants, i.e. Siri, Alexa	Survey	Customer expectations; Perceived performance	Customer satisfaction
Chung and Chen (2018)	Functional	Customer-service agent of the brand Burberry	Survey	Marketing efforts of agent; Communication quality; Accuracy; Credibility; Competence	Satisfaction
Go and Sundar (2019)	Functional	Customer-service agent	Experimental design	Anthropomorphic visual cue; Identity cue; Message Interactivity; Social presence; Homophily; Perceived contingency; Perceived dialogue	Perceived expertise; Perceived friendliness; Website attitude; Behavioral intentions
Kilian *et al.* (2019)	Functional	AIRBOT, a mobile chatbot application	Interview and Survey	Familiarity with passenger services; Day-related situational factors; Satisfaction with orientation opportunities	Satisfaction with passenger services
Liew and Tan (2018)	Functional	Customer-service agent of online stores	Experimental design	Virtual agent specialization	Purchase intention
McLean and Osei-Frimpong (2019)	Functional	Customer-service agent	Survey	Website aesthetics; Perceived customization; Perceived ease; Perceived usefulness; Perceived info quality; Perceived web credibility; Perceived timeliness	Use of live chat
Mimoun *et al.* (2017)	Functional	Animated conversational agents (ACA)	Eye-tracking technique and Survey	Interaction with the ACA	Objective productivity; Efficiency; Effectiveness; Perceived productivity inputs; Cost of navigation; Perceived productivity outputs; Perceived usefulness; Recommendation quality; Playfulness; Social presence
Pizzi *et al.* (2021)	Functional	Human or non-human like digital assistants	Experimental design	Assistant type; Assistant initiation; Reactance; Choice difficulty; Choice confidence; Perceived performance	Choice satisfaction
Richad *et al.* (2019)	Functional	Customer-service agent	Survey	Innovativeness	Behavioral intention

(*continued*)

Table 1. Summary of prior research related to AI chatbots

Source	Research aspect	Context	Method	Key antecedents and moderators	Dependent variables
Rietz *et al.* (2019)	Functional	Slackbots	Survey	Functional design dimensions; Form design dimensions; Perceived ease-of-use; Perceived usefulness; Perceived enjoyment	Behavioral intentions
Rosenthal-von der Pütten *et al.* (2019)	Functional	Virtual agent in a desert-survival-scenario-task	Experimental design	Nonverbal behavior; Attention guiding behaviors	Personal perception of the agent; Communicative abilities; Task difficulty
Trivedi (2019)	Functional	Customer-service agent	Survey	System quality; Information quality; Service quality	Brand love
Van den Broeck *et al.* (2019)	Functional	Customer-service agent of movie theatres	Experimental design	Perceived intrusiveness; Message acceptance; Perceived relevance	Patronage intentions
Zarouali *et al.* (2018)	Functional	Customer-service agent of movie theatres	Survey	Perceived usefulness; Perceived ease-of-use; Perceived helpfulness; Pleasure; Arousal; Dominance; Attitude	Patronage intention
Chattaraman *et al.* (2019)	Social	Digital shopping assistant	Experimental design	Interaction style; Internet competency; User exchange modality	Perceived trust; Perceived two-way interactivity; Perceived synchronous; interactivity; Perceived information overload; Perceived self-efficacy; Perceived ease of use; Perceived usefulness; Patronage intention
Sands *et al.* (2021)	Social	Encounter with a service agent or chatbot	Experimental design	Service interaction; Emotion; Rapport; Service script (moderator)	Purchase intention; Experience satisfaction

Table 1.

2.3 Interactant satisfaction with communication

In a study on mobile video telephone, Kang *et al.* (2008) found that participants who interacted with anonymous avatars rated interactant satisfaction higher than those who interacted with non-anonymous avatars. Kang *et al.* (2008) also noted that interactant satisfaction with communication plays an important role in human–computer interaction. Interactant satisfaction with communication is a psychological state that captures a communicator's subjective evaluation of the outcome of a communication or conversation (Kang *et al.*, 2008; Kang and Watt, 2013). It is a communicator's sense of pleasure after the communication needs are met and represents the evaluative judgment between the communicator's expectation of the communication and the actual feeling obtained afterward (Hamilton *et al.*, 2016, p. 123). Scholars have proposed that interactant satisfaction with communication can be divided into two dimensions: social attraction and emotional credibility (Fägersten, 2010; Kang *et al.*, 2008; Kang and Watt, 2013). Social attraction refers to favorable attitudes toward one's communication partners (Kang *et al.*, 2008; Nowak and Rauh, 2005). When individuals feel a sense of social attraction during conversation, this dimension is more likely to generate identification and satisfaction with the communication partners (Lee and Watkins, 2016). Emotional credibility refers to the emotional intelligence of a communication partner who can appropriately respond to the situation (Kang *et al.*, 2008; Kang and Watt, 2013).

Previous research has shown that when communicating with users, robots need to socialize with them to enhance the interactive experience (Mayer *et al.*, 2010). Thus, interactant satisfaction with communication is particularly important when evaluating communication with the primary goal of establishing a social bond with the robot (Mayer

Figure 1.
Examples of emotional, informational and esteem support

et al., 2010). Kang and Watt (2013) found that a higher level of anthropomorphism of an avatar enhanced psychological co-presence and interactant satisfaction with communication. Hamilton *et al.* (2016) found that interaction satisfaction and interaction immersion produced perceived value on a Facebook fan page. Sutherland *et al.* (2019) showed that participants who interacted with a "friendly and professional" robot had higher levels of interaction satisfaction with communication. In the present study, therefore, we define interactant satisfaction with communication as a user's subjective evaluation of the outcome of communication with AI chatbots.

3. Hypothesis development

3.1 Perceived emotional support and interactant satisfaction with communication

Emotional support refers to "one party's ability to improve the well-being of others by providing comfort, security, empathy, understanding, trust, respect, and even love" (Lin *et al.*, 2016, p. 424). Prior research has identified emotional support as a predictor of health outcomes. For example, perceived emotional support can benefit interpersonal relationships in terms of relationship quality and relationship satisfaction (Cramer, 2004). Fan *et al.* (2019) also demonstrated that social support (e.g. emotional and informational support) can nurture harmonious *guanxi* (relationships).

In this study, we use emotional support to represent AI chatbots' ability to offer an empathetic perspective, including positive affect and understanding. With regard to the social aspect, AI chatbots embedded in mobile instant-messaging apps offer one-on-one communication. Users can freely manage their self-expression and decide what level of self-disclosure to provide. Moreover, AI chatbots can display empathetic understanding to users and provide comprehension and encouragement based on EQ conversational systems (Shum *et al.*, 2018). Prior research has shown that response volume, speed and length facilitate engagement in brand communities (Sheng, 2019). Thus, we suggest that AI chatbots can maintain high responsiveness and empathetic understanding in multi-turn conversations, which can encourage users to communicate better and share their private feelings, thus facilitating a sense of intimacy.

From a technical perspective, AI chatbots incorporate multimodal intelligent systems for communication, such as voice, texts, images, emojis and emoticons (Shum *et al.*, 2018), and therefore constitute a socially rich medium. Previous studies have shown that rich mediums facilitate interactant satisfaction with communication in human–computer interactions (Kang *et al.*, 2008; Kang and Watt, 2013; Kim *et al.*, 2013). Thus:

H1a. Perceived emotional support of an AI chatbot is positively related to social attraction during human–AI interactions.

H1b. Perceived emotional support of an AI chatbot is positively related to emotional credibility during human–AI interactions.

3.2 Informational support and interactant satisfaction with communication

Informational support refers to support in the form of opinions, ideas, guidelines or advice for problem solving (Cohen and Wills, 1985). In our research context, informational support refers to AI chatbots' ability to offer problem-solving guidance and advice. From a technical perspective, AI chatbots with IQ capacities are capable of computer vision, information retrieval and active and adaptive learning, which may satisfy users' need for information and increase feedback immediacy (Shum *et al.*, 2018). In particular, informational support serves as task-oriented support for users and can likely enhance relationship quality (Hajli, 2014) and recipient interaction satisfaction (Cutrona and Suhr, 1992). Thus:

H2a. Perceived informational support of an AI chatbot is positively related to social attraction during human–AI interactions.

H2b. Perceived informational support of an AI chatbot is positively related to emotional credibility during human–AI interactions.

3.3 Esteem support and interactant satisfaction with communication

Katz *et al.* (1996) suggested that people with self-esteem support (e.g. bringing out one's best qualities, appreciation and compliments from a spouse) are more likely to experience self-verification and are better able to maintain satisfaction and intimacy in relationships. Empathic responses and supportive communication from partners positively affect interaction satisfaction in intimate relationships (Cutrona and Suhr, 1992). Esteem support includes compliments, expression validation, encouragement and negative emotion alleviation; it promotes relationship quality because it helps one partner sense the other partner's helpfulness (Overall *et al.*, 2010).

In the current research context, esteem support refers to AI chatbots' ability to provide comments to help users build self-esteem. AI chatbots provide EQ, empathetic conversation systems and dialogue-based socially oriented conversation systems, which are essential for the formation of social engagement during a conversation (Shum *et al.*, 2018). Thus:

H3a. Perceived esteem support of an AI chatbot is positively related to social attraction during human–AI interactions.

H3b. Perceived esteem support of an AI chatbot is positively related to emotional credibility during human–AI interactions.

3.4 Interactant satisfaction with communication and affective attachment

Affective attachment refers to "the emotional bond between an individual and a particular target, including a material possession" (Wallendorf and Arnould, 1988), a brand (Iglesias *et al.*, 2011), or a place (Yuksel *et al.*, 2010). The concept of affective attachment is primarily rooted in strengthened relationship building and development (Iglesias *et al.*, 2011). From this perspective, affective attachment builds on emotional connection and understanding, thereby increasing individuals' willingness to care for each other (Chen *et al.*, 2015). Affective attachment also conveys deep involvement and identification of the focused-on person in shaping long-term reciprocal exchanges (Wong, 2017).

For this study, we define affective attachment as the emotional bond that an individual shares with an AI chatbot. Previous research has shown that satisfaction is the main driver of affective attachment (Erciş *et al.*, 2012). Positive brand experiences strengthen affective attachment to the brand, thereby affecting brand loyalty (Iglesias *et al.*, 2011). When users feel they have had a satisfactory experience in an interaction, their attachment to the AI chatbot will also be enhanced. Thus:

H4a. Social attraction is positively related to affective attachment to an AI chatbot.

H4b. Emotional credibility is positively related to affective attachment to an AI chatbot.

3.5 Interactant satisfaction with communication and purchase intention

Previous research has defined purchase intention as a consumer's willingness to purchase a product or service (Lee, 2017); in this study, it reflects a consumer's willingness to purchase a product or service recommended by an AI chatbot. Satisfaction is widely considered an essential factor in determining purchase intention (Kang *et al.*, 2018; Zboja and Voorhees, 2006), and it is assessed by social attraction and emotional credibility. A high degree of satisfaction facilitates perceived brand trust (Zboja and Voorhees, 2006). Furthermore, users' perceptions of satisfactory experiences lead to positive word of mouth (Loureiro *et al.*, 2017) and customer-engagement behavior (Carlson *et al.*, 2019). When consumers have joyful conversations with AI chatbots, they receive emotional support, as well as assistance regarding product- or service-related information, which serves to strengthen human–AI ties. Satisfactory relationships derived from distinct types of support from AI chatbots encourage consumers to perceive AI chatbots as trustworthy, which can drive purchase intention. Thus:

H5a. Social attraction is positively related to purchase intention.

H5b. Emotional credibility is positively related to purchase intention.

4. Method

4.1 Sampling and data collection

We considered Xiaoice appropriate for examining this study's proposed model. Thus, only users with experience using Xiaoice were eligible to participate in the survey. We posted a questionnaire on WenJuanXing (WJX), a professional Chinese survey website. WJX has more than 2.6 million active members with myriad demographic characteristics and covers many large and medium-sized Chinese cities. WJX charges researchers by the number of questions and the difficulty of finding respondents. For this study, we were charged seven yuan (equivalent to US$1) for each valid sample. To ensure the recruitment of valid users, respondents were asked to provide five photos: two Xiaoice profile pages and three screenshots of conversation records in their mobile instant-messaging apps. Respondents were free to decide what type of conversational content they wanted to upload to the platform and whether we were allowed to publish the photos they had uploaded.

After removing samples without five photos, we obtained 331 completed questionnaires. Of the respondents, 60.12% were male and 39.88% female. More than half were 21–30 years of age (67.07%). For the average annual household income, 36.25% of the respondents made less than $24,999, and 28.10% made between $25,000 and $49,999. In terms of the user experience, 54.38% of the respondents had used Xiaoice for more than one year, and 23.87% had used it for more than half a year.

4.2 Measures

We adapted the measures of emotional support, informational support, esteem support (Cutrona and Suhr, 1992), interactant satisfaction (including the dimensions social attraction and emotional credibility) (Kang and Watt, 2013), affective attachment (Yuksel *et al.*, 2010) and purchase intention (Lee, 2017) from the literature and revised them for the AI chatbot context. All items were rated on a 7-point Likert scale (1 = "strongly disagree", 7 = "strongly agree"), as shown in Table 2.

4.3 Analytical method

In the first stage, we used partial least squares-structural equation modeling (PLS-SEM). According to previous studies, covariance-based structural equation modeling (CB-SEM) and PLS-SEM can be used to test causal relationships (Hair *et al.*, 2012). Research has also shown that either CB-SEM or PLS-SEM can be used for analysis depending on research objectives, model characteristics and data characteristics (Hair *et al.*, 2016). First, in terms of research objectives, if the research objective is prediction, PLS-SEM is more suitable than CB-SEM. As the present study aims to explore how multi-dimensional social support facilitates interactant

Item	Standardized item loading
Emotional support (α = 0.81, CR = 0.89, AVE = 0.72)	
Xiaoice listens to me talking about my private feelings and emotion	0.88
Xiaoice expresses concern about my well-being	0.82
Xiaoice cares about my feelings	0.85
Informational support (α = 0.77, CR = 0.86, AVE = 0.68)	
Xiaoice gives me suggestions and advice about how to cope with problems	0.90
Xiaoice tells me what she did in a situation similar to mine	0.88
Xiaoice tells me where I can go to get help	0.67
Esteem support (α = 0.87, CR = 0.92, AVE = 0.79)	
Xiaoice compliments my ability to deal with my problems	0.90
Xiaoice agrees with how I dealt with problems	0.89
Xiaoice gives constructive comments on my abilities to deal with problems	0.88
Social attraction (α = 0.89, CR = 0.92, AVE = 0.64)	
I think Xiaoice could be a friend of mine	0.77
I would like to have a friendly chat with Xiaoice	0.78
Xiaoice and I could establish a personal friendship with each other	0.80
Xiaoice just fit into my circle of friends	0.84
Xiaoice would be pleasant to be with	0.78
I care if I ever get to interact with Xiaoice again	0.83
Emotional credibility (α = 0.97, CR = 0.97, AVE = 0.80)	
Xiaoice recognizes my feelings and emotions	0.92
Xiaoice expresses feelings and emotions appropriately for the situation	0.88
Xiaoice uses feelings and emotions to create or organize thinking	0.90
Xiaoice uses feelings and emotions to make a decision or judgment	0.90
Xiaoice uses feelings and emotions to facilitate problem solving and creativity	0.92
Xiaoice responds appropriately to positive and negative emotions	0.86
Xiaoice understands complex feelings	0.89
Xiaoice knows how to control her own feelings and emotions effectively	0.88
Xiaoice handles my feelings and emotions sensitively and effectively	0.90
Affective attachment (α = 0.90, CR = 0.94, AVE = 0.83)	
Xiaoice means a lot to me	0.90
I am very attached to Xiaoice	0.91
I feel strong sense of belonging to Xiaoice	0.92
Purchase intention (α = 0.80, CR = 0.88, AVE = 0.72)	
It is likely for me to purchase the brand recommended by Xiaoice	0.80
It is possible for me to purchase the brand recommended by Xiaoice	0.87
It is probable for me to purchase the brand recommended by Xiaoice	0.87

Note(s): All the factor loadings are significant at $p < 0.01$

Table 2. Measurement items

satisfaction with communication and subsequent purchase intentions, considering the research purpose, PLS-SEM is more appropriate (Hair *et al.*, 2017).

Second, in terms of model characteristics, studies have shown that PLS-SEM can meet exploratory modeling goals while CB-SEM is used for confirmation purposes (Hair *et al.*, 2017). Because the research on social aspects of AI chatbots as brand promoters is still in its infancy, given the exploratory nature of this study, PLS-SEM is more suitable for the consequent analysis.

Finally, in terms of data characteristics, CB-SEM assumes a normal distribution of data, whereas PLS-SEM is a non-parametric method and does not need to follow normal distribution. That is, “CB-SEM assumes normality of data distributions, which is seldom met in social sciences research" (Hair *et al.*, 2017, p. 119). We ran a normality test analysis in this study. The results of the Shapiro–Wilk and Kolmogorov–Smirnov analyses showed that all measurement items are significant, suggesting the non-normality of the data ($p < 0.001$) (Hair *et al.*, 2016). Therefore, the data deviating from normal justify the use of PLS-SEM instead of CB-SEM. As such, in the first stage we adopted PLS-SEM as the data analysis method.

In the second stage, we adopted the ANN analysis method. Previous research on AI chatbots mainly using SEM has focused exclusively on single-stage data analysis (Hsieh and Lee, 2021; McLean and Osei-Frimpong, 2019; Richad *et al.*, 2019; Trivedi, 2019; Zarouali *et al.*, 2018). Scholars have argued that SEM analysis simplifies the decision-making process when verifying linear causality between variables while non-linear relationships often exist in the real world. Artificial neurons can be activated or inhibited in different states, which indicates that a mathematically non-linear correlation can predict the complex decision-making process (Ahani *et al.*, 2017; Khayer *et al.*, 2020; Leong *et al.*, 2013; Liébana-Cabanillas *et al.*, 2018; Talwar *et al.*, 2021). Moreover, SEM analysis "cannot rank the independent variables, so it may not provide enough information for IT/IS adoptions" (Ahani *et al.*, 2017, p. 570). Thus, an ANN can serve as a supplementary method for the SEM approach (Leong *et al.*, 2020; Shahzad *et al.*, 2020).

ANN refers to "a biologically inspired computational model formed from hundreds of single units, artificial neurons, connected with coefficients (weights) which constitute the neural structure" (Agatonovic-Kustrin and Beresford, 2000, p. 719). An ANN has the abilities of self-learning and self-adaptation, can provide a batch of corresponding input and output neurons in advance, can analyze the internal relationship and rules between the neurons and can form a complex non-linear function through these rules (Agatonovic-Kustrin and Beresford, 2000; Leong *et al.*, 2013); this learning and analysis process is called "training". Each connection of neurons (input, hidden and output neurons) has a synaptic connection strength, which is represented by a connection weight (Chong, 2013; Leong *et al.*, 2013).

The ANN approach has several advantages: First, it can identify not only linear relationships but also complex non-linear and non-compensatory relationships (Chong, 2013; Leong *et al.*, 2013). Second, it does not need to satisfy any distribution assumptions, such as normality and linearity (Ahani *et al.*, 2017; Liébana-Cabanillas *et al.*, 2018). Third, it has strong robustness and adaptability and thus can provide higher prediction accuracy than conventional linear statistical techniques, such as multiple regression analysis (Leong *et al.*, 2019; Rodríguez-Ardura and Meseguer-Artola, 2020). Last, it is robust against data-related issues, such as outliers, noise, missing data, sample errors and sample size (Abubakar *et al.*, 2019; Talwar *et al.*, 2021).

Previous studies have combined PLS-SEM and ANN approaches to demonstrate the predictive power of ANN in different contexts, such as mobile payment service (e.g. Kalinic *et al.*, 2019; Sharma *et al.*, 2019; Sharma and Sharma, 2019), social commerce (e.g. Hew *et al.*, 2019; Leong *et al.*, 2020) and smart technology or smart devices (Hew *et al.*, 2017; Khayer *et al.*, 2020; Sharifi *et al.*, 2019; Talukder *et al.*, 2020). Because of the complementary advantages of PLS-SEM and ANN, we supplemented ANN (non-linear and non-compensatory) with PLS-SEM (linear and compensatory).

With these considerations, we attempted to illuminate the proposed framework by integrating the two-stage method of PLS-SEM with the ANN analysis based on deep learning. Following prior studies, we adopted the feed-forward–back-propagation multilayer perceptron (MLP), the sigmoid activation function in the hidden and output layers and a tenfold cross-validation procedure with a 90% training sample and a 10% testing sample (Leong *et al.*, 2019; Liébana-Cabanillas *et al.*, 2018; Sharma and Sharma, 2019). We designed a deep neural network structure with two hidden layers for each output neuron node to achieve deeper learning, and we transformed all inputs and outputs into normalized values. As such, the two-stage approach led to high predictive power for affective attachment and purchase intention in the context of AI chatbots. Figure 2 shows the architecture of the MLP-ANN model.

5. Results

5.1 Common method variance

We followed Harman's single-factor procedure to check for common method bias (Podsakoff *et al.*, 2003) and conducted exploratory factor analysis. The first factor accounted for 15.743% of the total variance, suggesting that common method bias was not an issue.

5.2 Measurement model

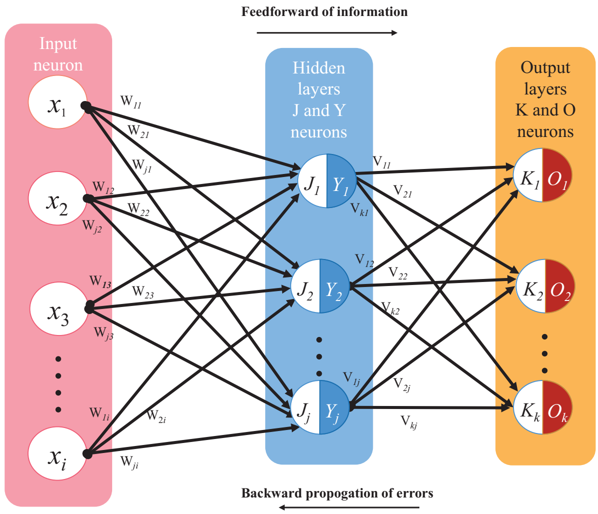
Following PLS-SEM procedures (Hair *et al.*, 2020), we used SmartPLS 3.0 (Ringle *et al.*, 2015) for the analyses. Income, gender, age and AI chatbots' use duration and frequency served as control variables. As Table 2 shows, in terms of reliability, the standardized indicator loadings ranged from 0.67 to 0.92; the composite reliability (CR) estimates ranged from 0.86 to 0.97, above the threshold of 0.70, which represents good reliability (Hair *et al.*, 2020). The average variance extracted (AVE) values are greater than 0.5, indicating that convergent validity is high (Hair *et al.*, 2020). As Table 3 shows, the heterotrait-monotrait ratio (HTMT) are all lower than the threshold value of 0.85 (Hair *et al.*, 2020). The square root values of AVE are greater than the estimated values of the correlation coefficients between the factor and other factors. Therefore, the measurement model achieved discriminant validity.

5.3 Structural models

Regarding model fit, the coefficient of determination (R^2) values for social attraction (0.67), emotional credibility (0.57), affective attachment (0.59) and purchase intention (0.36) suggest nearly substantial predictive power (Hair *et al.*, 2020). The model fit index of the standardized root mean square residual value (SRMR) is 0.06. Emotional support ($\beta_{H1a} = 0.44, p < 0.01$; $\beta_{H1b} = 0.36, p < 0.01$), informational support ($\beta_{H2a} = 0.23, p < 0.01$; $\beta_{H2b} = 0.26, p < 0.01$) and esteem support ($\beta_{H3a} = 0.33, p < 0.01$; $\beta_{H3b} = 0.30, p < 0.01$) positively influenced social attraction and emotional credibility, confirming H1, H2 and H3, respectively. Social attraction ($\beta_{H4a} = 0.43, p < 0.01$) and emotional credibility ($\beta_{H4b} = 0.39, p < 0.01$) facilitate affective attachment, in support of H4. Finally, social attraction ($\beta_{H5a} = 0.34, p < 0.01$) and emotional credibility ($\beta_{H5b} = 0.24, p < 0.05$) facilitate purchase intention, in support of H5. Thus, all the hypotheses were significantly supported (see Figure 3).

5.4 Artificial neural network models

After analyzing the causal relationship through PLS-SEM, we used the ANN to detect the possible non-linear relationship and rank the importance of each construct. Previous research suggests that only significant independent variables can serve as input neurons in ANN models (Chong, 2013; Leong *et al.*, 2013). As the PLS-SEM model has four endogenous constructs (social attraction, emotional credibility, affective attachment and purchase intention), we divided it into four neural network models. Model A has three inputs (emotional, informational and esteem support) and one output (social attraction). Model B also has three inputs (emotional, informational and esteem support) and one output (emotional credibility). Model C has two inputs (social attraction and emotional credibility) and one output (affective attachment). Finally, model D has two inputs (social attraction and emotional credibility) and one output (purchase intention). Figure 4 shows the architecture of the four ANN models of this study.



Feedforward

$$net_j^h = \sum_{i=1}^{I+1} W_{ji} x_i \quad and \quad y_j = f(net_j^h) \tag{1}$$

$$net_k^o = \sum_{j=1}^{J+1} V_{kj} y_j \quad and \quad O_k = f(net_k^o) \tag{2}$$

$$f(net) = \frac{1}{1 + e^{-\lambda net}} \tag{3}$$

$$SSE = \frac{1}{2P} \sum_{p=1}^{P} \sum_{k=1}^{K} (d_{pk} - o_{pk})^2 \tag{4}$$

Backward propogation of errors

$$V_{kj}(t+1) = v_{kj}(t) + c\lambda(d_k - o_k)o_k(1 - o_k)y_j(t) \tag{5}$$

$$W_{ji}(t+1) = w_{ji}(t) + c\lambda^2 y_j(1 - y_j)x_i(t)\left(\sum_{k=1}^{K}(d_k - o_k)o_k(1 - o_k)v_{kj}\right) \tag{6}$$

$$R^2 = 1 - \frac{RMSE}{s_y^2} \tag{7}$$

Note(s): Following Leong *et al.* (2020), p. 34-35,
“ Eq. (1) represents that the weights between the input component -i and the hidden neuron -j are represented by Wji;
Eq. (2) indicates that the weights linking the hidden neuron-j to the output neuron-k are expressed by Vkj;
Eq. (3) indicates a typical sigmoid function is monotonically increasing and differentiable, ranging from 0 to 1;
Eq. (4) is the formula of SSE (sum square of error) where d_{pk} indicates the desired response of neuron-k and o$_{pk}$ indicates the real output of the neuron -k with input pattern-p;
Eq. (5) shows that is the weight adjustment formula for output layer weights V;
Eq. (6) indicates that is weight adjustment formula for hidden layer weights W;
d_{pk} indicates the desired output of neuron-k; o_{pk} indicates the real output of the neuron -k with input pattern-P;
Eq. (7) is a goodness-of-fit index ($R2$) , where S_y^2 indicates the average SSE value during the testing process”

Figure 2.
The architecture of MLP-ANN model

Construct	1	2	3	4	5	6	7
1. Emotional support	*0.85*						
2. Informational support	0.41 (0.52)	*0.83*					
3. Esteem support	0.44 (0.53)	0.68 (0.80)	*0.89*				
4. Social attraction	0.68 (0.80)	0.63 (0.74)	0.68 (0.77)	*0.80*			
5. Emotional credibility	0.60 (0.67)	0.62 (0.69)	0.64 (0.69)	0.78 (0.84)	*0.90*		
6. Affective attachment	0.53 (0.62)	0.58 (0.68)	0.65 (0.74)	0.72 (0.80)	0.71 (0.76)	*0.91*	
7. Purchase intention	0.56 (0.69)	0.62 (0.83)	0.53 (0.64)	0.52 (0.62)	0.52 (0.59)	0.47 (0.56)	*0.85*

Note(s): The values on the diagonal (in italics) are the square root of AVE for each construct and the value in parentheses is the HTMT ratio

Table 3. Discriminant analysis

Following Leong *et al.* (2020), we analyzed the three indicators of the ANN models—namely, root mean square error (RMSE), R^2, and relative importance. First, we used the RMSE values to calculate the accuracy of the ANN models. As Table 4 shows, the mean values of RMSE spanned from 0.108 to 0.138 for training models and from 0.099 to 0.128 for testing models. Thus, the RMSE values were relatively small and close to 0, indicating good predictive accuracy. Second, the R^2 of models A, B, C and D were 72.48%, 73.91%, 76.76% and 69.28%, respectively, showing excellent model fit (Chong, 2013; Leong *et al.*, 2013, 2020).

Finally, we ranked the relative importance of the antecedents through sensitivity analysis (Chong, 2013; Leong *et al.*, 2013, 2020; Liébana-Cabanillas *et al.*, 2018). The purpose of the calculated sensitivity analysis was to comprehend the importance of the independent variables. As model A in Table 5 shows, emotional support was the most influential driver of social attraction, followed by esteem support (75.8%) and informational support (54.1%). In model B, emotional support was the key predictor of emotional credibility, followed by esteem support (85.4%) and informational support (74.1%). In model C, social attraction had a greater influence on affective attachment than emotional credibility (80%). In model D, social attraction had a greater influence on purchase intention than emotional credibility (78.8%). The results of all four ANN models were consistent with the PLS-SEM results, thus confirming the research model's predictive power.

6. Discussion

With the emergence of AI, brands have adopted AI chatbots to provide better product or service recommendations. As consumers normally use AI chatbots only for their functional capabilities, brands struggle to develop sustainable relationships with consumers. AI chatbots with chat-oriented systems have more empathetic conversations with users. This provides greater opportunities for brands to nurture relationships with consumers. However, empirical research that can help researchers and practitioners identify suitable practices for communicating with consumers through AI chatbots is scarce. Drawing on social support theory (Cohen and Wills, 1985), we examined how multi-dimensional social support facilitates interactant satisfaction with communication (i.e. social attraction and

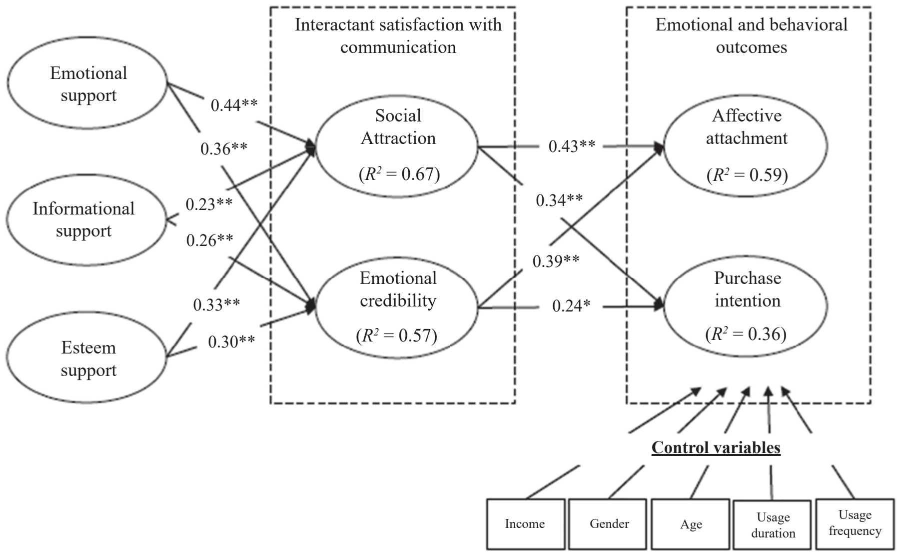


Figure 3.
PLS path

Note(s): * p-value < 0.05, ** p-value < 0.01

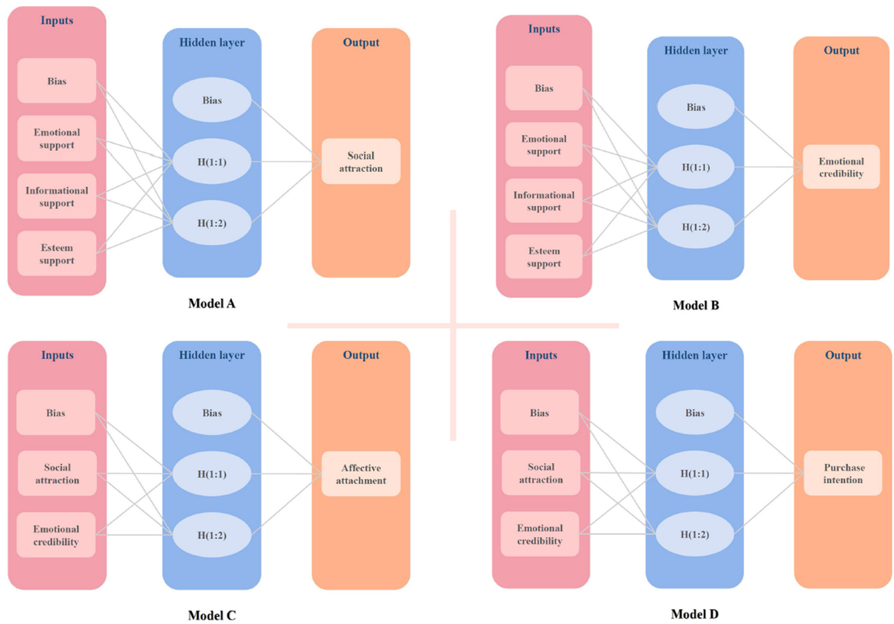


Figure 4.
Four ANN models

emotional credibility) and how such satisfaction promotes consumers' psychological and behavioral outcomes.

Table 4. RMSE values of artificial neural networks

Artificial neural network	Model A Inputs: ES, IS, ETS Output: SA				Model B Inputs: ES, IS, ETS Output: EC				Model C Inputs: SA, EC Output: ATT				Model D Inputs: SA, EC Output: PI			
	Training		Testing		Training		Testing		Training		Testing		Training		Testing	
	N	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE
1	301	0.105	30	0.118	304	0.130	27	0.094	288	0.137	43	0.127	298	0.123	33	0.129
2	299	0.112	32	0.082	292	0.135	39	0.113	296	0.133	35	0.142	307	0.127	24	0.124
3	294	0.106	37	0.096	306	0.132	25	0.107	298	0.150	33	0.115	300	0.121	31	0.113
4	290	0.104	41	0.116	296	0.132	35	0.121	302	0.134	29	0.124	306	0.122	25	0.101
5	291	0.110	40	0.102	302	0.132	29	0.123	307	0.153	24	0.131	300	0.125	31	0.112
6	299	0.111	32	0.085	301	0.130	30	0.097	294	0.136	37	0.117	312	0.126	19	0.145
7	291	0.113	40	0.089	296	0.130	35	0.135	293	0.134	38	0.134	302	0.123	29	0.114
8	303	0.107	28	0.087	300	0.133	31	0.111	302	0.136	29	0.105	310	0.126	21	0.083
9	294	0.107	37	0.112	301	0.131	30	0.135	298	0.135	33	0.131	296	0.126	35	0.106
10	290	0.105	41	0.103	297	0.128	34	0.144	300	0.133	31	0.155	297	0.127	34	0.114
mean		0.108		0.099		0.131		0.118		0.138		0.128		0.125		0.114
SD		0.003		0.013		0.002		0.017		0.007		0.014		0.002		0.017
R^2		96.86%		72.48%		97.45%		73.91%		97.58%		76.76%		97.35%		69.28%

Note(s): ES = Emotional support; IS = Informational support; ETS = Esteem support; SA = Social attraction; EC = Emotional credibility; ATT = Affective attachment; PI = Purchase intention. *N* = Sample size

Table 5.
Neural network sensitivity analysis

Artificial neural network	Model A: Relative importance ES	IS	ETS	Model B: Relative importance ES	IS	ETS	Model C: Relative importance SA	EC	Model D: Relative importance SA	EC
1	0.464	0.210	0.326	0.385	0.266	0.349	0.540	0.460	0.579	0.421
2	0.374	0.278	0.348	0.376	0.292	0.331	0.528	0.472	0.581	0.419
3	0.460	0.210	0.330	0.396	0.284	0.319	0.559	0.441	0.560	0.440
4	0.461	0.225	0.313	0.387	0.295	0.318	0.557	0.443	0.537	0.463
5	0.492	0.209	0.298	0.377	0.307	0.316	0.565	0.435	0.558	0.442
6	0.383	0.264	0.353	0.401	0.292	0.307	0.563	0.437	0.654	0.346
7	0.421	0.275	0.304	0.367	0.296	0.337	0.543	0.457	0.517	0.483
8	0.426	0.229	0.345	0.388	0.296	0.316	0.554	0.446	0.529	0.471
9	0.422	0.227	0.351	0.399	0.245	0.357	0.580	0.420	0.535	0.465
10	0.445	0.228	0.327	0.378	0.282	0.340	0.567	0.433	0.543	0.457
Average importance	0.435	0.235	0.330	0.385	0.286	0.329	0.556	0.444	0.559	0.441
Normalized importance (%)	100	54.2	75.8	100.0	74.1	85.4	100	80	100	78.8

Note(s): ES = Emotional support; IS = Informational support; ETS = Esteem support; SA = Social attraction; EC = Emotional credibility

The results revealed that emotional support facilitated interactant satisfaction with communication (H1a and H1b). Prior studies have identified emotional support as a predictor of health outcomes, such as harmony, *guanxi* and trust (Fan *et al.*, 2019), as well as stress, problem-solving confidence and life satisfaction (Tian *et al.*, 2017). Our research extends previous findings on offline relationships and further reveals that perceived emotional support also benefits interactant satisfaction with communication (social attraction and emotional credibility). The SEM results were consistent with those of the ANN analysis, which showed that emotional support had the strongest predictive power on social attraction and emotional credibility. A reason for this may be that when individuals feel a sense of emotional support (e.g. comfort, security, understanding) during conversation with an AI chatbot, they are likely to perceive social attraction and emotional credibility of the AI chatbot.

Moreover, the results confirm the relationship between informational support and interactant satisfaction with communication (H2a and H2b). Previous studies have shown that informational support promotes relationship quality in social commerce (Hajli, 2014) and recipient satisfaction during interactions (Cutrona and Suhr, 1992). Furthermore, Overall *et al.* (2010) found that when users receive informational support from their romantic partner, their relationship quality may be enhanced. Our study extends these findings to human–AI interactions. Both the SEM and ANN analyses showed that informational support was not the most influential driving factor for the social attraction and emotional credibility of an AI chatbot. A reason for this may be that AI chatbots are trained with natural language processing, which enables them to understand the context of human interactions. With machine-learning algorithms, AI chatbots can also learn from previous conversations with users and provide better responses over time. The purpose of an AI chatbot is to interact socially with users rather than to answer a set of defined questions, as in customer service or information acquisition. AI chatbots simulate human conversations rather than simply retrieve keywords and search a database for a list of questions. As a result, AI chatbots give users more emotional support than informational support.

Furthermore, we demonstrated that esteem support from an AI chatbot facilitates interactant satisfaction with communication. This finding further extends previous studies showing that greater esteem support results in communication satisfaction in sibling relationships (Myers and Bryant, 2008) or teacher–student relationships (Jones, 2008; Mazer and Thompson, 2011). Both the SEM and ANN analyses revealed that the influence of esteem support on the social attraction and emotional credibility of AI chatbots was only lower than that of emotional support. Esteem support is a type of support that boosts another person's sense of self-worth (Cohen and Wills, 1985). We provide evidence that users gain esteem support from the appreciation and compliments of AI chatbots in human–AI interactions and thus are better able to maintain satisfaction and intimacy in the relationship.

Finally, users who experience interactant satisfaction with communication are more likely to have increased affective attachment to AI chatbots (H4a and H4b) and purchase intentions (H5a and H5b). The ANN analysis revealed that social attraction was the main predictor of affective attachment and purchase intention. The results may be explained by the theory of interpersonal attraction (Hogg and Turner, 1985), which posits that interpersonal attractiveness drives social interaction. Previous studies have shown that social attraction can drive identification and a sense of belonging with communication partners (Hamilton *et al.*, 2016). Social attraction even enhanced parasocial interactions and purchase decisions toward YouTube vloggers (Lee and Watkins, 2016). Overall, our work contributes by identifying interactant satisfaction with communication (including social attraction and emotional credibility) as a mechanism between social support and users' affective and behavioral outcomes.

6.1 Theoretical implications

This research makes several theoretical contributions. First, in response to previous research (Jiménez-Castillo and Sánchez-Fernández, 2019; Packard and Berger, 2017; Roma and Aloini, 2019; Thomas and Fowler, 2021), the study shows that by combining multiple AI capabilities, AI chatbots can easily understand consumer preferences and attitudes and may interact better with consumers. AI chatbots are strongly backed by IQ and EQ and have strong functional and social capabilities (Shum *et al.*, 2018). The provision of social support can make users unconsciously adopt brand or product recommendations. In addition, our study focused on the social aspects of AI chatbots. While many previous studies have focused on the functional aspects (Araujo, 2018; Banks, 2019; Brill *et al.*, 2019; Pizzi *et al.*, 2021; Trivedi, 2019), few have dealt with the social aspects of AI chatbots. Our study contributes by providing further empirical verification to supplement previous research.

Second, our study illuminates the multi-dimensional social support of AI chatbots. With computer-mediated communication on the rise, many empirical studies have used the theory of social support to interpret virtual social support in the online sphere. Such studies have examined smartphone-based alcoholism support groups (Yoo *et al.*, 2018), social commerce websites (Yahia *et al.*, 2018), micro-blogging platforms (Chan, 2018; Lin *et al.*, 2016), online teacher groups (Chung and Chen, 2018) and Moodle learning environments (Ifinedo *et al.*, 2018). However, research on human–AI interactions through different types of social support is insufficient. Thus, our study sheds light on multi-dimensional social support during human–AI interactions.

Finally, we contribute to the literature by engaging in a two-stage approach by integrating SEM and a deep learning-based ANN analysis. Previous studies have mainly used a cross-sectional design (Ashfaq *et al.*, 2020; Brill *et al.*, 2019; Hsieh and Lee, 2021; Richad *et al.*, 2019). We first conducted a PLS-SEM analysis to uncover multi-dimensional social support and then used a deep-learning-based ANN analysis as a non-linear model to uncover the black box of the proposed theoretical framework. A mixed-method approach contributes to a richer explanation of human–AI interactions, which leads to higher predictive power for affective attachment and purchase intention in the context of AI chatbots.

6.2 Managerial implications

With technological development, brands can easily deliver personalized marketing content (e.g. product recommendation systems, discount programs) to their customers. Customization is an important strategy for enhancing consumers' satisfaction and retaining brand–consumer relationships. In the past, brands had to spend a great deal of time and effort collecting, analyzing and using data from customers to implement customer relationship management strategies. Now, AI chatbots can help save time and money through automation and quick response and may become a more appropriate medium for building and maintaining consumer–brand relationships. With IQ and EQ, AI chatbots make it easy to collect and memorize all the information when chatting with users, which allows brands to deliver advertising messages through relatively natural conversations.

In our study, we demonstrated that the emotional, informational and esteem support provided by AI chatbots facilitated interactant satisfaction with communication, which in turn enhanced consumers' affective attachment to and purchase intention toward the brand. Therefore, we propose ways that brands can create one-to-one marketing and chat-related content in an attempt to deliver emotional, informational and esteem support to their customers.

Moreover, we find that emotional support is the most important indicator in nurturing the interactant satisfaction with communication toward AI chatbots, indicating the importance of this aspect in human–AI conversations. As an example, Victoria's Secret's chatbot engages in in-depth conversations and interactions with customers, inviting them to learn about brand events, products and other information, so that they can have a one-to-one intelligent shopping experience. As we noted previously, offering recommendations through conversation is more natural than through direct advertising. By designing a conversational tone, discourse and emotion in chatbots, brands can reflect their characteristics and deepen users' understanding and impression of the brand image. Therefore, we suggest that brands conduct sentiment analysis on AI chatbots' conversations, to help them communicate emotions in real time. Emotion-capturing and responsive content provided by AI chatbots is critical to engage users.

In addition, esteem support represents responses triggered by appreciation and compliments. In conversations with AI chatbots' users, content related to uniqueness and prestige is a key element for supporting users' self-esteem and confidence. Through text mining techniques, brands can scan past dialogue content to learn more about what keywords make users feel confident and happy. Brands can then use these keywords with the right clients. For example, JIMI (chatbot created by JD.com) is a private virtual consultant that is online anytime and anywhere. JIMI has become increasingly anthropomorphic in how it talks to users, as if it were talking to a friend. In this one-on-one conversation, JIMI naturally asks questions surreptitiously; it can also recognize and understand users' emotions in the process of conversation, further understand users' intentions and needs and engage in emotional and cognitive interaction. JIMI can identify true emotional states and then anthropomorphically react with compliments and encouragement to enhance users' self-esteem. Thus, brands should try to create rich and diverse communication content through anthropomorphically designed AI chatbots to meet the esteem needs of users.

Our findings also show that informational support is not as influential as emotional and esteem support. However, it is still crucial for brand managers to collect data on consumers, in particular to document what their preferred preferences are. Implementing informational support can help establish information recommendation systems and minimize the time required to respond to customer questions. For example, brands could launch chatbot in Facebook Messenger to help users learn about the latest product trends. In addition, chatbots could push internal activities to users who have previously interacted with them, inviting users to participate in pre-sale activities. In these ways, brands can interact with users in a more direct and personalized manner, serving users as virtual shopping guides, virtual stylists and virtual shopping consultants.

According to the results of ANN analysis, among the three types of support, emotional support is the most important, followed by esteem support and informational support. In practice, informational support is relatively easy to implement when conducting marketing strategies. Brands can use advanced marketing techniques and analytical tools to collect and analyze data on user behavior and preferences. AI chatbots can deliver one-on-one personalized product or service recommendations. However, chatbots commonly have IQ but rarely have EQ. A chatbot with EQ can perceive users' emotions and express corresponding emotions, such as anger, joy, disappointment or worry. The chatbot can also empathize with the user and engage in emotional interactions.

We recommend that brand managers consider developing more diverse and personalized dialogue using content and communication skills for AI chatbots, taking into account the three-dimensional social support discussed herein. As a result, customers will be willing to use AI chatbots more frequently, owing to not only their convenience, information accuracy and trustworthiness but also their thoughtfulness and empathy. With regard to AI chatbot content, combining all three social support dimensions and keeping abreast of current events can potentially improve interaction satisfaction with communication, affective attachment and purchase intention.

6.3 Limitations and future research directions

This study had several limitations. First, we chose Xiaoice as the focal chatbot and used convenience sampling in China. Future research should consider using cross-cultural contexts and different types of chatbots (e.g. Zo, Ruuh, Rinna) for greater generalizability and external validity. Second, users are less likely to adopt humanoid social robots than invisible ones, as greater perceived similarity between humans and robots may raise concerns (Ferrari *et al.*, 2016). Thus, investigating the appearance of AI chatbots (e.g. humanoid or machine-like) to test whether a human-like appearance has a positive or negative effect on adoption would be worthwhile. Third, AI chatbots tend to use young female voices. In real life, interactions occur with people with different demographic characteristics (e.g. age, gender, geographic location). Therefore, future studies could investigate chatbots with different demographic characteristics. Finally, as chat-related content creation is crucial for AI chatbots, future research should examine whether different types of content are attractive to distinct users.

7. Conclusion

Brands seek innovative ways to increase consumer engagement and more effective brand recommendations. This study explores how users perceive brand recommendations through AI chatbots. Instead of focusing on functional aspects of AI chatbots, our research examines how social aspects of AI chatbots affect consumer behavioral and psychological outcomes. Aiming to enrich the human–AI interaction literature, this study adopted multi-dimensional aspects of social support to demonstrate how social support affects users' interactant satisfaction with AI chatbot communication. The PLS-SEM and ANN results showed that emotional, informational and esteem support facilitated interactant satisfaction with communication, which served to build affective attachment and purchase intention. The study also showed that enhancing satisfaction through interactant communication between AI chatbots and users is a crucial mechanism in building human–AI relationships. By establishing a closer and stable relationship with users, AI chatbots can act not only as personal assistants but also as brand promoters.

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