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AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior

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ABSTRACT

The present study is grounded in social exchange theory and resource exchange theory. By exploring customers' satisfaction with chatbot services and their social media engagement, it examined the effects of responsiveness and a conversational tone in dialogic chatbot communication on customers. To test the proposed mediation model, we surveyed a representative sample of customers (N = 965) living in the U.S. After examining the validity and reliability of our measurement model, we tested the hypothesized model using structural equation modeling (SEM) procedures. All proposed hypotheses were supported, indicating the significant direct effects of (1) responsiveness and a conversational tone on customers' satisfaction with chatbot services, (2) customers' chatbot use satisfaction on social media engagement, (3) customers' social media engagement on price premium and purchase intention, and (4) purchase intention on price premium. In addition, we examined satisfaction, social media engagement, and purchase intention as significant mediators in the proposed model. Theoretical and practical implications of the study were then discussed.

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1. Introduction

In recent years, customer engagement has rapidly gained attention from both communication and marketing researchers (Eisingerich et al., 2019; Rutz et al., 2019; van der Meij, 2018). Artificial intelligence-powered technologies (e.g., service robots or chatbot services) enable organizations' two-way, dialogic interactions with their customers (Belk, 2009, 2013; Fryer et al., 2017; Hill et al., 2015; Hollebeek et al., 2014, 2016; Kumar et al., 2016; Shumanov & Johnson, 2021; Tsai et al., in press). Such dialogic interactions contribute to non-transactional customer engagement, such as gathering information about an organization's chatbot services from an online brand community, posting reviews about an organization's chatbot services, socializing with other customers using the same organization's chatbot services, and sharing opinions about how to improve the organization's chatbot services via social media (Chang et al., 2018; King et al., 2014; Moe & Schweidel, 2014; van der Meij, 2018; Verhoef et al., 2007). The aforementioned non-transactional customer engagement poses great opportunities and challenges for organizations to manage engagement-facilitating technologies to sustain the long-term wellbeing of their businesses (Hollebeek & Belk, 2019).

Advances in technology led to the popularity of using conversational agents, such as chatbot agents, in organizations' marketing communication efforts (Dale, 2016). Chatbots are software-based and can interact with users via a text-based interface (Feine et al., 2019). Using a natural dialogue, where they do not operate based on some predetermined keywords or command phrases, chatbots are deployed on organizational websites, instant messaging apps, or social media, and can be easily made accessible (Karri & Kumar, 2020; McTear et al., 2016). Chatbots mimic real-life interpersonal communication, allowing users to feel comfortable launching a conversation and distinguish similarities between chatbots and themselves (Feine et al., 2019; Go & Sundar, 2019; Prasetya et al., 2018). Dialogic chatbot communication offers customers real-time information, feedback and fulfillment of their needs, alongside product or service consumption (Reinartz et al., in press). Customers likely prefer to interact with chatbot service agents who enable value creation through responsiveness and conversational tones (Fadhil & Schiavo, 2019; Rybalko & Seltzer, 2010; Verhoef et al., 2007).

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Consequently, customers' post-consumption evaluation of chatbot services can be highly satisfactory (Chung et al., 2020). Social cues, which signal a humanlike interaction from chatbot dialogues, were also found to enhance trust, social presence, customer satisfaction, positive attitudes toward organizations, long-term relationship with customers, and purchase intention (Araujo, 2018; Bickmore & Picard, 2005; Chung et al., 2020; De Visser et al., 2016; Holzwarth et al., 2006; Liebrecht, Sander, & van Hooijdonk, 2020; Verhagen et al., 2014).

When an organization's chatbot agent communicates with its customers through a dialogic manner and customers are satisfied with its chatbot services, then customers' response and acceptance can be determined (Chiang et al., 2017). Customer engagement "refers to 'a customer's voluntary resource contribution to [an organization]'s marketing function, going beyond financial patronage'" (Harmeling et al., 2017, p. 316). This study thus focused on customers' non-transactional social media engagement behavior. As the CLASS model of online brand community engagement implies, customers' abilities to acquire information, create knowledge, build communities, advocate chatbot services, and brainstorm innovation in the social media community can result from highly satisfactory user experiences with an organization's chatbot service agents (Brodie et al., 2013; Carlson et al., 2019; Zhu et al., 2016).

Given the increasing use of AI-powered chatbot services in marketing communication and customers' social media engagement, a central research question for researchers has risen. How can organizations leverage chatbot technologies to affect customers' social media engagement and their own long-term business wellbeing (Hollebeek & Belk, 2019)? In this study, we focused on two key indicators of supportive actions of customers: price premium and purchase intention (Kim et al., 2010; Netemeyer et al., 2004). To examine the research question, we drew theoretical insights from social exchange theory, resource exchange theory, relevant prior literature, and a survey involving 965 customers based in the U.S. market (Blau, 1964; Brinberg & Wood, 1983). We investigated how responsiveness and a conversational tone in chatbot dialogic communication and customers' satisfaction with chatbot services led to their social media engagement and behavior toward organizations' long-term wellbeing.

The purpose of this study was thus multi-fold: (1) To examine how responsiveness and a conversational tone in dialogic chatbot communication influenced customers' satisfaction with top-ranked corporate bots in the U.S. market across industries; (2) to map out how customers' chatbot use satisfaction led to their social media engagement; (3) to investigate the impact of customers' social media engagement on customer behavior—price premium and purchase intention, which is key to business wellbeing in the long run; and (4) to benefit AI and business communication professionals by generating ways to improve chatbot communication with customers, facilitating customers' social media engagement, and boosting supportive and loyal customer behavior toward organizations.

2. Literature review

2.1. Theoretical foundations

We situated our research in social exchange theory and resource exchange theory (Blau, 1964; Brinberg & Wood, 1983). Social exchange theory (SET) states that relational parties, such as organizations and their customers, weigh rewards and costs to determine the benefits and risks associated with certain actions, as they interact with each other (Saks, 2006). Likewise, resource exchange theory (RET) also explains reciprocal social interactions of humans and various social institutions (Foa & Foa, 1975). The core tenets of RET include (1) humans exchange resources (e.g. love, information, money, goods, etc.) and parties involved in the exchange influence the value of a shared resource and determine the appropriateness of any exchange; (2) institutions (e.g., organizations, marketers, etc.) in resource exchange can bring together individuals, for instance, customers with similar, reciprocal motivations for exchanging resources in a setting (Greenberg et al., 2013), such as in an online brand or social media community.

By integrating both theories in our study, we sought to build a model that links engagement-facilitating technology (i.e., chatbot services with customers), customers' satisfaction with the services, and their social media engagement behaviors to the long-term business wellbeing of organizations. Based on social exchange theory (SET) and resource exchange theory (RET), we argued that when an organization's chatbot service agents are responsive to customers' needs and conversational in communication, customers will reciprocate as they perceive benefits and receive valued resources from chatbot experiences with the organization—Customers tend to be satisfied with their chatbot use; as customers' "voluntary resource contribution" to an organization's business (Harmeling et al., 2017, p. 316), customers also learn from, share and socialize with other customers who use the same organization's chatbots in a social media community, advocate for using the chatbots, and co-develop innovative ideas for strengthening the organization's chatbot services; finally, customers may reciprocate with strong intentions toward price premium and purchasing the organization's products and services.

2.2. Conceptualizations and design of hypotheses

Dialogic chatbot communication. Business researchers have long identified the critical role of dialogic communication in building relationships with customers via strategically designed advanced technologies, such as AI-powered chatbot services (Rybalko & Seltzer, 2010). 'Dialogic loop,' a key principle that Kent and Taylor (1998) proposed, is seen in the examination of organizations' digital communication with customers (Tanev et al., 2011). A dialogic loop allows customers to raise queries and requires organizations to respond to their questions and concerns (aka being responsive) (Hinson et al., 2018; Schamari & Schaefers, 2015). One of chatbots' main functions is to respond to queries (Sundar & Limperos, 2013; Wang et al., 2016). Relevant replies help organizations remain interactive and competitive in the increasingly chat-app-centric business world (Business Insider Intelligence, 2016). Previous chatbot literature demonstrated that responsiveness could enhance chatbots' credibility, social presence, and customer attitudes and behaviors by increasing humanness (Go & Sundar, 2019; Schuetzler et al., 2019; Sundar, 2008; Sundar et al., 2012, 2016, pp. 73–100; Vendemia, 2017).

Apart from responsiveness, analyzing the degree to which chatbot agents can interact with customers in a conversational text-based natural language is key to measuring service satisfaction (Feine et al., 2019). Prior literature on user-conversation chatbot interaction has focused on examining interactive dialogue systems, specifically, the personalities that a conversational bot agent assumes while interacting with customers (Fadhil & Schiavo, 2019). Chatbot agents must develop an easy connection with customers in an intimate one-on-one space, making them feel as if they were chatting with a friend and perceive dynamic control over the nature of interaction (Lee & Choi, 2017; Sundar & Limperos, 2013). Likeable, competent, and cooperative conversational chatbot agents are expected to establish a strong bond with customers by displaying behaviors indicative of empathy, compassion, care, and even humor (Augello et al., 2008).

Responsiveness. A human-to-human dialogue embeds certain conversational norms regarding the content, timing, and flow of the conversation (Schuetzler et al., 2019). One of the conversational norms is relation, which indicates the expectation that the dialogue partner will provide a tailored response by adjusting the responses to the conversation accordingly (Schuetzler et al., 2019). This responsive process refers to the conversational relevance of responses (Sundar et al., 2015). For a chatbot to maintain relevance, it is necessary to process customers' messages and add context to sustain continuity from the preceding messages, which allows the chatbot to appear natural and even conversationally skilled (Morrissey & Kirakowski, 2013).

According to Go and Sundar (2019), a key feature of interpersonal communication is contingency in responses since a response in dialogues is contingent upon the preceding messages. Considering the back-and-forth nature of human conversations, Go and Sundar (2019) termed the level of contingency in exchanging messages as message interactivity. Rafaeli (1988) also highlighted the importance of contingency for a conversation to be considered fully responsive. Additionally, in a chatbot context, having message-interactivity makes chatbots appear more anthropomorphic because it mimics the responsiveness, observed from human-to-human interactions (Go & Sundar, 2019; Rafaeli, 1988). An empirical study also uncovered that higher message interactivity in an online chat elevates social presence as people are more likely to evaluate the interaction as a dialogue since message interactivity resembles human interactions (Sundar et al., 2015).

Situated in the aforementioned literature on relevance, contingency, and message interactivity, examples of responsiveness in chatbot communication thus include chatbot service agents providing prompt feedback to customers' comments, making adequate changes based on their feedback, addressing their complaints in a positive and prompt manner, and staying sensitive to customers' needs throughout the communication process (Go & Sundar, 2019; Rafaeli, 1988; Schuetzler et al., 2019).

Being conversational. With respect to conversing with a system, the interaction style is crucial as the system functions as a dialogue partner (Deuter et al., 2013). A conversational tone especially provides users with familiarity and life-like interactions when communicating with a machine or bot (Deuter et al., 2013; van der Meij, 2018). Hence, chatbots employ natural conversational language to mimic human-to-human communication, generating an illusion that users are communicating with a human agent (Ciechanowski et al., 2019). For instance, the social cues in chatbot dialogues such as language style—informal, empathetic, and invitational—and the capability of expressing emotion allude users to perceive the interaction as human-like since these cues are usually observed from actual conversations with humans (Feine et al., 2019). In dialogic chatbot communication, chatbot service agents with a conversational language style would make customers feel as though they are treated as real communication partners, their perspectives or opinions are respected, and they are invited to an open dialogue where chatbot service agents avoid dominating the conversations to establish a common ground of understanding with customers (Ciechanowski et al., 2019; Feine et al., 2019; Deuter et al., 2013; van der Meij, 2018).

Customers' satisfaction with chatbot services. In previous business literature, customer satisfaction was frequently examined by measuring how a company's products or services meet or surpass customer expectations (Chung et al., 2020; Santini et al., 2018). Through this study, we focused on customers' evaluation of chatbot services. When post-consumption evaluations are positive, high customer satisfaction is then displayed. For instance, scholars found that accurate, competent, customized, and credible communication via chatbot services can reduce uncertainty and positively motivate customers' level of satisfaction (Bitner et al., 2000; Chung et al., 2020; Hutter et al., 2013).

Dialogic communication in shaping customers' satisfaction with chatbot services. Scholars found that like human agents, chatbots can efficiently interact with customers, provide timely and relevant responses to their inquiries or complaints, and practice in-depth conversations in dialogic communication (Chung et al., 2020; Mimoun et al., 2017). According to Kent and Taylor (2002), dialogic communication could significantly improve the relationship between an organization and its customers, along with increasing their level of customer satisfaction.

The relationship between dialogic communication and customers' satisfaction with chatbot services can be explained by social exchange theory (SET) which posits that customer satisfaction depends on their cost-benefit analysis (Emerson, 1976). In other words, if customers perceive that the benefits of chatbot interaction are higher than its costs, they tend to feel more satisfied with using chatbots (Ashfaq et al., 2020). In this case, chatbots' dialogic features including being responsive and conversational can offer humanlike interaction which is easy to utilize and familiar to customers. Moreover, customers' comments, feedback, complaints, and needs are addressed adequately and promptly, which makes customers perceive chatbot use as a rewarding experience. Hence, the ease, familiarity, and efficiency of using chatbots enable customers to estimate the perceived benefits of their chatbot interaction to be higher than its costs, which will elicit higher satisfaction according to SET. Likewise, resource exchange theory (RET) also explains the reciprocal customer-chatbot interaction (Greenberg et al., 2013). Responsive and conversational chatbot agents give a positive signal that organizations care about hearing stakeholders' needs, which reinforces the interconnectedness between an organization and its stakeholders and their psychological contract with the organization (Dutta & Mishra, 2021). In our study context, customers, in return, are likely to respond favorably to those chatbot agents—Customers' need fulfillment results in positive attitudes and behaviors toward organizations' practices, for instance, customers' satisfaction with chatbot use.

The extant literature has examined the way dialogic communication shapes customers' satisfaction with chatbot services. Guided by the Computers Are Social Actors (CASA) paradigm, which states that users tend to socially engage with machines in a manner similar to humans, prior literature concluded that linguistic cues, the name of the agent, and text qualities affect the level of humanness that users perceive of chatbots (Nass et al., 1994; Nass & Moon, 2000; Xu & Lombard, 2017). Human identity cue, such as being a responsive and conversational dialogue partner, is crucial since it elicits higher social presence and perceived homophily from chatbot users, which is found to incite favorable attitudes and emotional connectedness (Araujo, 2018; Biocca et al., 2003; Go & Sundar, 2019; Rhee & Choi, 2020). Chatbot dialogues, mimicking human-human interactions, can result in higher communication quality, customer satisfaction, and social reactions (Edwards, Beattie, Edwards, & Spence, 2016; Mou & Xu, 2017; Verhagen et al., 2014). This is due to people reinforcing conversational norms from interpersonal communication onto chatbot communication, personifying the technology (Taddei & Contena, 2013). Interactivity of chatbots has been empirically examined to positively affect attitudes, customer satisfaction, brand engagement, willingness to use, and purchase intention (Chung et al., 2020; Ciechanowski et al., 2019; Ischen et al., 2020; Luo et al., 2019; Marinova et al., 2017; Toader et al., 2020). Chatbots with conversational interfaces and humanness cues were found to draw stronger user attention and engagement (Araujo, 2018; Go & Sundar, 2019; Wargnier et al., 2015). Users tend to perceive a higher cognitive fit with the virtual agent when it offers suggestive guidance and interacts with them in a conversational style (Chen et al., 2021). Empirically, previous research identified a significant increase in satisfaction among customers when online banking services became more responsive (Hammoud et al., 2018). In the social media industry, Twitterbot services successfully interacted with customers in conversations and built customer satisfaction through computer-mediated communication (Business Insider Intelligence, 2016).

In sum, when chatbot agents have open, responsive, dialogic conversations with customers, the level of chatbot use satisfaction can be relatively high amongst customers. Thus, based on SET, RET, and the aforementioned research findings on chatbots, H1 and H2 were proposed as follows:

H1. Responsiveness in dialogic chatbot communication is positively related to customers' satisfaction with chatbot services of an organization.

H2. A conversational tone in dialogic chatbot communication is positively related to customers' satisfaction with chatbot services of an organization.

Customers' social media engagement. As customers' experiences with products and services are increasingly shared on digital media platforms, business and social media researchers have started to study their online engagement (Habibi et al., 2014; Strauss & Frost, 2014; Zaglia, 2013). Customers may establish a network of relationships or form an organization-specific community with fellow customers and even marketers on social networks (Baldus et al., 2015). Recent scholarship examining online brand community engagement suggested that customers' engagement with an organization, for instance, communication with an organization's chatbot service agent and their interactive experience with other customers in the same social media community, reflects their experience with the organization's business performance and communication (Chiang et al., 2017).

Brodie et al.'s (2013) online brand community engagement model consists of multiple sub-processes of learning, sharing, advocating, socializing, and co-developing. By applying this model, we studied how customers' social media engagement behaviors are related to chatbot use experiences with an organization. Through *learning* from others, customers can acquire useful information about an organization's chatbot services, gain something new or interesting, and possibly share the values of other customers. Customers using an organization's chatbot services also *share* relevant information and experience about chatbot use to contribute to knowledge creation in the social media community. *Advocating* occurs when customers actively recommend an organization's chatbot services to others. *Socializing* denotes non-transactional interactions between customers, for instance, interacting or getting connected with other customers using the same chatbot services. These interactions can develop attitudes, build norms, and even establish a community language. Finally, *co-developing* refers to a process in which customers can contribute new information and innovative ideas to further the popularity, development, or improvement of an organization's chatbot services. When the level of customers' social media engagement is high, it may enhance loyalty and satisfaction toward an organization, customer empowerment, emotional bonding amongst fellow customers, and commitment to the online community and the organization (Brodie et al., 2013; Chiang et al., 2017; Jaakkola & Alexander, 2014).

Customers' social media engagement as an outcome of satisfaction with chatbot services. The proposed path between customer satisfaction and social media engagement also resonates with social exchange theory (SET) and resource exchange theory (RET) which imply that customers with similar reciprocal motivations are inclined to exchange resources including services, once they perceive the resources as appropriate for an exchange (Foa & Foa, 1971). When customers are satisfied with services after estimating associated benefits, they tend to engage in reciprocal actions of sharing knowledge as well as communicating, exchanging, and learning information in online communities (Davenport et al., 1998; Greenberg et al., 2013). These reciprocal actions correspond to social media engagement processes—learning, sharing, advocating, socializing, and co-developing. Although these theories have been applied to explain exchange motivations for online group buying and crowdsourcing (Greenberg et al., 2013; Shiau & Luo, 2012), they have not been extensively examined in relation to chatbot information exchange on social media, which attests to the significance of the present study.

Customer satisfaction has been found to elicit customer behaviors on social media (Casaló et al., 2011; 2017b). New technology engagement was motivated by satisfying customers' needs (Edvardsson et al., 2011; Kim et al., 2013). For instance, satisfaction with smartphone engagement provided value for customers to continue engaging on mobile devices (Harter et al., 2004). The overall satisfaction of customer services was essential for successful mobile or digital media engagement including feedback, influencer, and continuance intention behaviors (Carlson et al., 2019). In online brand communities, customer satisfaction was positively related to engagement behaviors such as providing feedback, recommendations, and assistance to other customers (Zhu et al., 2016). Satisfaction was the strongest predictor of continued and frequent use of social media which cultivated social media users' relationships with their virtual communities (Bhattacherjee, 2001). Customer characteristics—user satisfaction, brand commitment, and brand attachment—were antecedents to customer engagement (van Doorn et al., 2010). Furthermore, drawing upon the uses and gratification theory, researchers revealed that satisfaction motivated users to engage more by following other social media accounts and interacting with other social media users (Casaló et al., 2017a, 2017b). Although the existing social media research tested the positive relationship between satisfaction and engagement (Bowden, 2009; Kumar & Pansari, 2016; Mazzarolo et al., 2021), limited attention has been dedicated to exploring social media engagement pertaining to chatbot services. For example, customers' dissatisfaction with chatbot services can induce negative word-of-mouth (WOM) (Um et al., 2020). WOM is often considered an example of customer engagement since it involves active participation and co-creation in brand communities (Brodie et al., 2011; Hollebeek et al., 2014).

Applying SET, RET, and the aforementioned empirical evidence, we proposed the following hypothesis:

H3. Customers' satisfaction with chatbot use is positively associated with their social media engagement to promote an organization's chatbot services, including learning, sharing, socializing, advocating, and co-developing.

Price premium and purchase intention. As one of the most researched areas in the field of business communication and marketing, customer behavior is "concerned with all activities directly involved in obtaining, consuming and disposing of products and services, including the decision processes that precede and follow these actions" (Engel et al., 1995, p. 4; Kim & Ko, 2010; Laroche et al., 2013; Verma et al., 2012). In this study, we focused on two key indicators of customer behavior—price premium and purchase intention (Schnebelen & Bruhn, 2018; Zhang et al., 2018). Price premium refers to the price that a customer is willing to pay for the preferred brand over other competing brands of the same size and quantity (Netemeyer et al., 2004). Some scholars perceived price premium as an indicator of brand strength and shareholder value (Ba & Pavlou, 2002; Netemeyer et al., 2004; Yoo & Donthu, 2001). A more prevalent way of understanding price premium is brand equity, as some scholars considered price premium a way to measure brand equity (Aaker, 1996; Farquahar, 1989). Purchase intention, however, predicts customers' future behavior based on their attitudes toward organizations, which considers customers' current interests and possibilities of buying products or services in the future (Kim et al., 2010).

Effects of customers' social media engagement on price premium and purchase intention. Social exchange theory (SET) states that individuals and organizations intend to interact in a way to maximize rewards and minimize costs associated with their behaviors (Salam et al., 1998). Resource exchange theory (RET) was developed to account for reciprocal social interactions of humans—People exchange six distinct categories of resources, including love, status, information, money, goods and services (Foa & Foa, 1971). Motivated by the theories, researchers have examined the impact of knowledge (or information) sharing in virtual communities on online group buying intentions (Shiau & Luo, 2012; Tsai et al., 2011). Key tenets of the knowledge sharing model include—(1) Expectations (e.g., rewards, social associations, and contributions) and anticipations (e.g., extrinsic rewards and reciprocal relationships) determine people's knowledge or information sharing behaviors in virtual communities; (2) the motives—expectations and anticipations—can be both egoistic and altruistic; (3) and in the exchange of information, interaction, and sharing in virtual communities, people believe they obtain benefits from the exchange and are also willing to increase the welfare of others without expecting personal returns; and (4) knowledge sharing factors rooted in expectations and anticipations influence people's attitudes and behavioral intentions (Shiau & Luo, 2012, p. 2432).

The knowledge sharing factors—altruism, expected reciprocal benefit, reputation, trust, and expected relationship—contributed significantly to blog users' positive attitudes toward their blog communities (Hsu & Lin, 2008). Another key knowledge sharing factor—the sense of virtual community—was found to predict customers' online group buying intention (Tsai et al., 2011). Extending SET, RET, and the knowledge sharing model in our chatbot research, we predicted a significant positive relationship between customers' online engagement behavior toward chatbot services (i.e., learning, sharing, socializing, advocating, and co-developing) and customer behavior (i.e., price premium and purchase intention).

Electronic word-of-mouth (eWOM), a part of the sharing and advocating dimensions of social media engagement, could predict willingness to pay a price premium (Torres et al., 2018). Customers' engagement in an organization's activities on social media, namely, eWOM, compelled them to have a strong identification of self with the organization, thereby resulting in their lower sensitivity to price changes and willingness to pay a premium price (Keh & Xie, 2009; Torres et al., 2018). In addition, in a survey study, a positive association was demonstrated between customers' social media engagement and their willingness to pay a price premium for their preferred organizations (Yazdanparast et al., 2016).

Engagement comprehensively embraces the concept of co-creative, interactive experiences, which sets engagement apart from other relational concepts, such as involvement and participation (Brodie et al., 2011; Hollebeek et al., 2007; van Doorn et al., 2010). In the new media environment, such engagement takes place on social media where customers proactively co-create their experiences and values via dialogue (Vargo & Lusch, 2004, 2008). In other words, an organization's value is now being co-created through network relationships and interactions among customers (Merz et al., 2009). This change reinforces the critical role of social media in facilitating community building and active customer engagement, which empowers customers to influence organizations' values and equity (Hutter et al., 2013). Co-creative customer experiences with an organization or a product were also found to affect a stronger relationship between customers and organizations by evoking favorable relational and behavioral outcomes such as purchase intention (Brodie et al., 2011, 2013; Kull & Heath, 2016). For instance, customers with higher engagement with a product's Facebook page demonstrated higher purchase intention (Hutter et al., 2013).

Purchase intention denotes the mental stage in the decision-making process, which reflects the intention to take actions toward a product or an organization (Dodds et al., 1991; Wells et al., 2011). Hence, customers involved in the active co-creating process on social media tend to have regular contact with an organization and therefore, are more likely to repurchase its products due to the strong organization-customer relationship (Jahn & Kunz, 2014). Furthermore, active customers are able to build brand power by promoting brand awareness and stimulating purchases (Rahman et al., 2018). Other studies also revealed that customers with more active communal engagement and interactions on social media were more inclined to not only purchase the products or services promoted in the communities but also trigger purchase intention within the communities by actively making recommendations (Cheung et al., 2015; Hsu, 2017). Active social media engagement fosters customer loyalty, which often leads to sustained repurchases of a product (Hsu, 2017; Tregua et al., 2013). Other scholars operationalized social media engagement as the number of likes, shares, and comments and tested its positive effect on purchase intention (Mahrous & Abdelmaaboud, 2017). For example, customers' digital visual engagement, such as liking and following products' image-based contents on Instagram, predicted their purchase intention toward those products (Valentini et al., 2018).

Price premium intention can be defined as the degree of willingness to which customers would pay without affecting their purchasing decisions (Suha & Sharif, 2018). Applying the theory of planned behavior (TPB) to examine price premium, researchers studied customers' willingness to pay a price premium for ecotourism (Hultman et al., 2015). The study concluded that customers' purchase intention was the strongest predictor of premium price intention. Extending the above research to businesses that provide customers AI-enabled chatbot communication services, we investigated whether customers' solid purchase intention would affect their perception of price premium.

Based on the above theory discussions and reviewed literature, we expected customers' social media engagement to have a positive and direct influence on their willingness to pay a premium price and purchase intention. Purchase intention is also a significant predictor of price premium intention. H4, H5, and H6 were then posited as follows:

H4. Customers' social media engagement is positively related to price premium.

H5. Customers' social media engagement is positively related to purchase intention.

H6. Customers' purchase intention is positively associated with their price premium intention.

All reviewed prior studies demonstrated that an organization's dialogic chatbot communication—responsiveness and a conversational tone—can have a significant positive influence on customer behavior via satisfaction with chatbot services and customers' social media engagement as mediators. In other words, dialogic chatbot communication induces higher satisfaction and social media engagement from customers, which can eventually lead to higher price premium and purchase intention (Go & Sundar, 2019; Mimoun et al., 2017; Nguyen et al., 2021; Shumanov & Johnson, 2021; Torres et al., 2018). In previous chatbot studies, customer satisfaction was corroborated to mediate the positive effects of chatbot gratifications and chatbot attitudes on behavioral intentions (Cheng & Jiang, 2020; Moriuchi et al., 2019). Customers' brand engagement was also found to mediate the positive relationship between chatbots' attributes and behavioral intentions (McLean et al., 2021). Hence, considering the above-mentioned relationships among chatbots' dialogic features, user satisfaction, social media engagement, and customer behavior as well as the empirical findings on mediating effects of satisfaction and engagement in the chatbot context, we proposed a mediation hypothesis as follows:

H7. Customers' satisfaction with chatbot services and their social media engagement mediate the positive relationship between dialogic chatbot communication (i.e., responsiveness and a conversational tone) and customer behavior (i.e., price premium and purchase intention) (See Fig. 1).

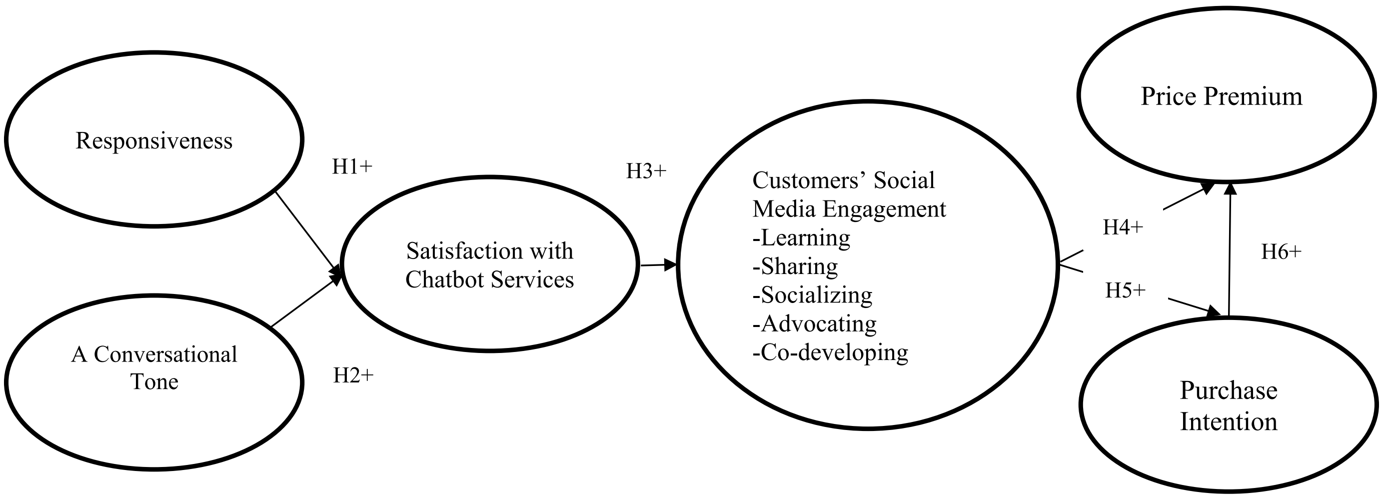

Fig. 1. Conceptual Model. Note: H7 is the hypothesis about the mediation effects in the model.

3. Method

3.1. Procedures for data collection

After receiving IRB's approval for conducting the present research, the authors created a Qualtrics survey and collected data through Amazon Mechanical Turk (MTurk) in December 2018. Only participants who lived in the U.S. were recruited as this study focused on the chatbots that organizations in the U.S. used to communicate with their customers. Data collected via Mturk are strong in quality because it randomly selects participants across key demographic and psychographic variables (Ross et al., 2010). More than 100,000 respondents from more than 100 countries participated in MTurk survey daily (Buhrmester et al., 2011). Previous literature has also uncovered no significant difference between an MTurk sample and other samples including those drawn from a panel or a student subject pool (Kees et al., 2017). Our Qualtrics survey recorded 965 valid responses. Each participant who completed the survey was rewarded 1 US dollar as compensation.

Before participants started with the main questions of our survey, instructions were given to explain what chatbots referred to in our study— "A chatbot (also known as smartbots, talkbot, chatterbot, Bot, IM bot, interactive agent, Conversational Interface, or Artificial Conversational Entity) is a computer program or artificial intelligence, which conducts a conversation via auditory or textual methods." We also provided some real-life examples to help participants understand what apps, websites, or platforms were considered an organization's AI-powered chatbot services in our study. Participants were asked to select one organization from a list of 30[1] based on if they had used the organization's chatbot services before and if they felt most confident answering questions about the services at the time of data collection. Considering no list was completely exhaustive, we also allowed participants to identify an organization that was not included in the list of 30. They were instructed to do so if they believed they were more knowledgeable about their own identified organization's chatbot services.

3.2. Sample characteristics

The mean age of our 965 participants (46.3% male, n = 447; 52.8% female, n = 510; 0.4% other, n = 4; 0.4% prefer not to answer, n = 4) was 36.03 (*SD* = 11.13). In terms of race/ethnicity, 70.2% of the participants self-identified as Caucasian/White (non-Hispanic) (n = 677), and 12.3% of them reported as Black/African American (non-Hispanic) (n = 119), with 7.8% as Asian American/Pacific Islander (n = 75), 6.3% as Latino/Hispanic Native (n = 61), 1.9% as American/American Indian (n = 18), and 1.6% as other (n = 15). A total of 216 participants (22.4%) reported their annual household income range as $20,001 to $40,000, followed by $40,001 to $60,000 (n = 197; 20.4%), $60,001 to $80,000 (n = 192; 19.9%), $100,001 and higher (n = 120; 12.4%), $80,001 to $100,000 (n = 112; 11.6%), $20,001 or under (n = 110; 11.4%), and prefer not to say (n = 18; 1.9%). As for participants' highest level of education, three largest groups included 420 Bachelor's degree in college (4-year) (43.5%), 180 some college but no degree (18.7%), and 136 Master's degree (14.1%). The top three corporate Chatbot services that participants selected included Bank of America (n = 119; 12.3%), Microsoft (n = 110; 11.4%), and PayPal (n = 73; 7.6%). See the complete participants' profile in Table 1.

3.3. Independent and dependent measures

All items adopted to measure the variables in our hypotheses used a seven-point Likert-type scale (i.e., "strongly disagree" = 1 to "strongly agree" = 7) (see Table 3). We adapted 10 questions from Sweetser and Kelleher (2016) and Yang and Lim (2009) to measure participants' perceived dialogic chatbot communication with their selected organization. This included five items for responsiveness ($\alpha = 0.88$) and five items for a conversational tone ($\alpha = 0.85$). We adopted five survey items from Chung et al. (2020) to assess participants' satisfaction with their selected organization's chatbot services. They demonstrated high reliability ($\alpha = 0.95$). We used a 15-item scale to measure customers' social media engagement behavior ($\alpha = 0.97$), consisting of five dimensions: learning ($\alpha = 0.90$), sharing ($\alpha = 0.94$), advocating ($\alpha = 0.94$), socializing ($\alpha = 0.91$), and co-developing ($\alpha = 0.88$) (Brodie et al., 2013; Lim & Jiang, 2020). We also used 6 items from previous research (Godey et al., 2016) to measure price premium ($\alpha = 0.89$) and purchase intention ($\alpha = 0.83$).

[1] All 30 corporations are Fortune 500 brands & businesses and were included in a list of top 100 Best Bots that have led their industries in bot innovation (https://www.topbots.com/100-best-bots-brands-businesses/). The list was grouped by industries—Beauty, Consumer Goods, Entertainment, Fashion, Finance, Food & Beverage, Health, Insurance, Media & Publishers, Real Estate, Retail & E-Commerce, Social Good, Sports, Travel & Hospitality, Automotive, Utilities, and other. We selected representative brands from the aforementioned industry sectors, including 1-800-FLOWERS, Airbnb, Bank of America, Burger King, Disney, Domino's Pizza, eBay, Expedia, Fandango, Fitbit, H & M, HealthTap, Hellmann's and Best Foods, Lyft, Microsoft, Nordstrom, Macy's, PayPal, Pizza Hut, Sephora, Starbucks, Staples, Taco Bell, Trulia, Uber, UPS, Victoria's Secret, and Whole Foods.

Table 1
Participant profile for the study (n = 965).

Sample Characteristics		Valid n Sample	Valid % Sample
Gender		965	100.0%
	Male	447	46.3
	Female	510	52.8
	Other	4	.4
	Prefer not to answer	4	.4
Age		965	
	Mean = 36.03; SD = 11.13		
Race/Ethnicity		965	100.0%
	Black/African American (non-Hispanic)	119	12.3
	Asian American/Pacific Islander	75	7.8
	Caucasian/White (non-Hispanic)	677	70.2
	Latino/Hispanic Native	61	6.3
	American/American Indian	18	1.9
	Other	15	1.6
Annual Household Income		965	100.0%
	$20,000 or under	110	11.4
	$20,001 to $40,000	216	22.4
	$40,001 to $60,000	197	20.4
	$60,001 to $80,000	192	19.9
	$80,001 to $100,000	112	11.6
	$100,001 and higher	120	12.4
	Prefer not to say	18	1.9
Highest Level of Education		965	100%
	Less than high school degree	7	.7
	High school graduate (high school diploma or equivalent including GED)	78	8.1
	Some college but no degree	180	18.7
	Associate degree in college (2-year)	123	12.7
	Bachelor's degree in college (4-year)	420	43.5
	Master's degree	136	14.1
	Doctoral degree	21	2.2
Companies' Chatbot Services/Brand Selected		965	100.0%
	1-800-FLOWERS	18	1.9
	Airbnb	35	3.6
	Bank of America	119	12.3
	Burger King	17	1.8
	Disney	28	2.9
	Domino's Pizza	60	6.2
	eBay	58	6.0
	Expedia	35	3.6
	Fandango	9	0.9
	Fitbit	17	1.8
	H & M	10	1.0
	HealthTap	2	.2
	Hellmann's and Best Foods	1	.1
	Lyft	11	1.1
	Microsoft	110	11.4
	Nordstrom	15	1.6
	Macy's	15	1.6
	PayPal	73	7.6
	Pizza Hut	31	3.2
	Sephora	11	1.1
	Starbucks	22	2.3
	Staples	4	.4
	Taco Bell	6	.6
	Trulia	5	.5
	Uber	40	4.1
	UPS	59	6.1
	Victoria's Secret	12	1.2
	Whole Foods	3	.3
	Other	139	14.4

Table 2
Descriptive statistics (alpha, mean, standard deviation, and correlations) (n = 965).

	Alpha	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11
1	.88	5.05	1.12	1										
2	.85	4.90	1.10	.72**	1									
3	.95	5.21	1.29	.73**	.65**	1								
4	.90	4.49	1.52	.44**	.49**	.49**	1							
5	.94	4.25	1.70	.37**	.43**	.40**	.75**	1						
6	.94	3.92	1.71	.34**	.40**	.38**	.74**	.80**	1					
7	.91	3.97	1.65	.47**	.51**	.53**	.71**	.71**	.75**	1				
8	.88	4.05	1.55	.34**	.40**	.40**	.72**	.76**	.80**	.78**	1			
9	.97	4.13	1.46	.44**	.50**	.49**	.87**	.90**	.92**	.88**	.90**	1		
10	.89	4.24	1.55	.36**	.40**	.43**	.46**	.46**	.51**	.56**	.48**	.55**	1	
11	.83	5.26	1.15	.50**	.50**	.57**	.43**	.38**	.34**	.42**	.36**	.43**	.58**	1

Note. **Correlation is significant at $p < .01$ (2-tailed). *Correlation is significant at $p < .05$ (2-tailed).
1 = Responsiveness; 2 = A Conversional Tone; 3 = Satisfaction with Chatbot Services; 4 = Learning; 5 = Sharing; 6 = Socializing; 7 = Advocating; 8 = Co-Developing; 9 = Engagement; 10 = Price Premium; 11 = Purchase Intention.

Table 3
Results of the measurement model, AVE & CR (n = 965).

Factors/Latent Variables		Indicators/Scale items	Loadings	AVE & CR
Dialogic chatbot Communication-Responsiveness		This company's chatbot service agent provides prompt feedback to customers' comments.	.70***	(AVE = .57 CR = .87)
		This company's chatbot service agent makes an adequate change based on customers' feedback.	.75***	
		This company's chatbot service agent addresses customers' complaints in a timely manner.	.77***	
		This company's chatbot service agent is sensitive to customers' needs at the moment.	.77***	
		This company's chatbot service agent addresses customers' complaints positively.	.79***	
Dialogic chatbot Communication-A Conversational Tone		This company's chatbot service agent treats its customers as real communication partners.	.76***	(AVE = .52 CR = .84)
		This company's chatbot service agent respects customers' perspectives or opinions.	.74***	
		This company's chatbot service agent avoids dominating the conversation with customers.	.62***	
		This company's chatbot service agent invites customers to an open dialogue.	.73***	
		This company's chatbot service agent tries to establish a common ground of understanding with customers.	.74***	
Satisfaction with chatbot Services		I am satisfied with the chatbot service agent.	.91***	(AVE = .78 CR = .95)
		I am content with the chatbot service agent.	.92***	
		The chatbot service agent did a good job.	.89***	
		The chatbot service agent did what I expected.	.78***	
		I am happy with the chatbot service agent.	.90***	
Customers' Social Media Engagement (AVE = .83 CR = .96)	Learning (.87***)	Based on your interactions with the selected company's chatbot service agent, please indicate how likely you would conduct the actions below on social media (e.g., Facebook, Twitter, Instagram, etc.).	.88***	(AVE = .74 CR = .90)
		I would get useful information from other users of this company's chatbot services.		
		Get to learn something new or interesting from other users of this company's chatbot services.	.92***	
		Take the opinions of other users of this company's chatbot services seriously.	.78***	
	Sharing (.90***)	Share information about the company's chatbot services with other customers of the company.	.94***	(AVE = .84 CR = .94)
		Share chatbot service agent-related experiences with other customers of the company.	.92***	
		Share my opinions about the company's chatbot services with other uses.	.89***	
	Socializing (.93***)	Interact with other users of the company's chatbot services.	.90***	(AVE = .83 CR = .94)
		Connect myself to other users of the company's chatbot services.	.93***	
		Get to know people through talking about the company's chatbot services.	.90***	
	Advocating (.93***)	Tell others who do not already engage with the company how good the company's chatbot services are.	.82***	(AVE = .72 CR = .88)
		Click "Like" for information about the company's chatbot services if the company promotes such information, for instance, on its Facebook page.	.84***	
		Click "Like" for this company's chatbot services to talk them up to other customers.	.88***	
	Co-Developing (.93***)	Interact with other users of the company's chatbot services to discuss how the services can be further improved.	.82***	(AVE = .72 CR = .89)
		Respond to questions or comments of other users of the company's chatbot services.	.85***	
		Contribute to the online community that users of the company's chatbot services form by adding useful information.	.88***	
Price Premium		I am willing to pay more money for this brand products/services than for other competing brands.	.85***	(AVE = .69 CR = .87)
		I am willing to pay a higher price for this brand than for other brands.	.84***	
		The price of this brand would have to increase quite a bit before I would switch to another brand.	.80***	
Purchase Intention		I intend to keep purchasing products/services from this brand.	.63***	(AVE = .59 CR = .81)
		I would strongly recommend others to use products/services from this brand	.80***	
		I would expand to using other products/services of the brand.	.85***	

Note. $\chi^2 = 1689.34$, df = 558, $\chi^2/df = 3.03$, SRMR = 0.05, RMSEA = 0.046 [90% CI = 0.043-0.048], CFI = 0.96, TLI = 0.96, n = 965; AVE = Average Variance Extracted; CR = composite reliability; ***$p < .001$.

3.4. Data Analysis

Structural equation modeling (SEM) with Mplus was used for data analysis. The analysis of our proposed model followed a two-step latent variable SEM modeling approach: (1) Step 1 assessed the construct validity of the measurement model using Confirmatory Factor Analysis (CFA); (2) Step 2 analyzed the relationships among variables in the structural model.

To determine the data-model fit in the analyses, we followed the proposed criteria of Hu and Bentler (1999): Comparative Fit Index (CFI) ≥ 0.96 and Standardized Root Mean Square Residual (SRMR) ≤ 0.10 or Root Mean Square Error of Approximation (RMSEA) ≤ 0.06 and SRMR ≤ 0.10).

4. Results

4.1. Preliminary data analyses

Descriptive statistics. Given that a seven-point Likert-type scale (e.g., 1 = Strongly Disagree to 7 = Strongly Agree) was used to measure dialogic chatbot communication, chatbot use satisfaction, customers' social media engagement, price premium, and purchase intention, we used "low (1.00–2.50)," "moderately low (2.51–3.99)," "neutral (4)," "moderately high (4.01–5.49)," and "high (5.50–7.00)" as categories to evaluate the values of the variables. The results of the descriptive analysis indicated that overall, participants perceived moderately high levels of dialogic chatbot communication with their selected organization ($M_{\text{responsiveness}} = 5.05$, $SD = 1.12$; $\text{M}_{\text{a conversational tone}} = 4.90$, $SD = 1.10$). Participants also perceived a moderately high level of satisfaction with using their selected organization's chatbot services ($M_{\text{satisfaction with chatbot services}} = 5.21$, $SD = 1.29$). In addition, participants reported moderately high levels of customers' social media engagement behavioral intentions ($M_{\text{social media engagement}} = 4.13$, $SD = 1.46$; $M_{\text{learning}} = 4.49$, $SD = 1.52$; $M_{\text{sharing}} = 4.25$, $SD = 1.70$; $M_{\text{advocating}} = 3.92$, $SD = 1.71$; $M_{\text{socializing}} = 3.97$, $SD = 1.65$; $M_{\text{co-developing}} = 4.05$, $SD = 1.55$). Finally, participants demonstrated moderately high levels of customer behavior toward their selected organization too ($M_{\text{price premium}} = 4.24$, $SD = 1.55$; $M_{\text{purchase intention}} = 5.26$, $SD = 1.15$). Correlations between the factors in our proposed model ranged from 0.36 to 0.73 ($p < .01$; see Table 2).

Tests on control variables. Former chatbot studies controlled age, gender, and education, assuming that new media technology adoption and chatbot acceptability can differ across different demographic groups due to the digital divide (Adam et al., 2021; Huang & Chueh, 2021; Kasilingam, 2020; Manal, 2021; Miles, 2020). Age, gender, and education were also empirically found to affect attitudes and intentions to use chatbots (Kontos et al., 2014; Nadarzynski et al., 2019). In addition, chatbot use frequency was controlled, as prior chatbot knowledge (Laumer et al., 2019), prior chatbot service experience (Kasilingam, 2020), and frequency of the Internet usage (Kontos et al., 2014) were revealed to influence chatbot attitudes and intentions to use chatbots. Lastly, organization-specific factors such as the selected organization and participants' use frequency and use satisfaction toward the products and services of their selected organization were controlled to prevent respondents' prior perceptions, attitudes, and experiences from exerting confounding effects (Kim et al., 2004; Shao et al., 2020; Tsiotsou, 2006). Results of a series of hierarchical linear regression analyses also uncovered the significant predictors for all the latent variables in our proposed model: age, gender, the highest level of education, selected organization, frequency of using a corporate chatbot service, frequency of using the products/services from the selected organization, and satisfaction with using the products/services from the selected organization. Based on both the related prior literature and results of the preliminary analyses, we controlled the aforementioned variables in running our SEM model. They all turned out to be significant predictors[2] in our SEM analysis results (see Table 4). Some of the predictors are much more significant than others, for instance, brand use satisfaction—$\beta_{\text{brand use satisfaction-} > \text{responsiveness}} = .31$, SE = 0.04, $p < .001$ (BC 95% CI: 0.24 to 0.38); $\beta_{\text{brand use satisfaction->} \text{ a conversational tone}} = 0.31$, SE = 0.04, $p < .001$ (BC 95% CI: 0.24 to 0.38); and $\beta_{\text{brand use satisfaction-> purchase intention}} = .33$, SE = 0.04, $p < .001$ (BC 95% CI: 0.26 to 0.40).

4.2. Measurement Model/CFA analysis results

Consistent with prior literature, chatbot users' social media engagement formed a second-order construct with its underlying first-order factors. Our CFA model achieved good data-model fit ($\chi^2 = 1689.34$, df = 558, χ^2/df = 3.03, SRMR = 0.05, RMSEA = 0.046 [90% CI = 0.043-0.048], CFI = 0.96, TLI = 0.96, n = 965). Moreover, average variance extracted (AVE) and composite reliability (CR) values were computed to evaluate discriminant validity and internal consistency of the measures. See more details of the measurement model in Table 3.

4.3. Findings of hypothesis testing

The hypothesized structural model demonstrated good fit with the collected data: $\chi^2 = 2203.43$, df = 795, χ^2/df = 2.77, SRMR = 0.06, RMSEA = 0.043 [90% CI = 0.041-0.045], CFI = 0.96, TLI = 0.95; n = 965 (see Fig. 2).

Direct effects. As hypothesized in H1, a strong positive effect of responsiveness in dialogic chatbot communication upon customers' satisfaction with the selected organization's chatbot services was observed [$\beta_{\text{responsiveness-} > \text{satisfaction with chatbot services}} = 0.61$, SE = 0.06, $p < .001$ (BC 95% CI: 0.48 to 0.73), H1 supported]. Second, a conversational tone in dialogic chatbot communication had a positive and direct effect on customers' satisfaction with the selected organization's chatbot services as well [$\beta_{\text{a conversational tone-} > \text{satisfaction with chatbot services}} = 0.18$, SE = 0.07, $p < .01$ (BC 95% CI: 0.04 to 0.31), H2 supported]. Consistent with the prediction in H3, a positive effect of customers' satisfaction with the selected organization's chatbot services on customers' social media engagement was uncovered [$\beta_{\text{satisfaction with chatbot services-} > \text{customers' social media engagement}} = 0.55$, SE = 0.03, $p < .001$ (BC 95% CI: 0.49 to 0.60), H3 supported]. Customers' social media engagement had an additional positive and direct effect on customers' price premium [$\beta_{\text{customers' social media engagement-} > \text{price premium}} = .34$, SE = 0.04, $p < .001$ (BC 95% CI: 0.25 to 0.42), H4 supported] and purchase intention [$\beta_{\text{customers' social media engagement-} > \text{purchase intention}} = .54$, SE = 0.04, $p < .001$ (BC 95% CI: 0.47 to 0.61), H5 supported]. Finally, as predicted in H6, purchase intention had a significant positive effect on price premium [$\beta_{\text{purchase intention-} > \text{price premium}} = .53$, SE = 0.05, $p < .001$ (BC 95% CI: 0.44 to 0.62), H6 supported].

Indirect effects for H7. Results of the mediation tests with a bias-corrected bootstrapping procedure ($N = 5000$ samples) indicated that customers' satisfaction with chatbot services and their social media engagement were significant mediators in our proposed model (see the complete results in Table 4). For instance, satisfaction with chatbot services significantly mediated the relationship between responsiveness

[2] A Likert-type scale ranging from 'Strongly Disagree (coded as 1)' to 'Strongly Agree (coded as 7)' was used to measure dialogic chatbot communication, chatbot use satisfaction, customers' social media engagement, price premium, and purchase intention in our proposed model. We also used reverse coding as a validation technique to rephrase some survey items to check if our participants were paying attention and giving consistent answers in filling out our questionnaire. For instance, chatbot use frequency and brand use frequency were measured on a scale ranging from 'Every Time (coded as 1)' to 'Never (coded as 7).'

Table 4
Results of mediation analysis with structural equation modeling (n = 965).

Structural equation model (Direct effects)				BC 95% CI	
Paths	Estimate	S.E.	Z	Lower	Upper
H1: Responsiveness→Satisfaction with Chatbot Services	.61	.06	9.69***	.48	.73
H2: A Conversational Tone→ Satisfaction with Chatbot Services	.18	.07	2.63**	.04	.31
H3: Satisfaction with Chatbot Services→Customers' Social Media Engagement	.55	.03	19.32***	.49	.60
H4: Customers' Social Media Engagement→Price Premium	.34	.04	7.88***	.25	.42
H5: Customers' Social Media Engagement→Purchase Intention	.54	.04	15.02***	.47	.61
H6: Purchase Intention→Price Premium	.53	.05	11.26***	.44	.62
Control variables					
Paths	Estimate	S.E.	Z	BC 95% CI Lower	Upper
Chatbot Use Frequency→Responsiveness	-.09	.04	−2.40*	-.16	-.02
Brand Use Frequency→Responsiveness	-.11	.04	−3.12**	-.18	-.04
Brand Use Satisfaction→Responsiveness	.31	.04	8.94***	.24	.38
Chatbot Use Frequency→A Conversational Tone	-.16	.04	−4.29***	-.23	-.09
Brand Use Frequency→A Conversational Tone	-.10	.04	−2.60**	-.17	-.02
Brand Use Satisfaction→A Conversational Tone	.31	.04	8.77***	.24	.38
Brand Name→Satisfaction with Chatbot Services	-.06	.03	−2.52*	-.10	-.01
Chatbot Use Frequency→Satisfaction with Chatbot Services	-.07	.02	−2.90**	-.11	-.02
Brand Use Satisfaction→Satisfaction with Chatbot Services	.11	.03	4.37***	.06	.16
Brand Name→Customers' Social Media Engagement	-.16	.03	−5.46***	-.21	-.10
Age→Customers' Social Media Engagement	-.07	.03	−2.41*	-.13	-.01
Education→Customers' Social Media Engagement	-.07	.03	−2.69**	-.13	-.02
Chatbot Use Frequency→Customers' Social Media Engagement	-.19	.03	−6.63***	-.25	-.14
Age→Price Premium	-.12	.03	−4.40***	-.17	-.06
Brand Use Frequency→Price Premium	-.05	.03	−1.70*	-.10	-.01
Gender→Purchase Intention	.05	.03	1.72*	-.01	.11
Age→Purchase Intention	.05	.03	1.72*	-.01	.11
Chatbot Use Frequency→Purchase Intention	.08	.04	2.17*	.01	.16
Brand Use Frequency→Purchase Intention	-.17	.04	−4.66***	-.24	-.10
Brand Use Satisfaction→Purchase Intention	.33	.04	9.16***	.26	.40
Mediation analysis					
Paths	Estimate	S.E.	Z	BC 95% CI Lower	Upper
Responsiveness→Satisfaction with Chatbot Services→Customers' Social Media Engagement	.34	.04	8.52***	.26	.42
A Conversational Tone→Satisfaction with Chatbot Services→ Customers' Social Media Engagement	.10	.04	2.58**	.03	.17
Responsiveness→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Price Premium	.11	.02	5.87***	.08	.15
A Conversational Tone→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Price Premium	.03	.01	2.37*	.01	.06
Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Price Premium	.19	.03	7.07***	.14	.24
Responsiveness→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention	.18	.03	6.86***	.13	.24
Responsiveness→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention→Price Premium	.10	.02	5.96***	.07	.13
A Conversational Tone→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention	.05	.02	2.51*	.01	.10
A Conversational Tone→Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention→Price Premium	.03	.01	2.52*	.01	.05
Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention	.30	.03	10.16***	.24	.35
Satisfaction with Chatbot Services→ Customers' Social Media Engagement→Purchase Intention→Price Premium	.16	.02	8.22***	.12	.20
Chatbot Users' Social Media Engagement→Purchase Intention→Price Premium	.29	.03	9.69***	.23	.35

Note: $\chi^2 = 2203.43$, df = 795, χ^2/df = 2.77, SRMR = 0.06, RMSEA = 0.043 [90% CI = 0.041-0.045], CFI = 0.96, TLI = 0.95; n = 965. BC 95% CI: Bias-corrected 95% bootstrapped confidence interval (CI) based on 5000 resamples. *$p < .05$, **$p < .01$, ***$p < .001$.

and customers' social media engagement [$\beta = .34$, SE = 0.04, $p < .001$ (BC 95% CI: 0.26 to 0.42)]; customers' social media engagement mediated the relationship between satisfaction with chatbot services and price premium [$\beta = .19$, SE = 0.03, $p < .001$ (BC 95% CI: 0.14 to 0.24)] as well as that between satisfaction with chatbot services and purchase intention [$\beta = 0.30$, SE = 0.03, $p < .001$ (BC 95% CI: 0.24 to 0.35)].

5. Discussion and implications

Drawing upon literature in business, marketing, and social media and digital communication, the present study examined the relationships among responsiveness and a conversational tone in organizations' dialogic chatbot communication, customers' chatbot use satisfaction, customers' social media engagement, and their price premium and purchase intentions. We surveyed 965 customers living in the U.S. who have used any chatbot services from 30 Fortune 500 organizations included in a list of 100 best bots for brands & businesses (https://www.topbots.com/100-best-bots-brands-businesses/). Results of our SEM analysis indicated that responsiveness and a conversational tone, as key components of dialogic chatbot communication, had significant direct effects on customers' satisfaction with chatbot services, along with indirect effects on social media engagement, price premium, and purchase intention. Meanwhile, satisfaction with chatbot services was positively related to customers' social media engagement and with their price premium and purchase intention. In addition, results found that social media engagement predicted customers' behavioral intentions—price premium and purchase intention—toward organizations. Finally, purchase intention was a significant predictor of price premium. We discussed the theoretical and practical implications of these findings below.

First, this research enriched discussions on AI-powered chatbot communication and brand community building by applying social exchange theory (Blau, 1964) and resource exchange theory (Brinberg & Wood, 1983) in a new digital communication context—chatbot services

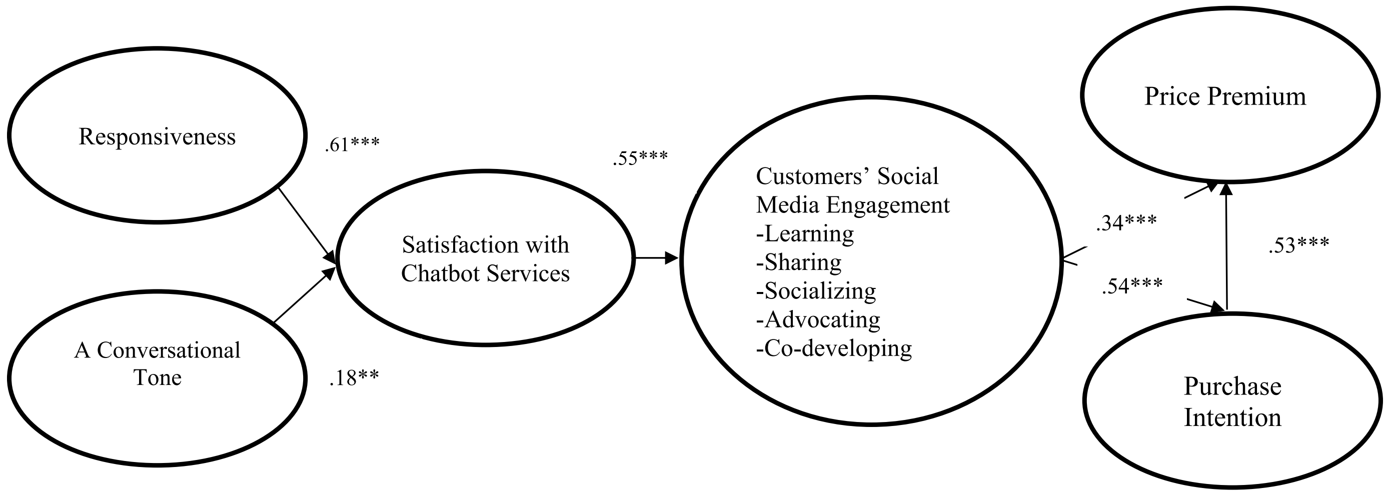

Fig. 2. χ^2 = 2203.43, df = 795, χ^2/df = 2.77, SRMR = 0.06, RMSEA = 0.043 [90% CI = 0.041-0.045], CFI = 0.96, TLI = 0.95; n = 965.

for customers. In the field of chatbot marketing efforts (CMEs) and communication, researchers examined such topics as customers' gratifications, communication quality of chatbot marketing/communication activities, perceived privacy risk, satisfaction with chatbot use, customers' continued use of chatbot services, organization-customer relationship outcomes, and brand preferences and loyalty (Bickmore & Picard, 2005; Chiang et al., 2017; Chung et al., 2020; Liebrecht et al., 2020; Verhagen et al., 2014). To add to the growing body of knowledge on chatbots, this study explicated how dialogic chatbot communication (i.e., responsiveness and a conversational tone) acts as one type of positive brand experience and exchange of resources—information that customers need for consumption purposes and others beyond that—leading to reciprocal perceptions of satisfaction, social media engagement, and other supportive behavior, including price premium and purchase intention, amongst customers (Godey et al., 2016; Kim et al., 2010; Netemeyer et al., 2004; Truong et al., 2010). It investigated a model of chatbot communication and customer engagement from a new theoretical perspective.

Second, this study answered the call for more research to examine the critical role of dialogic communication in organizations' digital interactions with customers, especially when the business world sees an increase in AI-powered services such as conversational chatbots (Rybalko & Seltzer, 2010). As one recent study indicated, chatbot-enabled dialogue played a significant role in chatbots' communication, leading to customer engagement (Tsai et al., in press). In the present study, these dialogic communication efforts—providing prompt feedback to customers' comments, making an adequate change based on their feedback, addressing their complaints in a timely and positive manner, being sensitive to customers' needs, treating them as real communication partners, respecting their perspectives or opinions, avoiding dominating a conversation with customers, and creating an open, understanding dialogue—were identified as positive predictors of customers' satisfaction with an organization's chatbot services, echoing previous similar findings (Hammoud et al., 2018). This study contributed to a growing amount of research on dialogue in AI-powered chatbot communication with customers and called for more future studies theorizing dialogic chatbot communication (Fadhil & Schiavo, 2019; Hinson et al., 2018; Schamari & Schaefers, 2015; Youn & Jin, 2021).

Third, the present study drew upon and extended Brodie et al.'s (2013) research by applying their online brand community engagement model to a chatbot communication context. The extant engagement literature focused on customers' engagement in using chatbot services (e.g., Tsai et al., in press). Few researchers have applied Brodie et al.'s (2013) model to examine customers' social media engagement behavior in terms of information acquisition (learning), knowledge creation and community building with fellow customers (sharing and socializing), advocacy for an organization's chatbot services (advocating), and collective contribution of innovative ideas for the development of chatbot services (co-developing). The extant scholarship still lacks empirical studies on the drivers, conditions, and outcomes of customer engagement that AI technologies facilitate and empower. This study thus filled this gap and extended the application of this online brand community engagement model in digital marketing and communication research.

Finally, this study offered important practical implications for AI designers, brand managers, and business communication professionals working in the United States. Organizations should strategically use chatbot services—in a dialogic communication style—to cultivate high-quality relationships with their customers. Additionally, they should acknowledge the contribution of supportive customer behavior to organizations' long-term business wellbeing. In addition, more attention needs to be paid to customers' social media engagement, which should be focused on learning, sharing, advocating, socializing, and co-developing contributing to strengthening organizations' chatbot services and relationship cultivation with the market. Most research and practice heavily focused on techniques—social media marketing/communication activities. Strategies are always the key.

6. Limitations and future research

In this study, several limitations must be addressed. First, this study was only conducted in the United States, and most organizations are rooted in the local culture here. Scholars may conduct comparative studies to explore different patterns of dialogic interactions, customers' social media engagement, and customer behavior across various cultures. Second, demographic variables such as gender and education played a role in the proposed model, and future studies should explore additional effects (e.g., moderating) of those variables as well. Finally, this pioneering study aimed to provide an overall understanding of AI-powered chatbot communication with customers, and future research may compare the industrial usage and effectiveness of various types of chatbot services. In addition, the list of 100 best bots for brands & businesses (https://www.topbots.com/100-best-bots-brands-businesses/) was from March 2017. In future studies, researchers should use a more recent list, if there is any, as bot technologies do innovate very quickly.

Credit author statement

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