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RESEARCH ARTICLE

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Artificial intelligence changes the way we work: A close look at innovating with chatbots

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Abstract

An enhanced understanding of the innovative use of artificial intelligence (AI) is essential for organizations to improve work design and daily business operations. This study's purpose is to offer insights into how AI can transform organizations' work practices through diving deeply into its innovative use in the context of a primary AI tool, a chatbot, and examining the antecedents of innovative use by conceptualizing employee trust as a multidimensional construct and exploring employees' perceived benefits. In particular, we have conceptualized employee trust in chatbots as a second-order construct, including three first-order variables: trust in functionality, trust in reliability, and trust in data protection. We collected data from 202 employees. The results supported our conceptualization of trust in chatbots and showed that three dimensions of first-order trust beliefs have relatively the same level of importance. Further, both knowledge support and work–life balance enhance trust in chatbots, which in turn leads to innovative use of chatbots. Our study contributes to the existing literature by introducing the new conceptualization of trust in chatbots and examining its antecedents and outcomes. The results can provide important practical insights regarding how to support innovative use of chatbots as the new way we organize work.

KEYWORDS

artificial intelligence, chatbot, data protection, innovative use, knowledge support, trust, work–life balance

1 | INTRODUCTION

Organizations have increasingly invested in artificial intelligence (AI) in general and chatbots in particular (Glikson & Woolley, 2020; Østerlund et al., 2021). It is predicted that more than 50% of businesses will invest more in chatbots than in traditional mobile apps by 2021 (Knight, 2019). Organizations expect that the market size supported by AI will increase dramatically. For example, consumer retail spending via chatbots is predicted to reach $142 billion by 2024, rising from just $2.8 billion in 2019 (Insider Intelligence, 2021). Thus, AI represents great opportunities for organizations to enhance their performance by improving work design and business operations (Mikalef & Gupta, 2021).

Contrarily, despite AI's great potential, organizations often find that it is challenging to fully achieve AI's performance benefits (Fountaine et al., 2019) and AI often provides little or no positive business outcomes (Ransbotham et al., 2019). One possibility is that AI is underutilized (Lankton et al., 2014; Maruping & Magni, 2015). Specifically, after certain AI technologies have been adopted, employees can use them in various ways and to differing degrees. When employees fail to try the technologies' new features and engage in innovative use (Li et al., 2013), the business benefits realized from the AI investment can be limited (Jasperson et al., 2005). Therefore, it is essential to understand how to support employees' innovative uses of AI. However, to the best of our knowledge, very few studies have attempted to understand such an important role in the context of AI. Our study aims to *provide an enhanced understanding of how to support employees' innovative use of chatbots*. Our study focuses on how chatbots support customer services, given companies' increasing adoption of chatbots to support customer services and a major predicted increase in sales generated by chatbots (Insider Intelligence, 2021). To increase generalizability, we will not be focusing on specific chatbot types or contexts.

Because innovative use of chatbots involves new use approaches, this type of use can be risky (Ahuja & Thatcher, 2005). It is essential to develop a safe environment and let employees feel comfortable engaging in innovative chatbot use. Our study thus focuses on the development of employee trust, important for successfully integrating AI tool into organizations (Glikson & Woolley, 2020). Because chatbots involve different aspects (Mikalef & Gupta, 2021), there is a need to develop a contextualized understanding of employee trust in chatbots (Hong et al., 2014). Based on the unique features of chatbots and the literature on trust (Mcknight et al., 2011; Tams et al., 2018), we have conceptualized trust in chatbots as a multidimensional construct, including trust in functionality, trust in reliability, and trust in data protection.

Given that chatbots have brought significant changes to organizations, it is important to understand how these changes have influenced employees' development of trust in chatbots. Chatbots can significantly change customer services in two ways. First, chatbots' automating capabilities can help finish routine tasks (Jarrahi, 2019). They can remove the burden on service employees to answer customers' questions late at night or during weekends, enhancing employees' *work–life balance*. Second, chatbots have the information capabilities to conduct predictive analytics and generate new insights (Jarrahi, 2019). These newly generated insights can offer employees *knowledge support*, and provide a better understanding of customers. These two variables are also consistent with the social-technical infrastructure of AI (Jarrahi et al., 2021).

This study makes a significant original contribution to AI literature by enhancing our understanding of innovative use of chatbots from an employee benefits perspective. The focus on chatbots will also allow us to develop a contextual understanding (Hong et al., 2014) of the innovative use of AI. Specifically, there are three main contributions. First, our study highlights the important role of trust in supporting imaginative use of chatbots. Our research thus extends the literature on post-adoptive use (Tams et al., 2018) to the context of chatbots. Such examination can help us understand how to support employees to explore new features of chatbots and use them innovatively, so that the various ways chatbots benefit organizations (McLean & Osei-Frimpong, 2019) can all be realized. Second, our study conceptualizes trust in chatbots as a multidimensional construct and describes the role of each dimension. Our study can thus help understand how various chatbot attributes support employees' trust development toward chatbots (Mcknight et al., 2011). Third, our study examines antecedents of trust in chatbots by focusing on the benefits of chatbots. Unlike the literature aiming to study chatbots from a consumer perspective (i.e., service receivers), our study assesses chatbots from an employee perspective (i.e., service providers). Practically speaking, our study can help practitioners understand how to achieve further benefits from chatbot investments.

2 | LITERATURE REVIEW AND THEORIES

2.1 | Related studies on chatbots

The term chatbots refers to conversational agents that "leverage natural language processing to engage in conversations with human users" (Schuetzler et al., 2020, p. 875). Chatbots have brought various benefits, such as high-quality communication, improved response times, and stable 24/7 assistance (Følstad et al., 2018). Thus, chatbots can greatly enhance productivity. Chatbots can automate everyday business work and analyze data to reach insightful conclusions. In the context of customer service, chatbots help to establish initial contact with customers and provide post-purchase services by automatically initiating conversations about use experiences and future needs (Davenport & Ronanki, 2018). Chatbots can also automate online purchases and maintain outstanding responsiveness to customer inquiries (De, 2018). By integrating chatbots into their business processes, organizations could establish an innovative channel for communication with customers and resolution of complaints in addition to handling demands in a timely fashion (e.g., Chung et al., 2020; Jain et al., 2018; Shumanov & Johnson, 2021).

Given that chatbots rely on algorithms, such as natural language processing, to train themselves, they can also generate new knowledge from data (Pérez et al., 2020). For example, as chatbots are trained based on previous conversations with customers, new insights and knowledge can be generated to help understand customers and their needs, acquire new customers, and optimize pricing (Murray & Wardley, 2014). They can generate new knowledge as they source answers from internal systems and external trusted third-party sites (Astutesolutions, 2020). Chatbots enable effective knowledge exchange not only external to but also within organizational networks (Frommert et al., 2018; Lebeuf et al., 2017). Thus, employees can receive knowledge support not previously available in the workplace. Chatbots also affect employees' lives outside of the workplace. For example, because chatbots can interact with customers and provide answers to common questions 24/7, they can reduce employees' work overload (Rietz et al., 2019) and free employees from working late into the night or during the weekend, thus enhancing their work–life balance.

Although the literature has examined different aspects of chatbots (see Table 1), these studies mainly focused on consumers. First, the literature has examined consumers' chatbot adoption. For example, Pillai and Sivathanu (2020) and Schuetzler et al. (2020) found that perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and perceived anthropomorphism influence the adoption intention of chatbots. Recent studies have also begun to pay attention to the postadoption of chatbots. For example, Li et al. (2021) found that reliability, assurance, and interactivity can enhance post-use confirmation, which then increases continued use.

Contrarily, few studies have examined chatbots from the employees' perspective. Brachten et al. (2021) is one exception. They showed that employees' intrinsic and extrinsic motivations could support their intention to use enterprise bots. Nevertheless, more studies are needed, especially those focusing on employees' post-adoption use, such as employees' innovative use of chatbots. Such an effort is important to help understand how to achieve further benefits from chatbots. For example, McLean and Osei-Frimpong (2019) indicated that chatbot use helps provide high-quality customer service and realize various benefits, including word-of-mouth publicity and higher customer satisfaction rates. Obviously, these benefits will not be achieved when chatbots are underutilized. Therefore, our study aims to fill this gap, and our first research objective is to examine how to support employees' innovative use of chatbots. The effect of trust is the focus; innovative use can be risky, and employees need a safe environment in which to engage in innovative use, which can be supported by trust (Tams et al., 2018).

Second, the literature has also recognized the importance of consumers' trust in chatbots, and studies have shown that trust is important to support consumers' adoption intentions (Pillai & Sivathanu, 2020; Rodríguez Cardona et al., 2021). Trust refers to "the willingness of a

TABLE 1 A summary of the literature on chatbots

Study	Focus	Topic	Summary
Adam et al. (2020)	Customer	Adoption	Anthropomorphism and the need to stay consistent can enhance consumers' compliance.
Ashfaq et al. (2020)	Customer	Postadoption	High-quality information and services can improve customer satisfaction and continuance intention.
Brachten et al. (2021)	Employee	Adoption	Intrinsic and extrinsic motivation can increase employees' intention to use enterprise bots.
Laumer et al. (2019)	Customer	Adoption	The authors developed a model focusing on chatbot acceptance in health care.
Li et al. (2021)	Customer	Postadoption	Reliability, assurance, and interactivity increase post-use confirmation, facilitating continued use.
Pillai and Sivathanu (2020)	Customer	Adoption	Perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism predict adoption intention.
Pizzi et al. (2021)	Customer	Adoption	Anthropomorphism reduces both satisfaction and reactance.
Rese et al. (2020)	Customer	Adoption	The results of the technology acceptance model are compared with those of the use and gratification theory.
Roy and Naidoo (2021)	Customer	Adoption	The fit between time orientation and conversation type can enhance chatbot attitude and purchase intention.
Schuetzler et al. (2020)	Customer	Adoption	Chatbots with tailored responses and response variety have a higher social presence, which leads to perceived humanness and partner engagement.
Sheehan et al. (2020)	Customer	Adoption	Anthropomorphism can increase chatbot adoption.

party [the trustor] to be vulnerable to the actions of another party based on the expectation that the other [the trustee] will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995, p. 712). While such a definition is initially developed to examine interpersonal trust, it emphasizes the trustee's predictability (Ross & LaCroix, 1996), which is consistent with our context, where developing predictable operations can help chatbots develop trust with employees and support customer services. Contrarily, few studies have examined employees' trust in chatbots or conceptualized trust in chatbots as a multidimensional construct. Such an examination is important to further understand trust in chatbots from the employees' perspective, which is probably different from that of the consumers, as well as the roles of different dimensions. Therefore, our second research objective is to conceptualize employees' trust in chatbots as a multidimensional construct.

Third, the literature has examined why consumers trust chatbots. For example, Følstad et al. (2018) argued that factors such as interpretation and advice, human-likeness, self-presentation, and professional appearance influence consumers' trust. Nordheim et al. (2019) summarized their findings to say factors influencing trust in chatbots could be chatbot related (e.g., expertise), environment related (e.g., brand), and user related. Toader et al. (2020) found that social presence and competence were important to support users' trust. Contrarily, few studies have examined how to support employees' trust. Because employees use chatbots as service providers, rather than as service receivers, different factors would be involved in supporting employees' trust in chatbots. Therefore, our third research objective is to examine how to support employees' trust in chatbots. Trust can develop through the mental mechanism of assessing gains (Gefen et al., 2003), and chatbots' capabilities are vital to provide these gains (Glikson & Woolley, 2020). As previously discussed, two important capabilities of chatbots are to provide knowledge support and help achieve work–life balance. Therefore, these two factors were selected as antecedents of trust. In the next section, we conceptualize employees' trust in chatbots based on the literature.

2.2 | Employees' trust in chatbots

Using chatbots to provide customer services involves the risk and uncertainty of undesirable outcomes (e.g., wrong answers provided to customers' questions) occurring, so trust is essential (Fukuyama, 1995) when employees need to depend on chatbots to provide customer services. Our study focuses on trust beliefs (Mcknight et al., 2011), which represent employees' perceptions toward certain chatbots. Such trust beliefs describe trustee attributes that increase trustworthiness. In other words, individuals are willing to depend on another party due to certain attributes (Rousseau et al., 1998).

To understand the trust-relevant attributes of chatbots, our dimensions are based upon trust in technology rather than in people. Although the concept of trust was initially developed to examine trust in people, recent literature has conceptualized trust in technology to directly examine the role of the information technology (IT) artifact (Lin et al., 2019; Mcknight et al., 2011; Tams et al., 2018). Unlike trust in people, which deals with volitional factors from a moral agency such as a person, trust in technology deals with nonvolitional factors from an amoral agency such as technology (Mcknight et al., 2011). For example, trust in technology can include dimensions such as functionality and reliability. As summarized by Mcknight et al. (2011), functionality is similar to competence, as both represent trustees' competence. Reliability is similar to integrity, as both describe trustees' consistency and predictability. However, functionality and reliability focus on the amoral agency (i.e., technology), and are nonvolitional, while competence and predictability focus on the moral agency (i.e., people), and are volitional.

Mcknight et al. (2011) argued that trust in technology can allow researchers to better understand how individuals' beliefs about (technology) vendors relate to their thoughts about technological features. In other words, adopting trust in technology can help understand how technological attributes (e.g., functionality and reliability), rather than human attributes (i.e., competence, benevolence, and integrity), influence employees' trust development toward chatbots. Indeed, trust in technology "affords researchers an opportunity to tease apart how beliefs toward a [technology] vendor, such as Microsoft or Google, relate to cognitions about features of their products" (Mcknight et al., 2011, p. 12,13). Therefore, by focusing on trust in technology, our study can help understand which chatbot attributes increase their trustworthiness.

Drawing on Gefen et al. (2003) and Mcknight et al. (2011), we have conceptualized trust in chatbots as the result of beliefs about the favorable features of chatbots. Hence, we propose that trust in chatbots includes three dimensions: *trust in functionality*, *trust in reliability*, and *trust in data protection*. To elaborate, the dimensions of functionality and reliability were selected based on the literature on trust (Mcknight et al., 2011), and the large volume of data required by chatbots creates challenges for data protection (Sağlam & Nurse, 2020), additionally necessitating this dimension to conceptualize trust.

Trust in functionality refers to employees' expectations that the technology's function is consistent with the requirements of their tasks and can support their work responsibilities (Mcknight et al., 2011). For example, marketing employees' primary work responsibility is to interact with customers and provide customer services. When chatbots can facilitate customer services, chatbots' functions are aligned with employees' work responsibilities, thus supporting their trust in functionality.

Trust in reliability deals with employees' expectations that technology can function and provide support in a consistent manner (Mcknight et al., 2011). In other words, individuals want to be able to predict technology's performance based on accepted criteria. For example, when chatbots always provide accurate answers to customers' common questions, employees perceive that chatbots always perform in the same way for the same questions, facilitating their trust in reliability. Otherwise, when chatbots provide different answers for the same questions, employees could feel that chatbots do not behave reliably, which hinders their trust in chatbots' reliability.

Because of the uniqueness of AI technology in general and chatbots in particular, we also argue that trust in data protection is an important dimension of trust in chatbots. One unique quality of the chatbots (as one type of AI) is that their development requires a large amount of high-quality data (Mikalef & Gupta, 2021). Specifically, massive loads of high-quality data need to be fed into algorithms (e.g., natural language processing) to teach chatbots how to interact with customers. Therefore, chatbots need to access customers' data, including their personal identification information and conversation history. This process is sustained to let the chatbot enhance their performance and handle new issues from customers, creating a challenge for organizations as they try to collect, store, and use customers' data. During this process, organizations need to ensure that customers' data is well-protected. Otherwise, employees may feel reluctant to innovate and explore new features of chatbots because new approaches may leak or misuse customer data. A recent study shows that customers also care about how their data is used and stored during interactions with chatbots (Følstad et al., 2018). Thus, our study defines trust in data protection as employees' expectations that the technology can protect customers' data and respect customers' privacy effectively. For example, when chatbots can protect customers' data, based on organizational policies, employees can feel more comfortable to further integrate chatbots into their work and explore different approaches.

It is worth noting the following: First, trust in functionality and trust in reliability are two distinct dimensions of trust proposed by Mcknight et al. (2011), and their discriminant validity has been well supported in the literature (Mcknight et al., 2011; Tams et al., 2018). In our study, these two variables are also distinct. For example, chatbots may perform reliably (e.g., provide the same answers for the same question) but lack certain important functionalities (e.g., cannot process certain customer requests). In such a scenario, employees may have a high level of trust in reliability but a low level of trust in functionality. Mayer et al. (1995) proposed three dimensions when conceptualizing interpersonal trust: ability (i.e., competence), benevolence, and integrity. As summarized by Mcknight et al. (2011), trust in functionality is similar to trust in competence as both represent trustees' capabilities. Trust in reliability is comparable to trust in integrity as both describe trustees' consistency and predictability.

Second, although other dimensions of trust in technology (e.g., Söllner et al., 2012) have also been proposed, our study follows Mcknight et al. (2011)'s conceptualization for two main reasons. First, Mcknight et al. (2011) focused on knowledge-based trust, consistent with the focus of our study, contrasting with Söllner et al. (2012), which focused on initial trust. Second, Mcknight et al. (2011)'s conceptualization has been applied to understand post-adoptive use (Tams et al., 2018). This is also consistent with the focus of our study.

In summary, our study proposes that trust in chatbots is multidimensional and includes trust in functionality, trust in reliability, and trust in data protection. Our study focuses on knowledge-based trust, which persists longer than initial trust (Mcknight et al., 2011) and has been shown to influence post-adoption use (Tams et al., 2018). Our conceptualization derives from the literature on trust in technology (Mcknight et al., 2011; Tams et al., 2018) and the uniqueness of chatbots (Følstad et al., 2018).

2.3 | Antecedents of trust in chatbots

Our study identifies knowledge support and work–life balance as antecedents of trust in chatbots, reflecting chatbots' informating and automating capabilities, respectively (Jarrahi, 2019). Knowledge support refers to the knowledge gained using AI such as chatbots. It can enhance employees' job performance by facilitating learning (Davenport & Klahr, 1998; Stahl, 2006). Specifically, chatbots can provide knowledge support by strengthening knowledge creation, storage, dissemination, and management processes and achieving superior analysis, comprehension, and prediction capabilities (Ghahramani, 2015). Jarrahi (2019) also argued that AI's informating capacities are critical for pioneering intellectual skills in the process of automation and augmentation. Thus, chatbots can support knowledge building and data analytics, allowing employees to gain new knowledge and improve their task performance (Mithas et al., 2011).

Work–life balance refers to the "individual perception that work and nonwork activities are compatible and promote growth in accordance with an individual's current life priorities" (Kalliath & Brough, 2008, p. 326). Here, nonwork activities may include those spent with family, friendly get-togethers, sports events, and entertainment. Work–life balance has been an essential topic for over half a century (Chandra, 2012; Fleetwood, 2007). Proper work–life balance can enhance employee performance and satisfaction. For example, when employees work reduced hours, they show greater productivity, higher morale, and higher job satisfaction (Hill et al., 1998). Chatbots can support work–life balance through their automating capabilities (Jarrahi, 2019), specifically, answering customers' routine questions outside working hours, thereby reducing the burden on service employees. By relying on chatbots to provide customer services late at night or during weekends, employees can perceive that work activities will not intervene in their nonwork activities outside working hours.

3 | RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

Our research model is shown in Figure 1. We argue that beneficial outcomes, including knowledge support (work-related benefits) and work–life balance (nonwork-related benefits), can support employees as they develop their trust in chatbots, ultimately facilitating innovative use. Our study treats knowledge support and work–life balance as antecedents rather than outcomes of trust in chatbots for two main reasons. First, our study focuses on knowledge-based trust, which is based on employee knowledge and experience with chatbots (Mcknight et al., 2011). In other words, once employees become familiar with chatbots and how they provide knowledge support and facilitate work–life balance, they can anticipate how chatbots will function in the future. Thus, our model is consistent with the concept of knowledge-based trust. Second, according to Mayer et al. (1995), trust represents the trustors' willingness to depend on trustees, meaning trust in chatbots represents employees' expectations of chatbots' future actions. Knowledge support and work–life balance reflect chatbots' informating and automating capabilities, respectively (Jarrahi, 2019). These capabilities are inherent to chatbots and do not change as employees' expectations vary.

In other words, trust in chatbots reflects employees' expectations about chatbots, which may or may not be consistent with their actual capabilities. For example, on the one hand, chatbots' high level of knowledge support is due to their high informating capabilities, and employees' expectations cannot change these inherent capabilities. On the other hand, knowledge support reflecting chatbots' informating capabilities can influence employees' future expectations of chatbots' performance. Therefore, our model conceptualizes knowledge support and work–life balance as antecedents, rather than outcomes, of trust in chatbots. We describe each hypothesis in more detail in the following sections.

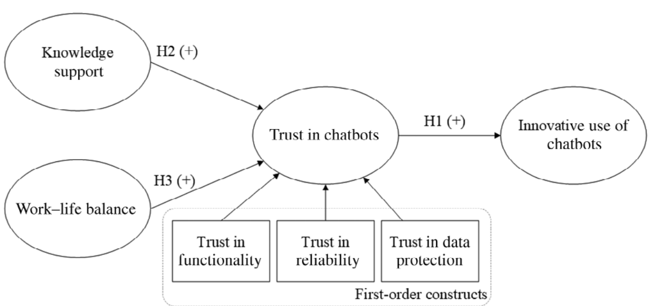

FIGURE 1 Research model

3.1 | The outcome of trust in chatbots

Innovative use of chatbots refers to individuals' employment of them to support customer services (Li et al., 2013), a specific type of post-adoptive use (Venkatesh & Goyal, 2010). Specifically, after chatbots have been adopted in organizations, employees can use their features to varying degrees, spending different amounts of time learning how to use chatbots in different ways (Nambisan et al., 1999). Innovative use of chatbots is thus an important type of post-adoptive use, allowing organizations to receive further benefits from chatbot investments. Contrarily, supporting innovative use can be challenging. As employees explore new approaches to use chatbots, they can lose time and make mistakes (Ahuja & Thatcher, 2005). Thus, when employees perceive that innovative use of chatbots is highly risky, they are less willing to engage in innovative use.

One approach to support innovative use of chatbots is to enhance trust in chatbots. The literature has argued that trust is vital to support post-adoptive usage (Tams et al., 2018). Trust in chatbots can establish a safe environment in which employees feel comfortable with taking risks (Tams et al., 2018). Specifically, employees' trust in functionality allows them to explore chatbots' features because they expect that chatbots can provide customer service in various ways. Employees' trust in reliability allows them to use chatbots in innovative ways because they can predict their performance, which minimizes risk. Trust in data protection ensures that employees can collect and analyze customer data, based on organizational policies, thus alleviating employees' perceptions of risk and uncertainty associated with innovative use (Mcknight et al., 2011) and encouraging further innovation (Tams et al., 2018).

Therefore, we hypothesize the following:

> **Hypothesis H1.** *Higher employees' trust in chatbots leads to higher innovative use of chatbots.*

3.2 | The antecedents of trust in chatbots

Chatbots are effective for identifying and retrieving information from customer service (Makhalova et al., 2019). They can establish and maintain communication with customers while collecting and cataloguing information on customers' requirements, expectations, and preferences (Chung et al., 2020; De, 2018; McLean & Osei-Frimpong, 2019; Rese et al., 2020). After analyzing these customer data, chatbots can generate new knowledge and support employees' learning, which allows employees to improve customer service and respond to market dynamics (Mithas et al., 2011). In this scenario, knowledge support can enhance all three dimensions of trust in chatbots.

First, knowledge support improves employees' understanding of customers' needs and requests, enhancing their interactions with customers; the chatbot thus fulfills its main purpose. Therefore, employees are likely to perceive that chatbots provide necessary features and support their responsibilities of serving customers, reinforcing trust in functionality (Mcknight et al., 2011). Second, with knowledge support, chatbots enable companies to provide consistent responses to customers' requests, thus improving their communication with customers. Therefore, employees are likely to perceive that chatbots perform reliably, leading to increased trust in reliability (Mcknight et al., 2011). Lastly, chatbots provide employees knowledge support with their key abilities to handle and analyze a large volume of high-quality data to produce business insights (Mikalef & Gupta, 2021). With a higher level of knowledge support, employees are more likely to trust chatbots' capabilities in managing and processing data, leading to a sense of data protection. In addition, when employees perceive that chatbots can protect customers' privacy while analyzing their data, their trust in data protection is further enhanced.

Furthermore, according to Mcknight et al. (2011), trust in technology can be facilitated by situational normality, which is defined as the belief that "using a specific class of technologies in a new way is normal and comfortable within a specific setting" (p. 8). Using chatbots to provide customer services can be new to service employees. By receiving knowledge support from chatbots, employees can better understand customers' needs and feel more comfortable using chatbots, thus enhancing their trust in them. Overall, we hypothesize the following:

> **Hypothesis H2.** *Higher knowledge support leads to higher trust in chatbots.*

Proper work–life balance can be achieved by reducing work–life conflict. Greenhaus and Reutell (1985) identified three factors in work–life conflicts: time, strain, and behavior. Chatbots can mitigate all three. Specifically, chatbots reduce time commitment to work and job overload and involvement and improve job flexibility, each of which resolves time-based, strain-based, and behavior-based conflicts, respectively. In this case, proper work–life balance can enhance all three dimensions of trust in chatbots.

First, by recognizing how chatbots provide support during nonworking hours, employees probably feel that chatbots can capably provide customer services. Their subsequent reduction in time commitment means employees are likely to be more satisfied with their work, which increases their trust in functionality (Mcknight et al., 2011). Second, employees probably perceive that chatbots can provide reliable services to customers because chatbots can serve customers reliably without an employee's involvement, enhancing their trust in reliability (Mcknight et al., 2011). Lastly, to be able to provide these services with less employee involvement, chatbots need to process a large amount of high-quality data so that they can learn how to best respond to customers (Mikalef & Gupta, 2021). When employees perceive that chatbots can do so while respecting customers' privacy, their trust in data protection can also be supported. Specifically, with a high work–life balance, employees feel comfortable enough to rely on chatbots to provide customer services. In such a scenario, employees experience less stress as they do not need to worry about whether chatbots can manage customers' data with respect and securely protect this data. As a result, employees are likely to develop a high level of trust in data protection.

Furthermore, trust in technology can be supported by situational normality (Mcknight et al., 2011). Using chatbots to provide customer services, especially outside working hours, can take a while to get used to. However, having a better work–life balance and reduced late-night or weekend working hours can help employees realize that relying on chatbots can be quite comfortable, ultimately increasing their trust in chatbots. Therefore, we hypothesize the following:

Hypothesis H3. *Higher work–life balance leads to higher trust in chatbots.*

4 | RESEARCH METHODOLOGY

4.1 | Data collection procedure and sample

A survey company maintaining national panels was hired to recruit participants from American employees with systematic sampling. We conducted a survey during January and February 2021, and the company provided bonus points (convertible into money) to encourage survey participation. We focused on marketing employees who used chatbots to provide customer services. The survey included screening questions to ensure participants worked in the marketing department and used chatbots to provide customer services.

We first collected participants' demographic information. Then participants were asked to answer questions about knowledge support, work–life balance, trust, and innovative use based on their experiences with chatbot usage in their companies. On average, the survey took participants about 15 min to finish. We received 202 valid responses (Table 2). Of the participants, 94.5% were full-time employees. Participants worked for their current companies for 8.11 years (*SD*: 4.78) on average and used various chatbots, such as Bold360, Aivo, and Twilio.

TABLE 2 Participants' demographic background

Category	Sample ($N = 202$)
Gender	
Female	31.7%
Male	68.3%
Age	
18–24	5.9%
25–34	37.6%
35–44	38.6%
45–54	15.3%
55 or older	2.5%
Education	
High school or below	13.9%
Some college education or bachelor's degree	56.4%
Graduate degree	29.7%
Company size	
1–100	10.3%
101–200	12.3%
201–500	19.5%
501–1,000	26.2%
1,001–3,000	21.5%
>3,000	10.3%

4.2 | Measures

Our measures were adapted from the literature (see Appendix). Items of knowledge support were adapted from Lin et al. (2019) and modified to fit our context. Items of the work–life balance had been adapted from Brough et al. (2014). Items of trust in functionality and trust in reliability were adapted from Tams et al. (2018). Items of trust in data protection were adapted from Al-Natour et al. (2020). Items of innovative use were adapted from Li et al. (2013). All measures used 7-point Likert scales from 1 (strongly disagree) to 7 (strongly agree).

4.3 | Data analysis and results

Both procedural and statistical remedies were used to alleviate common method bias (CMB) (Podsakoff et al., 2003). During the data collection, we tried to reduce CMB procedurally by ensuring participants' anonymity, to reduce their evaluation apprehension. Then, two tests were conducted to assess CMB. First, Harman's single factor analysis revealed five factors, and the first factor explained 38.28% of the total variance. Second, a common method factor including all items was created (Podsakoff et al., 2003). Then, for each item, we calculated the variance explained by the focal factor and by the method. The average variance explained by the focal factor was .72, while the average variance explained by the method factor was .01. The ratio was approximately 51:1, and most method factor loadings were nonsignificant. Therefore, CMB was probably not a major issue.

Smart PLS with the bootstrap resampling method (using 5,000 samples) was adopted to analyze our data. Shapiro–Wilk tests were significant, indicating that our measures were not normally distributed. According to Hair Jr et al. (2016), PLS is appropriate for analyzing non-normally distributed data.

The measurement model was assessed first. All measures loaded significantly on their focal constructs, and all loadings were above .70 (Table 3). Further, the measures had good reliability: the Cronbach's alpha and composite reliabilities (CRs) were all above .70. The average variance extracted (AVE) was also above .50 (Table 3). Thus, our measures had good convergent validity. Next, the square root of each construct's AVE exceeded all correlations between that construct and any other construct, indicating the discriminant validity (Table 4). Thus, our measures had good psychometric properties.

We then validated the second-order construct of trust in chatbots. The results (Table 5) showed that the path coefficients of the first-order constructs (i.e., formative indicators) were all significant. Further, all of the variance inflation factors (VIFs) were below 3.3 (Petter et al., 2007), indicating that multicollinearity was not an issue. These results supported modeling trust in chatbots as a second-order construct.

Next, the hypotheses were tested (Figure 2). H1, stating that trust in chatbots is positively related to innovative use, was supported ($\beta = .57$, $p < .001$). H2, stating that knowledge support enhances trust in chatbots, was supported ($\beta = .52$, $p < .001$). Finally, H3, stating that work–life balance is positively associated with trust in chatbots, was supported ($\beta = .29$, $p < .001$). These results provide strong support for our model. The R^2 of trust is 47%, and there were five arrows (two from the structural model and three from the measurement model) pointing at trust. Following Hair Jr et al. (2016), a minimum sample size of 45 is sufficient to achieve 80% statistic power in such a scenario. Therefore, our analysis (and our post-hoc analysis below) has enough statistical power.

TABLE 3 Item descriptive statistics

Item	Mean	*SD*	Loading	Alpha	CR	AVE
WLB1	5.35	1.36	.84	.95	.91	.76
WLB2	5.24	1.39	.87			
WLB3	5.43	1.28	.89			
KS1	5.68	1.04	.86	.83	.90	.75
KS2	5.73	1.13	.87			
KS3	5.62	1.29	.87			
TF1	5.64	1.08	.88	.79	.88	.71
TF2	5.67	1.10	.79			
TF3	5.75	1.17	.85			
TR1	5.58	1.13	.78	.81	.87	.63
TR2	5.30	1.36	.81			
TR3	5.44	1.21	.80			
TR4	5.19	1.35	.79			
TDP1	5.65	1.12	.84	.77	.87	.68
TDP2	5.71	1.07	.82			
TDP3	5.70	1.06	.83			
INV1	5.43	1.25	.88	.80	.88	.71
INV2	5.50	1.25	.84			
INV3	5.56	1.29	.81			

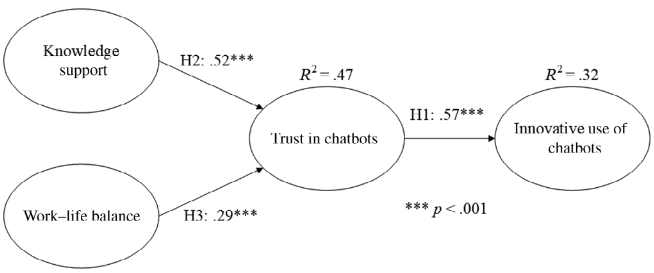

FIGURE 2 Model testing results

TABLE 4 Correlation between constructs and square-root of AVEs (on diagonal)

	1	2	3	4	5	6
1. Work–life balance	**.86**					
2. Knowledge support	.37	**.87**				
3. Trust in functionality	.41	.62	**.84**			
4. Trust in reliability	.43	.49	.59	**.79**		
5. Trust in data protection	.40	.49	.62	.61	**.83**	
6. Innovative use	.38	.48	.53	.42	.51	**.85**

TABLE 5 Formative indicator weights and VIFs

Second-order construct	Formative indicator (first-order construct)	VIF	Weight	*t*-value
Trust in chatbots	Trust in functionality	1.83	.38	16.72***
	Trust in reliability	1.78	.43	15.33***
	Trust in data protection	1.89	.36	17.11***

Note: ***$p < .001$.

TABLE 6 Comparison between subsamples

Relationship	High-level chatbot adoption ($N = 102$)	Low-level chatbot adoption ($N = 100$)	Path comparison
Knowledge support → trust	.34**	.56***	$t = -14.99$***
Work–life balance → trust	.32**	.25**	$t = 4.58$***

Note: ** $p < .01$; *** $p < .001$.

4.4 | Post hoc analysis

We conducted additional analyses to further understand how employees develop trust in chatbots under different levels of adoption. We measured the extensiveness of chatbot adoption in individual companies using three items following Li et al. (2013): the use of chatbot (a) has been incorporated into our regular business operations; (b) is pretty much integrated as part of our normal business operations; (c) is now a normal part of our business operations (Cronbach's alpha: .79). We calculated chatbot adoption based on the average of these items, and the sample was then divided into two sub-samples (low vs. high adoption) based upon the standardized score of chatbot adoption. Specifically, we calculated the median of chatbot adoption's standardized scores (−.004). The low adoption subsample included those whose standardized scores of chatbot adoption were equal to or below −.004, and the high adoption subsample included those whose standardized scores of chatbot adoption were above −.004.

First, we calculated the average scores of knowledge support and work–life balance. The results indicated that knowledge support under high adoption (6.10) is higher than that under low adoption (5.28) ($p < .001$). Work–life balance under high adoption (5.66) is also higher than that under high adoption (5.04) ($p < .001$). These tendencies show that chatbot adoption can increase employees' knowledge support and work–life balance.

Second, we tested our model with two subsamples and compared the effects of knowledge support and work–life balance on trust in chatbots following Keil et al. (2000) (Table 6). Our results showed that knowledge support under high adoption ($\beta = .34$, $p < .01$) has a weaker effect on trust in chatbots than that under low adoption ($\beta = .56$, $p < .001$), with a significant difference between the two path coefficients ($p < .001$). On the other hand, work–life balance under higher adoption ($\beta = .32$, $p < .01$) has a stronger effect on trust than that under low adoption ($\beta = .25$, $p < .01$), with, again, a significant difference between the two path coefficients ($p < .001$).

5 | DISCUSSION

This study's aim was to further our understanding of innovative chatbot usage in companies by proposing a new conceptualization of trust in chatbots by examining its antecedents and outcome. The results support our modeling of trust as a second-order formative construct. Further, knowledge support and work–life balance enhance trust in chatbots, which in turn leads to innovative use. Our study has important theoretical and practical implications.

5.1 | Implications for theory

First, our study advanced the trust literature by proposing an approach to modeling trust in chatbots as a multidimensional construct. This allowed us to develop contextual understanding about the nature of trust based on the unique features of specific information systems (Hong et al., 2014). Based on the literature, we defined and conceptualized trust in chatbots as a second-order formative construct, including the dimensions of trust in functionality, reliability, and data protection. Our conceptualization has been validated by the research results of this study, and all three dimensions are vital to developing employees' trust perceptions of chatbots as used in organizations. In particular, our results confirmed that trust in data protection is an important dimension of trust in chatbots. This again highlighted the importance of security issues in the design and development of AI tools in organizations. Our study has thus contributed to the literature by enhancing our understanding of trust in chatbots. It has also supported the importance of conceptualizing trust in new AI tools to allow contextual understanding of new IS phenomena (e.g., Hong et al., 2014; Lin et al., 2019).

Our study has also shown that trust in chatbots can support employees' innovative use, which is consistent with the literature (Tams et al., 2018). As such, we confirm the effects of employee trust on developing innovative methods of chatbot usage, thus changing the way they work in companies (e.g., Jarrahi et al., 2021; Østerlund et al., 2021). This finding offers valuable empirical evidence to underpin the effective implementation of chatbots through trust development in companies. Therefore, these results have contributed to the literature by enriching the understanding of the important role of trust and its outcomes in the context of chatbots.

Second, our study proposes knowledge support and work–life balance as antecedents of trust in chatbots. Our study extends the work–life balance theory by identifying the use of information technology, specifically chatbots, as a factor in work–life balance. Chatbots can benefit employees by increasing efficiency; reducing overall workload; allowing a more flexible working schedule; and enabling alternative working arrangements, such as working from home. The benefits of a better work–life balance encourage employee trust in chatbots and thus promote the use of chatbot technology. These findings can also help us rethink how new AI tools can help change the way we perform our daily job duties, thus motivating the design and development of AI tools to better gain employee trust in organizations.

Additionally, chatbot use gives employees confidence that they have access to more information, knowledge, and resources that will help enhance their job performance. They consider chatbots helpful for business operations, reliable in job accomplishments, and trustworthy for data protection. Therefore, higher knowledge support promotes the use of chatbots and presumably other AI technologies that offer the same or similar advantages.

Further, our post hoc analysis shows that knowledge support can best enhance trust when chatbots are initially adopted, likely because employees find the additional information chatbots generate to be considerably useful in this situation. However, as chatbots are more widely adopted, fewer new insights are generated, and the positive effect of knowledge support on trust therefore decreases. In addition, when chatbots become highly adopted, employees will be able to allocate more routine work to chatbots, providing better work–life balance than when chatbots are only initially adopted. Overall, these results contribute to the literature by clarifying the development of trust in chatbots, which is critical for encouraging the leveraging of AI tools within organizations.

5.2 | Implications for practice

Our study could also have important practical implications. First, our results highlight that trust in chatbots is a multidimensional construct and employees develop trust in chatbots through their perception of functionality, reliability, and data protection. Therefore, vendors of chatbots need to make efforts to increase employees' trust perception in all three areas. For example, vendors need to ensure that chatbots provide essential functionalities and operate reliably so that employees can integrate chatbots into their work processes. Organizations also need to collaborate with vendors to ensure that customers' privacy will be well protected. Otherwise, employees may feel hesitant to engage in innovative use, and the benefits of chatbots not be fully achieved.

Our study also provides suggestions regarding how to support employees' trust in chatbots. Our results indicate a need for anthropomorphic multidomain or even open-domain chatbots to reduce sources of work–life conflict. These chatbots can be expected to help employees achieve a better and more stable work–life balance through reductions in time commitment, job overload, and job involvement while increasing job flexibility. Such chatbots should be designed to collect; store; and share information, knowledge, and resources with employees. Our results also indicate that increases in both work–life balance and knowledge support increased employee trust in chatbots, which in turn resulted in higher job and organizational performance. Therefore, we encourage organizations to create a culture that facilitates work–life balance. For example, we suggest that organizations allow flexibility in employee working schedules and enable modes such as remote working to reduce work stress and reduce or eliminate time and energy wasted in commuting. Our study also presents more incentives for companies to share information with their employees and provide larger, stronger pools of resources and knowledge support.

5.3 | Limitations and future directions

Our study had a few limitations. First, our participants were recruited by a survey company. While participants came from various backgrounds, it would still be possible that our sample was biased. Second, our data were collected from American employees, and the results may not have held with responses from people from other cultural backgrounds. For example, it is possible that the effect of work–life balance varies across cultures that place different degrees of emphasis on family relationships (Haar et al., 2014). Third, our study did not collect knowledge support, work–life balance, trust, and innovative use in different time periods. Although CMB is not a concern, we cannot assess the directionality of our relationships. Future studies are needed to collect cross-lagged data and further validate our model. Studies can also be conducted to examine how trust in chatbots leads to different approaches in usage, which can lead to a variety of benefits.

Future studies can extend our study in several ways. First, other antecedents of trust in chatbots can be explored based on other mechanisms. Second, other outcomes of trust can be examined. It would be particularly interesting to examine how dimensions of trust lead to different outcomes. Third, future studies could also explore how certain variables (e.g., chatbot use and organizational structure) moderate the relationship between trust and its antecedents. Besides, chatbots could threaten normal employees by replacing their role in standardized work. Therefore, future studies can extend our study by considering threats and fears regarding chatbots. For example, moderators such as "identity threat" or "attitudes toward chatbots" can be included. Fourth, our study focuses on two types of benefits that chatbots generate in the context of customer services. Future studies can examine other benefits of chatbots (or other types of AI) in other contexts. Future studies can also examine the negative side of chatbot use (or other types of AI) in the workplace, such as stress and anxiety (Li & Huang, 2020). Lastly, while our study proposes important dimensions of trust in chatbots, it is not a complete list and potentially excludes other important dimensions, such as transparency. Our study does not include transparency because its effect is still arguable and the recent literature has shown that transparency can actually decrease users' trust (Schmidt et al., 2020). Felzmann et al. (2019) also observed that individuals' transparency perception may differ depending on the AI investigated, as well as the organization and cultural context. Nevertheless, it may be relevant for certain types of AI, and we encourage future studies to explore additional dimensions of trust in chatbots (or trust in AI in general).

6 | CONCLUSION

Chatbots have dramatically changed organizations' work practices, and it is important to promote their innovative use to further achieve their benefits. Our study examined the role of trust in chatbots in supporting innovative use and conceptualized it as a second-order construct. Our results have supported the proposed conceptualization and shown that our model is preferred to alternative models. We also showed that knowledge support and work–life balance can support trust in chatbots. Future studies can extend our study by examining antecedents from other theoretical mechanisms.

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REFERENCES

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*, 1–19.

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: Effects of work environment and gender on post-adoption information technology use. *MIS Quarterly*, *29*, 427–459.

Al-Natour, S., Cavusoglu, H., Benbasat, I., & Aleem, U. (2020). An empirical investigation of the antecedents and consequences of privacy uncertainty in the context of mobile apps. *Information Systems Research*, *31*(4), 1037–1063.

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

Astutesolutions. (2020). Building a customer service chatbot: 8 elements of a great interaction.

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The acceptance of chatbots in an enterprise context: A survey study. *International Journal of Information Management*, *60*, 102375. https://doi.org/10.1016/j.ijinfomgt.2021.102375

Brough, P., Timms, C., O'Driscoll, M. P., Kalliath, T., Siu, O.-L., Sit, C., & Lo, D. (2014). Work–life balance: A longitudinal evaluation of a new measure across Australia and New Zealand workers. *The International Journal of Human Resource Management*, *25*(19), 2724–2744.

Chandra, V. (2012). Work–life balance: Eastern and western perspectives. *The International Journal of Human Resource Management*, *23*(5), 1040–1056.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587–595.

Davenport, T. H., & Klahr, P. (1998). Managing customer support knowledge. *California Management Review*, *40*(3), 195–208.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

De, A. (2018). A look at the future of chatbots in customer service.

Felzmann, H., Villaronga, E. F., Lutz, C., & Tamò-Larrieux, A. (2019). Transparency you can trust: Transparency requirements for artificial intelligence between legal norms and contextual concerns. *Big Data & Society*, *6*(1), 1–14.

Fleetwood, S. (2007). Why work–life balance now? *The International Journal of Human Resource Management*, *18*(3), 387–400.

Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018). What makes users trust a chatbot for customer service? An exploratory interview study. Paper presented at the International conference on internet science.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62–73.

Frommert, C., Häfner, A., Friedrich, J., & Zinke, C. (2018). Using chatbots to assist communication in collaborative networks. Paper presented at the working conference on virtual enterprises.

Fukuyama, F. (1995). *Trust: The social virtues and the creation of prosperity*. The Free Press.

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

Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452–459.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.

Greenhaus, J. H., & Reutell, N. J. (1985). Sources of conflict between work and family roles. *Academy of Management Review*, *10*(1), 76–88.

Haar, J. M., Russo, M., Suñe, A., & Ollier-Malaterre, A. (2014). Outcomes of work–life balance on job satisfaction, life satisfaction and mental health: A study across seven cultures. *Journal of Vocational Behavior*, *85*(3), 361–373.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hill, E. J., Miller, B. C., Weiner, S. P., & Colihan, J. (1998). Influences of the virtual office on aspects of work and work/life balance. *Personnel Psychology*, *51*(3), 667–683.

Hong, W., Chan, F. K., Thong, J. Y., Chasalow, L. C., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information Systems Research*, *25*(1), 111–136.

Insider Intelligence. (2021). Chatbot market in 2021: Stats, trends, and companies in the growing AI chatbot industry.

Jain, M., Kumar, P., Kota, R., & Patel, S. N. (2018). Evaluating and informing the design of chatbots. Paper presented at the proceedings of the 2018 designing interactive systems conference.

Jarrahi, M. H. (2019). In the age of the smart artificial intelligence: AI's dual capacities for automating and informating work. *Business Information Review*, *36*(4), 178–187.

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2021). Algorithmic management in a work context. *Big Data & Society*, *8*(2), https://doi.org/10.1177/2053951721102033

Jasperson, J. S., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly*, *29*(3), 525–557.

Kalliath, T., & Brough, P. (2008). Work-life balance: A review of the meaning of the balance construct. *Journal of Management & Organization*, *14*(3), 323–327.

Keil, M., Tan, B. C., Wei, K.-K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, *24*, 299–325.

Knight, C. (2019). Key statistics driving chatbot and AI adoption.

Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into expectation disconfirmation theory. *The Journal of Strategic Information Systems*, *23*(2), 128–145.

Laumer, S., Maier, C., & Gubler, F. T. (2019). Chatbot acceptance in healthcare: Explaining user adoption of conversational agents for disease diagnosis.

Lebeuf, C., Storey, M.-A., & Zagalsky, A. (2017). How software developers mitigate collaboration friction with chatbots. Paper presented at the in talking with conversational agents in collaborative action workshop at the 20th ACM conference on computer-supported cooperative work and social computing (CSCW '17).

Li, J., & Huang, J.-S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, *63*, 101410.

Li, L., Lee, K. Y., Emokpae, E., & Yang, S.-B. (2021). What makes you continuously use chatbot services? Evidence from chinese online travel agencies. *Electronic Markets*, *31*, 1–25.

Li, X., Hsieh, J. P.-A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information Systems Research*, *24*(3), 659–682.

Lin, X., Wang, X., & Hajli, N. (2019). Building E-commerce satisfaction and boosting sales: The role of social commerce trust and its antecedents. *International Journal of Electronic Commerce*, *23*(3), 328–363.

Makhalova, T., Ilvovsky, D., & Galitsky, B. (2019). Information retrieval chatbots based on conceptual models. Paper presented at the international conference on conceptual structures.

Maruping, L. M., & Magni, M. (2015). Motivating employees to explore collaboration technology in team contexts. *MIS Quarterly*, *39*(1), 1–16.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734.

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems (TMIS)*, *2*(2), 1–25.

McLean, G., & Osei-Frimpong, K. (2019). Chat now … examining the variables influencing the use of online live chat. *Technological Forecasting and Social Change*, *146*, 55–67.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434.

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS Quarterly*, *35*, 237–256.

Murray, G., & Wardley, M. (2014). The math of modern marketing: How predictive analytics makes marketing more effective. IDC White Paper. http://www.sap.com/bin/sapcom/en_us/downloadasset

Nambisan, S., Agarwal, R., & Tanniru, M. (1999). Organizational mechanisms for enhancing user innovation in information technology. *MIS Quarterly*, *23*, 365–395.

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

Østerlund, C., Jarrahi, M. H., Willis, M., Boyd, K. T., & Wolf, C. (2021). Artificial intelligence and the world of work, a co-constitutive relationship. *Journal of the Association for Information Science and Technology*, *72*(1), 128–135.

Pérez, J. Q., Daradoumis, T., & Puig, J. M. M. (2020). Rediscovering the use of chatbots in education: A systematic literature review. *Computer Applications in Engineering Education*, *28*(6), 1549–1565.

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly*, *31*, 623–656.

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*, 3199–3226.

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, *129*, 878–890.

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

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2019). Winning with AI. *MIT Sloan Management*

Review, 61180. https://sloanreview.mit.edu/projects/winning-with-ai/

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, *56*, 102176.

Rietz, T., Benke, I., & Maedche, A. (2019). *The impact of anthropomorphic and functional chatbot design features in enterprise collaboration systems on user acceptance*. 14th International Conference on Wirtschaftsinformatik, February 24-27, 2019, Siegen, Germany.

Rodríguez Cardona, D., Janssen, A., Guhr, N., Breitner, M. H., & Milde, J. (2021). A matter of trust? Examination of chatbot usage in insurance business. Paper presented at the proceedings of the 54th Hawaii international conference on system sciences.

Ross, W., & LaCroix, J. (1996). Multiple meanings of trust in negotiation theory and research: A literature review and integrative model. *International Journal of Conflict Management*, *7*, 314–360.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, *23*(3), 393–404.

Roy, R., & Naidoo, V. (2021). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, *126*, 23–34.

Sağlam, R. B., & Nurse, J. R. (2020). Is your chatbot GDPR compliant? Open issues in agent design. Paper presented at the proceedings of the 2nd conference on conversational user interfaces.

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, *29*(4), 260–278.

Schuetzler, R. M., Grimes, G. M., & Scott Giboney, J. (2020). The impact of chatbot conversational skill on engagement and perceived humanness. *Journal of Management Information Systems*, *37*(3), 875–900.

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, *115*, 14–24.

Shumanov, M., & Johnson, L. (2021). Making conversations with chatbots more personalized. *Computers in Human Behavior*, *117*, 106627. https://doi.org/10.1016/j.chb.2020.106627

Söllner, M., Hoffmann, A., Hoffmann, H., Wacker, A., & Leimeister, J. M. (2012). *Understanding the formation of trust in IT artifacts*. International Conference on Information Systems (ICIS) 2012, Orlando, FL.

Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge (acting with technology)*. The MIT Press.

Tams, S., Thatcher, J. B., & Craig, K. (2018). How and why trust matters in post-adoptive usage: The mediating roles of internal and external self-efficacy. *The Journal of Strategic Information Systems*, *27*(2), 170–190.

Toader, D.-C., Boca, G., Toader, R., Măcelaru, M., Toader, C., Ighian, D., & Rădulescu, A. T. (2020). The effect of social presence and chatbot errors on trust. *Sustainability*, *12*(1), 256.

Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: Polynomial modeling and response surface analysis. *MIS Quarterly*, *34*, 281–303.

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APPENDIX

Measures

Knowledge support (Lin et al., 2019) Because of the use of chatbot in my company,	
KS1	I have access to more information than ever that is helpful for my job performance.
KS2	I have access to more knowledge than ever that is useful for my job performance.
KS3	I have access to more resources than ever that help me enhance my job performance.
Work–life balance (Brough et al., 2014)	
Because of the use of chatbot in my company,	
WLB1	I currently have a good balance between the time I spend at work and the time I have available for nonwork activities.
WLB2	I feel that the balance between my work demands and nonwork activities is currently about right.
WLB3	Overall, I believe that my work and nonwork life are balanced.
Trust in functionality (Tams et al., 2018)	
TF1	Chatbots have the functionality my company needs.
TF2	Chatbots have the features required by my company.
TF3	Chatbots have the ability to do what my company wants them to do.
Trust in reliability (Tams et al., 2018)	
TR1	Chatbots are very reliable.
TR2	Chatbots do not fail my company.
TR3	Chatbots are extremely dependable.
TR4	Chatbots do not malfunction for my company.
Trust in data protection (Al-Natour et al., 2020)	
TDP1	I trust that chatbots would keep customers' best interests when protecting customers' information.
TDP2	Chatbots are generally predictable when protecting customers' information.
TDP3	Chatbots are generally consistent when protecting customers' information.
Innovative use (Li et al., 2013)	
INV1	Discovered new uses of chatbots to enhance business operations.
INV2	Used chatbots in novel ways to support business operations.
INV3	Developed new applications based on chatbots to support business operations.