International Journal of Information Management 66 (2022) 102535

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

How does artificial intelligence create business agility? Evidence from chatbots

Xuequn Wang [a], Xiaolin Lin [b,*], Bin Shao [c]

[a] School of Business and Law, Edith Cowan University, Joondalup, WA 6027, Australia
[b] Department of Information Systems and Business Analytics, College of Business, California State University, Sacramento, CA, USA
[c] Department of Computer Information and Decision Management, Paul and Virginia Engler College of Business, West Texas A&M University, 2501 4th Ave, Canyon, TX 79016, USA

ARTICLE INFO

Keywords:
Artificial intelligence
Chatbot
Customer service
Agility
Routine use
Innovative use
Dynamic capabilities

ABSTRACT

Artificial intelligence (AI) is gaining increasing attention from business leaders today. As a primary AI tool, chatbots have seen increasing use by companies to support customer service. An understanding of how chatbots are used is essential for improving customer service. Based on the relevant literature, this study examined the impacts of chatbot-enabled agility (namely, internal and external chatbot agility) on customer service performance and explored the antecedents from the perspective of information technology use (both routine and innovative use). We collected data from 294 U.S. marketing employees from various industries, using a survey for the assessment of our research model. The results showed that both routine and innovative use of chatbots were positively related to internal and external agility. In particular, the innovative use of chatbots plays an important role in creating business agility. Moreover, internal and external agility are positively related to customer service performance. Through a close look at chatbots and their use, our study provides insight into the role of AI in creating business agility. Practically speaking, this study suggests that both the routine and the innovative use of chatbots should be encouraged to create agility and develop business sustainability.

1. Introduction

Artificial intelligence (AI) has provided great opportunities for companies to address challenges raised in today's rapidly changing marketplace (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2020; Duan, Edwards, & Dwivedi, 2019; Dwivedi et al., 2021; Hu, Lu, Pan, Gong, & Yang, 2021). For example, chatbots supported by AI have received increasing responsibility to provide effective customer communication (Chung, Ko, Joung, & Kim, 2020; Coombs, 2020; He, Zhang, & Li, 2021). These chatbots can process a large amount of data and train themselves to interact with customers (Mikalef & Gupta, 2021). Recent reports predict that retail sales via chatbots will reach $112 billion by 2023 (Williams, 2019). Chatbots constantly improve their conversational abilities (Watson, 2019), which can help companies respond to customer demand and market changes (Chiu & Chuang, 2021).

As such, chatbots have gained increasing popularity in creating new business agility enabled by information technology (IT) (Chung et al., 2020; McLean & Osei-Frimpong, 2019). Business agility refers to companies' ability to take advantage of their resources (e.g., technology) to efficiently identify and address opportunities and threats (Mathiassen & Pries-Heje, 2006). Companies must enhance business agility to respond to market changes by deploying proper IT. Such IT-enabled agility is critical to sustaining business success (Chuang, 2020; Trischler, Johnson, & Kristensson, 2020). To incorporate chatbots into customer service, practitioners need to recognize the business agility created by chatbots (Akhtar, Khan, Tarba, & Jayawickrama, 2018). Such chatbot-enabled business agility can help firms to better manage the changing environment and meet customer needs (Akhtar et al., 2018; Chuang, 2020).

The literature has suggested that IT use can enhance business agility. For example, Chuang (2020) reported that social-information processing capability and customer cocreation build social media agility, which then enhances the strength of customer–firm relationships. With the development of AI, organizations have increasingly used chatbots to support employees' work, which is likely to create new business agility. However, to the best of our knowledge, *few studies have attempted to investigate how the use of chatbots creates business agility and supports*

* Corresponding author.
E-mail addresses: xuequnwang1600@gmail.com (X. Wang), xiaolin.lin@csus.edu (X. Lin), bshao@wtamu.edu (B. Shao).

https://doi.org/10.1016/j.ijinfomgt.2022.102535
Received 27 May 2021; Received in revised form 26 May 2022; Accepted 27 May 2022
Available online 13 June 2022

customer service. It is meaningful to study business agility by exploring the use of chatbots, given that IT use can evolve (Petter, DeLone, & McLean, 2012). Therefore, our overall research question is: *How do chatbots create business agility and help support customer services?* Specifically, our study aims to do the following: (a) examine how chatbot use results in chatbot-enabled business agility and (b) examine the effects of chatbot-enabled business agility on customer service quality. To achieve our research aims, we draw upon the dynamic capability view (DCV) (Teece, Peteraf, & Leih, 2016) to develop our research model. DCV is an appropriate theory explaining how the use of chatbots can help organizations develop dynamic capabilities, such as sensing and seizing opportunities, which ultimately enhance customer service performance. We conducted a survey and tested our model with 294 U.S. marketing employees.

Our study makes two important contributions. First, our study shows how different types of chatbot use help achieve business agility. We argue that chatbot use within organizations can be divided into routine and innovative chatbot use (Li, Hsieh, & Rai, 2013; Roberts, Campbell, & Vijayasarathy, 2016). Routine and innovative use represent distinct post-acceptance information systems (IS) usage behaviors (Li et al., 2013) and were therefore selected for our study. Specifically, relying only on routine use often leads to the underutilization of IT, whereas engaging in innovative use allows employees to explore IT's new applications (Tams, Thatcher, & Craig, 2018). Therefore, fully comprehending the role of routine use versus innovative use is crucial to formulating methods of realizing the full value of chatbots. By examining their routine and innovative use as separate variables, our study can clarify how chatbots enable agility and which type of chatbot use is more important. Because different types of IT can be used in a variety of ways, the effects of routine and innovative use are probably different in other contexts.[1] Our study thus contributes to the literature by capturing the uniqueness of chatbots and clarifying how chatbot-enabled agility can be achieved through routine and innovative use.

Second, our study provides novel insights by demonstrating the importance of chatbot-enabled agility for enhancing customer service. The literature has suggested that agility adjusts *internal* operational changes and exploits *external* business environments (e.g., Akhtar et al., 2018; Lokshin, Belderbos, & Carree, 2008), making it essential to include both internal and external aspects when evaluating the role of agility in enhancing customer services. Following the literature (Chuang, 2020), our study conceptualizes agility as internal and external. Our results show that while both internal and external agility can significantly improve customer service, external agility plays a more important role. Our study thus contributes to the literature by describing how chatbot-enabled agility can enhance customer services. Our paper could also make significant original contribution to the AI literature, given that it is among the very first studies to attempt to conceptualize agility and investigate its impacts within the context of emerging AI tools. AI-enabled business agility will be the next frontier, and the results of this study provide helpful guidelines for companies to achieve new business agility and improve customer service via investment in the development and use of chatbots.

[1] For example, customer service can use chatbots to answer customers' standard questions (routine use) or to analyze customers' data and generate additional insights (innovative use). On the other hand, human resources can use chatbots to conduct initial screening (routine use). Chatbots can also be used to conduct satisfaction surveys, after which the collected data can be analyzed with novel approaches to better understand employee performance (innovative use).

2. Literature review and theories

2.1. Relevant studies on chatbots

The literature has increasingly recognized chatbots as an important technological trend in supporting customer service (Table 1). Some studies have investigated chatbot adoption. For example, based on the technology acceptance model and gratification theory, Rese, Ganster, and Baier (2020) reported that users' acceptance of chatbots can be determined by different factors, such as the authenticity of conversation, perceived usefulness, and perceived enjoyment. Conversely, although some prior studies have examined the adoption of chatbots in various industries such as telecommunications and clothing (Etemad-Sajadi & Ghachem, 2015; Roy & Naidoo, 2021), few studies have examined the actual use of chatbots. Among these few studies, McLean and Osei-Frimpong (2019) reported that factors such as website aesthetics and perceived customization can increase chatbot use. More recently, Shumanov and Johnson (2021) showed that consumers can use chatbots for longer when their personality is congruent with a chatbot's personality. Both studies examined the use of chatbots from the consumer perspective and in the context of mobile services.

As chatbots have become an innovative channel by which to interact with customers (e.g., Chung et al., 2020; Claessen, Schmidt, & Heck, 2017; Etemad-Sajadi & Ghachem, 2015; Jain et al., 2018; Shumanov & Johnson, 2021), some studies have started to examine the impacts of chatbot use on business outcomes with a focus on customer service through identifying chatbots' features and functionalities (e.g., Chung et al., 2020; Rese et al., 2020). For example, Schuetzler et al. (2020) suggested that the anthropomorphic character of chatbots, such as perceived humanness and partner engagement, improves users' experiences. Ashfaq et al. (2020) reported that the quality of information and services provided to customers could improve their satisfaction. McLean and Osei-Frimpong (2019) suggested that chatbots can help companies provide high-quality services to their customers and achieve various benefits, such as word-of-mouth referrals and customer satisfaction. More recently, Adam et al. (2020) showed that anthropomorphism (identity, small talk, and empathy) and fulfilling small requests increase the likelihood of consumer compliance.

To summarize, companies have been deploying chatbots to customers with the goal of improving customer service and customer satisfaction. The key to achieving this goal stems from the capacities and agility provided by chatbot integration into regular business operations. However, our review (Table 1) showed that few studies have examined chatbots from an employee perspective and assessed how employees' chatbot use can result in business agility and enhanced customer service. To fill this research gap, our study has focused on how chatbot use generates business agility, which in turn enhances customer service quality. Therefore, employees in the field of marketing were selected as the focus of this study. Next, we describe agility and ways of helping transition the use of chatbots into enhanced customer service performance.

2.2. Business agility: a chatbot perspective

The term *agility* refers to the ability of a company or an organization to rapidly react to changes and uncertainties (Akhtar et al., 2018; Chuang, 2020). *Business agility* can be defined as a company's ability to use its human resources, technology, processes, and knowledge to efficiently identify and address opportunities and threats, such as market changes, customer demands, and new technologies (Mathiassen & Pries-Heje, 2006). Teece et al. (2016) have defined agility as "the capacity of an organization to efficiently and effectively redeploy/redirect its resources to value creating and value protecting (and capturing) higher-yield activities as internal and external circumstances warrant" (p. 17). Nold, Anzengrubcr, Woclfle, and Michel (2018) argued that organizational agility can be conceptualized in four dimensions: culture,

Table 1
Summary of the chatbot literature.

Study	Method	Context	Independent variable	Dependent variable	Variables measuring chatbot use	Summary
Adam, Wessel, and Benlian (2020)	Experiment	Online banking	Anthropomorphic design cues; foot-in-the-door technique	User compliance		Anthropomorphism (identity, small talk, and empathy) and the need to stay consistent increase compliance.
Ashfaq, Yun, Yu, and Loureiro (2020)	Survey		Information quality; service quality; perceived enjoyment; perceived usefulness; perceived ease of use	Satisfaction; continuance intention		The need for interaction moderates the relationships between perceived ease of use and perceived usefulness and satisfaction.
Chung et al. (2020)	Survey	E-service agents for luxury brands	Interaction; entertainment; trendiness; customization, problem solving	Satisfaction		Service agents' marketing efforts can increase customers' satisfaction via accuracy and credibility.
Etemad-Sajadi and Ghachem (2015)	Survey	Airline carrier; travel agency; telecommunications; rail transport; furniture retailing; health insurance	Utilitarian and hedonic value	E-service quality		Utilitarian values influence nine dimensions of e-service quality, whereas hedonic values influence five dimensions of e-service quality.
Jain, Kumar, Kota, and Patel (2018)	Interview; second-hand data					Eight chatbots were evaluated.
Lalicic and Weismayer (2021)	Survey		values; reasons for/against chatbot	value co-creation; behavioral intention		Chatbot use intention can be explained by four different combinations.
McLean and Osei-Frimpong (2019)	Survey	Mobile services	Website aesthetics; perceived customization; perceived ease of use; perceived usefulness; perceived information quality; perceived web credibility; perceived timeliness; dissatisfaction with experience	Use of chatbot	Three items measuring the use of chatbot	Eight variables (e.g., website aesthetics, perceived customization) motivate chatbot use.
Pizzi, Scarpi, and Pantano (2021)	Experiment	Mobile services; car rental	Assistant type/initiation	Choice		Anthropomorphic chatbots can reduce reactance, but also reduce satisfaction.
Rese et al. (2020)	Survey	Clothing company		Behavioral intention		A technology acceptance model was compared with the use and gratification theory to predict chatbot acceptance.
Roy and Naidoo (2021)	Experiment	Hotel; smartphone; clothing company	Conversation style	Attitude toward brand; purchase intention		Consumers can have positive attitudes and higher purchase intentions when their time orientations match their conversation type.
Schuetzler, Grimes, and Scott Giboney (2020)	Experiment		Conversational skills	Social presence; perceived humanness; partner engagement		Chatbots with high conversational skills can lead to higher social presence and anthropomorphism.
Shumanov and Johnson (2021)	Experiment	Mobile services	Consumer-chatbot personality	Chatbot engagement; purchasing behavior	Chatbot engagement (the average interaction duration)	Congruence between consumer and chatbot personality increases consumer engagement and purchasing behaviors.

leadership, systems, and people.

Innovation represents the core of the business agility framework and is often influenced by IT. Flexible IT infrastructure significantly benefits agility (Tallon & Pinsonneault, 2011). Gao, Zhang, Gong, and Li (2020) described two research streams that examined the role of IT in creating organizational agility. The first stream deals with technical IT capabilities and focuses on IT flexibility and IT integration. The second stream investigates managerial IT capabilities, including factors such as IT skills, proactive stance, and business spanning capability. In the first stream, Ngai, Chau, and Chan (2011) showed that both IT integration and flexibility can enhance the agility of a supply chain. In the second stream, Overby, Bharadwaj, and Sambamurthy (2006) explored the specific ways in which IT and digital alternatives impact company agility and found that effective use of IT is one way firms can sustainably engage in sensing business environmental changes and in formulating responses. The use of advanced IT tools can enhance business agility because they provide companies and organizations with new ways of increasing agility (e.g., Akhtar et al., 2018; Lu & Ramamurthy, 2011).

The DCV is a useful theoretical lens through which to understand the business agility created by IT, which can emerge in the form of dynamic capabilities (e.g.,Gupta & Meissonier, 2020). It suggests that "firms whose managers have superior dynamic managerial capabilities can adapt and change more successfully than firms whose managers have less effective or no dynamic managerial capabilities" (Helfat & Martin, 2015, p. 1304). More specifically, dynamic capabilities include firms' abilities to identify and seize opportunities, and they comprise three main clusters: identifying and developing technological opportunities in response to customer needs (i.e., sensing), mobilizing resources to deal with these needs (i.e., seizing), and continual renewal (i.e., transforming) (Teece et al., 2016). Prior studies have demonstrated that IT can play a bridging role in developing dynamic capabilities by connecting organizational resources and operational business functions (e.g., Duan, Faker, Fesak, & Stuart, 2013; Gupta, Drave et al., 2020; Zhang, Qu, Ho, & Huang, 2011).

Therefore, sensing, seizing, and transforming are essential to achieving agility (Teece et al., 2016), which is created by IT from a DCV perspective. Sensing involves proactively developing new solutions based upon customer needs and evaluating the effectiveness of these solutions (e.g., scenario planning). Seizing deals with selecting appropriate solutions and implementing these solutions (e.g., developing "slack," re-engineering structures). Transforming includes iterative improvement through trialing, launching, and learning. When firms have dynamic capabilities that have emerged from IT, they can modify organizational resources to respond to customer needs and market changes, thereby achieving agility (Teece et al., 2016).

In addition, based on the DCV, the literature has argued that dynamic capabilities can have internal and external sourcing and that both internal and external capabilities can strengthen relationships with customers (e.g., Akhtar et al., 2018; Lokshin et al., 2008). In a recent study, Chuang (2020) categorized social media agility as either internal or external agility. Internal agility refers to firms' flexibility in dealing with customers' demands in their day-to-day operations (i.e., internal sourcing). External agility refers to firms' flexibility in responding to customers' requirements stemming from external information sources, links, and collaborative relationships (i.e., external sourcing).

In the digital age, AI can increase companies' flexibility and ability to respond to changes in the competitive business environment by underpinning such important business functions, such as automating business processes, gaining insight through data analysis, and engaging with customers and employees (Davenport & Ronanki, 2018). Chatbots have been increasingly used by companies to support customer service. They can effectively connect companies with their customers and improve customer service through various technical features, such as seamless live communication and 24/7 customer service (Ameen, Tarhini, Reppel, & Anand, 2021; Huang & Rust, 2018; Hui, Fong, & Jha, 2001). As such, chatbots enable companies to answer customers' questions and address their problems more efficiently. Companies using chatbots can also understand their customers better, identify customer demands, and identify changes in targeted marketing based on interaction with their customers. As such, they can better fulfill customer needs, react to changes more efficiently and effectively, and increase business agility. Therefore, it is clear that the merging of chatbots and business operations has created a new way for companies to achieve the agility to respond to both internal customer demand and external marketing changes, which we name *chatbot-enabled agility*.

Following Chuang (2020), we developed the concept of chatbot-enabled agility as one that has two dimensions: internal and external. Internal chatbot agility refers to the flexibility of companies enabled by chatbots to respond to customer demand by optimizing the delivery and offering of products and services and by resolving customers' questions efficiently and effectively. Specifically, chatbots can help achieve business agility through internal sourcing. Chatbots can analyze customer data via AI algorithms (e.g., machine learning) and understand how to address customers' questions (i.e., sensing). These solutions can then be implemented in chatbots to better serve customers (i.e., seizing). Last, such a process is interactive, and chatbots can improve their performance through ongoing learning from their interactions with customers (i.e., transforming). Thus, chatbots can help businesses achieve sensing, seizing, and transformation through internal sourcing and enabling of agility (Teece et al., 2016).

External chatbot agility refers to the flexibility of companies enabled by chatbots to respond to market changes efficiently and effectively and to identify new marketing opportunities (Chuang, 2020). Chatbots can also help achieve business agility through external sourcing. Chatbots can analyze market trends and changes from external sources via AI algorithms (e.g., machine learning) and develop their estimations of different markets (i.e., sensing). These estimations can then be integrated into chatbots to better understand customers and provide improved services (i.e., seizing). Last, given that the market keeps changing, such a process is interactive, and chatbots can help firms continuously adapt to the changing market (i.e., transforming). Thus, chatbots can also help achieve sensing, seizing, and transforming via external sourcing and achievement of agility (Teece et al., 2016).

Applying this distinction thus follows the literature, which posits that agility can be captured as either internal or external (Da Silveira, Borenstein, & Fogliatto, 2001; Huo, Gu, & Wang, 2018). One can define agility using two orientations: companies' ability to quickly address customer needs or to address market change. Internal agility addresses customers' needs via internal business processes, focusing on issues related to a company's products and services as well as the customers' requirements. External agility identifies and responds to dynamics in the external business environment (e.g., the market).

2.3. Routine versus innovative use

After chatbots have been implemented into organizations, they need to be used by marketing employees to provide customer service and to generate business value. Previous studies have examined consumers' general use of chatbots (McLean & Osei-Frimpong, 2019; Shumanov & Johnson, 2021), but few studies have taken the further step of examining different types of chatbot use within organizations. In the IS literature, the process of technology implementation has been divided into six stages (Cooper & Zmud, 1990): initiation, adoption, adaptation, acceptance, routinization, and infusion. Routinization refers to the integration of technology into the normal work process, and infusion refers to the deep and comprehensive embedding of technology into the work process. After employees accept the technology and commit to its use, routinization and infusion can occur during the post-acceptance stage. Further, the literature has argued that routinization and infusion do not need to happen sequentially and can coexist in parallel (Cooper & Zmud, 1990).

In the context of business intelligence systems, Li et al. (2013) proposed the concepts of routine and innovative use to reflect the routinization and infusion stages, respectively. Routine use is defined as "employees' using IS in a routine and standardized manner to support their work" (Li et al., 2013, p. 659). Innovative use refers to "employees' discovering new ways to use IS to support their work" (Li et al., 2013, p. 659). Routine use has a standardization orientation (Benner & Tushman, 2002). Under routine use, employees use technology as a normal part of their work activities (Li et al., 2013). Thus, routine use allows employees to become familiar with a certain technology and to improve their work efficiency.

Conversely, innovative use has an innovation orientation and challenges the repetitive work process (Benner & Tushman, 2002). Innovative use entails developing creative alternatives that further realize the value of the technology (Jasperson, Carter, & Zmud, 2005). Based on the work of Li et al. (2013), Roberts et al. (2016) identified routine and innovative use as two types of managerial use of decision support systems. They argued that the primary difference between the two kinds of use lies in the different ways managers use decision support systems to support their work. Managers may use these systems to accomplish assigned work in a standardized manner, such as learning about customers and sales. Managers may also use decision support systems to accomplish assigned work in an innovative manner, such as applying new data analysis skills and identifying new business opportunities.

Therefore, in our study, we argue that both routine and innovative use appear when using chatbots to support business operations and employees' work. Marketing employees can engage in routine use. For example, employees can use chatbots to answer customers' routine questions quickly and automatically to provide product information with web pages and tutorials, and to collect feedback from customers. Chatbots can also be trained to better answer routine questions. Marketing employees can participate in innovative use as well. For example, they can analyze conversational data with new methods to help identify additional marketing opportunities. Employees can also ask new questions when interacting with customers. The conversational data can then be used to train chatbots so they can deal with new types of questions or answer questions in new ways, based on specific contexts.

Firms can engage in both routine and innovative use of chatbots. They can integrate chatbots into routine business operations while also discovering new approaches to obtain additional benefits from chatbots. Whether a certain way to use chatbots is innovative depends on the specific context. Specifically, when a certain usage approach to chatbots has not been routinized at a certain point in time, it is considered innovative use and is consistent with operationalizations of routine and innovative use in the existing literature (Li et al., 2013). It is possible that certain approaches to innovative use may become routinized later and become routine use.

3. Research model and hypotheses development

Our model appears in Fig. 1. Based on the literature, we argue that marketing employees can engage in both routine and innovative use of chatbots. These two types of use can enhance both internal and external chatbot agility, which ultimately will enhance customer service performance. In the following text, we will describe each hypothesis in more detail.

3.1. The effect of agility on customer service performance

Previous studies have shown a significant positive correlation between business agility and performance (Queiroz, Tallon, Sharma, & Coltman, 2018; Tallon & Pinsonneault, 2011). Based on the DCV, recent studies have demonstrated that dynamic capabilities, which agility relies on, can improve various business outcomes, such as economic performance, to sustain the business (e.g., Gupta & Meissonier, 2020; Helfat & Martin, 2015). Accordingly, we argue that increased internal agility enabled by chatbots in organizations can boost customer service performance. AI-enabled chatbots can use various algorithms (e.g., natural language processing) and understand how to interact with customers (Mikalef & Gupta, 2021). Therefore, this growth in internal agility, enabled by chatbots, allows a business's daily operations to adjust to handle revisions in customer demands (Chuang, 2020). For example, chatbots can capture customers' feedback more quickly, in turn allowing the research and development department to redesign products to meet updated requirements more quickly.

With the help of chatbots, the marketing department will be able to determine the best times to offer promotions. Furthermore, through analysis of data from chatbots, companies can streamline the sensing and reflection of customer needs to enhance product and customer service quality (Pizzi et al., 2021). The aforementioned rise in adaptability to customer demands will also facilitate a more efficient system of product and service delivery (Pizzi et al., 2021). Without a doubt, chatbot-supported internal agility will allow companies to communicate with customers clearly and methodically and to decrease the difficulty of maintaining relationships with customers. Therefore, we hypothesized the following:

H1. : Internal chatbot agility is positively related to customer service performance.

Moreover, we argue that increased external agility, enabled by chatbots, can also improve customer service performance. The market is dynamic—especially in the digital era—and companies must present correct and timely responses to market changes to remain competitive (Weber & Tarba, 2014). Expected market changes include but are not limited to factors such as consumer demand, market capacity, industry inventory, competitor pricing, product quality, financing, interest rates, asset prices, the employment rate, and national and regional political stability. Through interactions with customers, chatbots can collect a large volume of data. Data analysis can improve understanding of customer profiles and needs and thus improve understanding of targeted marketing (Pizzi et al., 2021). Specifically, chatbots rely on AI algorithms such as machine learning, which can be trained to monitor market changes (Phansalkar, Kamat, Ahirrao, & Pawar, 2019). As such, chatbots can help companies monitor market dynamics and respond to their changes (Chuang, 2020). We also anticipate the appearance of new business models, taxes, and regulations—as well as a change in inflation rates. If a company is involved in the international market, external agility will also help it to withstand the fluctuation of exchange rates. Therefore, we proposed the following hypothesis:

H2. : External chatbot agility is positively related to customer service performance.

3.2. The effect of routine use on agility

It is understood that a particular type of IT use is likely to be associated with individuals' perceptions of outcomes resulting from the use (e.g., Bae, 2017). For example, Chuang (2020) showed that social-information process capability of social media can positively affect users' perceptions of social media agility. Social-information process capability can be considered a specific type of social media use, which increases the agility created by social media. Business agility has been referred to as a business's ability "to sense and respond rapidly to unpredictable events in order to satisfy changing customer demands" (Holmqvist & Pessi, 2006, p. 146). It thus deals with firms' capabilities to adapt to a changing environment driven by factors such as changing customer preferences and target markets (Overby et al., 2006). As previously discussed, internal agility can capture the capabilities of companies to deal with customers by optimizing internal business processes. In our study, we argue that routine use of chatbots can increase internal agility. As previously discussed, routine use refers to the integration of chatbots into a firm's standardized marketing process (Li et al., 2013). Based on the DCV, routines are important to support dynamic

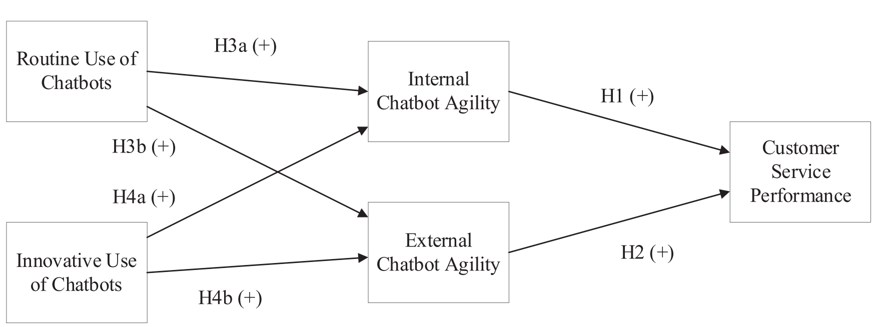

Fig. 1. Research model.

capabilities (Teece et al., 2016) because they can efficiently integrate the functions of chatbots into organizational functions in real-time. Following the DCV (Helfat & Martin, 2015), we argue that routine use can increase companies' dynamic capabilities, such as identifying and seizing, as well as reconfiguring, organizational assets (Roberts et al., 2016). Specifically, as marketing employees become more familiar with chatbots and incorporate them into their work, the marketing process can be better supported. With the incorporation of chatbots into the routine work process, they can enhance information processing within organizations and help collect a large amount of customer data that can be used to generate marketing insights (Akhtar et al., 2018). The chatbots' unique ability to handle high-volume data with improved accessibility and analysis facilitates the development of dynamic capability, which leads to agility. Therefore, routine use is more likely to provide offerings and promotions to meet customers' needs by enhancing efficiencies in the marketing process, thus increasing internal agility. Therefore, we hypothesized the following:

H3a. *Routine use of chatbots is positively related to internal chatbot agility.*

External agility can capture the capabilities of companies to identify and respond to new opportunities in the external environment (Chuang, 2020). The use of chatbots can provide companies with functions to actualize these capabilities. For example, social media functions such as information processing and customer cocreation can create social media agility (Chuang, 2020). In our study, we also argue that routine use of chatbots can increase external agility. AI algorithms can help chatbots keep track of customers' needs and concerns (Phansalkar et al., 2019). For example, by conducting routine analysis with conversational data between chatbots and customers, employees can better understand whether customer preferences have changed, enhancing sensing capabilities. By integrating chatbots into standard marketing procedures, employees can also examine whether customers request certain types of products or focus more on certain features of products in response to targeted marketing, increasing seizing capabilities. Altogether, routine use of chatbots provides insights that enhance an organization's dynamic capabilities, such as sensing and seizing (Teece et al., 2016), to assist in reconfiguring resources in response to market changes. As a result, external agility also increases. In other words, employees who use chatbots as part of their routine work processes can acquire knowledge about the market and thus seize marketing opportunities (Roberts et al., 2016). To summarize, routine use allows employees to be more aware of customer demand and market changes. Therefore, we hypothesized the following:

H3b. *Routine use of chatbots is positively related to external chatbot agility.*

3.3. The effect of innovative use on agility

The innovative use of chatbots can also increase internal agility. Innovative use refers to new ways of using chatbots to support customer service (Li et al., 2013, p. 659). Innovative use helps organizations achieve the full benefits of IT (Tams et al., 2018). With innovative use, employees can also benefit from the features of IT more extensively and expend more effort applying IT in innovative approaches (Nambisan, Agarwal, & Tanniru, 1999). The DCV argues that dynamic capabilities are not solely based on routines, and innovative thinking and actions are also vital for developing dynamic capabilities (Teece et al., 2016). Consistent with the DCV (Helfat & Martin, 2015), innovative use can also increase organizations' ability to sense opportunities and then reconfigure resources accordingly (Roberts et al., 2016). For example, marketing employees may let chatbots ask customers new questions and then try new approaches to serving them. Thus, marketing employees can challenge existing processes and develop creative approaches to responding to customers' needs while also enhancing internal agility. Next, new methods can be used to analyze conversational data resulting from interactions between chatbots and customers. As a result, new marketing opportunities can be identified, and firms can continuously provide new offerings or promotions to meet customers' additional needs (i.e., transforming), a process that also enhances internal agility (Teece et al., 2016). Therefore, we hypothesized that:

H4a. *Innovative use of chatbots is positively related to internal chatbot agility.*

The innovative use of chatbots can also increase external agility. Chatbots can be trained with new algorithms and can thus respond to market changes and address new requirements from customers (Chuang, 2020). Thus, the innovative use of AI can increase firms' dynamic capabilities related to sensing (Teece et al., 2016). Employees can also ask different questions during their interactions with customers and then train chatbots to deal with new issues from customers. Therefore, firms' dynamic seizing capabilities can also be enhanced. Last, given that such processes are iterative and chatbots can keep monitoring continuous changes to the market, firms' dynamic transforming capabilities can also be developed (Teece et al., 2016). In those contexts, innovative use of chatbots can help firms and employees better identify and respond to market changes and new opportunities and explore new growth paths, thus improving external agility. (Roberts et al., 2016). In addition, according to the DCV (Helfat & Martin, 2015), employees have bounded rationality, which limits their capacity to identify new marketing opportunities. Innovative use of chatbots can help employees overcome limitations and expand their capabilities, thus allowing them to explore new opportunities. The literature has also shown that innovative use can increase managers' abilities to sense opportunities for organizational innovation (Roberts et al., 2016), which can also contribute to marketing expansion. Therefore, we hypothesized the following:

H4b. *Innovative use of chatbots is positively related to external chatbot agility.*

3.4. The mediating effects of internal and external agility

In the previous discussions, we have hypothesized that routine use of chatbots has a positive effect on internal and external agility, in turn increasing customer service performance. Based upon DCV, we further argue that internal and external agility mediate the effect of routine use of chatbots on customer service performance (Teece et al., 2016). Specifically, routine use of chatbots can support organizations' standardized marketing processes, and enhancing these processes can generate dynamic capabilities (Teece et al., 2016) dealing with sensing, seizing, and transforming organizational assets (Roberts et al., 2016). Therefore, incorporating chatbots into routine workplaces should improve companies' understanding of customer needs and their tracking of marketing changes by processing massive amounts of customer data (Akhtar et al., 2018), generating both internal and external agility. Based on DVC, this enhanced business agility allows companies to provide better customer services (e.g., Gupta & Meissonier, 2020; Helfat & Martin, 2015). Therefore, we hypothesize:

H5. : Internal (H5a) and external chatbot agility (H5b) mediate the effect of routine use of chatbots on customer service performance.

Lastly, the previous hypotheses state that innovative use of chatbots positively impacts internal and external agility, which then enhance customer service performance. Based on DCV, we further argue that internal and external agility mediate the effect of innovative use of chatbots on customer service performance (Teece et al., 2016). In this mediated relationship, the innovative use of chatbots is important to generate dynamic capabilities in addition to routine use (Teece et al., 2016). Specifically, the innovative use of chatbots also strengthens companies' capabilities of sensing and seizing opportunities (Roberts et al., 2016). For instance, marketing employees may add new questions into chatbots and later use new methods to analyze customer data chatbots collect. These new approaches of using chatbots can help companies further understand customer preferences and market changes, enabling them to offer better customer services (e.g., Gupta & Meissonier, 2020; Helfat & Martin, 2015). We therefore hypothesize:

H6. : Internal (H6a) and external chatbot agility (H6b) mediate the effect of innovative use of chatbots on customer service performance.

4. Research method

4.1. Data collection and sample

We hired a professional research firm to recruit employees who work for companies that use chatbots, and the firm conducted a survey to collect data about employees' perceptions of the use of chatbots and its consequences. The survey contains items that measure our constructs as well as open-ended questions to help us further understand the impact of chatbot use. Therefore, our study is mainly quantitative, intended to test the model as developed, complemented by answers from qualitative questions. The research firm maintains national panels, and recruits and screens participants in a variety of industries. Our study focuses on employees who are familiar with the use of chatbots within organizations and who regularly interact with customers. Thus, our subjects are U.S. employees who work in marketing departments or other similar departments. Data collection occurred over two weeks around the beginning of 2021. The link to the survey was sent to potential participants via email. The survey contains quality control questions (e.g., "Please answer this question by selecting 'strongly disagree'") to detect careless answers. The sampling approach was systematic sampling. For example, if we planned to collect 200 participants and the national panels had about 100,000 individuals, then the survey invitations were sent out with the interval of 500 individuals. We included several screening questions, such as "Does your company use chatbots to support customer services?" and "What are your job responsibilities?" Participants would not qualify for our study if they selected "no" in response to the first question or did not select "marketing (using chatbots to interact with customer)" in response to the second question. In the survey, we also asked participants for the name of the chatbot they used. In total, we received 323 responses. After removing careless answers in response to the quality control questions, a total of 294 valid responses remained (valid rate: 91.02%). We tried to eliminate the nonresponse bias through several approaches (Rosenthal & Rosnow, 2008): (a) offering incentives (bonus points provided by the survey company, which could be converted to money) to encourage participation; (b) sending reminders to enhance participation; and (c) ensuring that participation was anonymous and no personal identification information would be collected. We also compared gender, age, and education between early and late participants, and there were no significant differences. Therefore, a nonresponse bias should not be an issue in our study. On average, the respondents had worked for their current companies for 7.86 years. The companies involved used chatbots such as SnatchBot and Bold360. Participants came from a variety of industries, such as bank/finance, health care, IT and telecommunication, retail, and hospitality, consistent with a recent report on the chatbot market (Mordor Intelligence, 2021). Demographic information appears in Table 2.

Table 2
Demographic information of subjects.

Category	Sample (N = 294)
Gender	Female: 37.8%
Age	
18–24	7.5%
25–34	38.4%
35–44	37.4%
45 or above	16.7%
Company size in number of employees	
1–200	22.5%
201–500	16.4%
501–1000	20.4%
1001–3000	17.9%
> 3000	22.9%
Education	
High school or below	9.5%
Some college education or bachelor's degree	61.2%
Graduate degree	29.3%
Industry	
Health care	9.9%
Manufacturing	13.3%
Education	4.8%
Higher education	2.0%
Banking/Finance	15.0%
Insurance	3.7%
Wholesale and distribution	4.1%
Transportation	5.1%
Government	2.4%
Retail	11.9%
Hospitality	1.4%
IT and telecommunication	6.5%
Other	20.0%

4.2. Measures

Our measures were adapted from prior literature (see Appendix A). This study used 7-point Likert scales, with anchor 1 indicating "strongly disagree" and anchor 7 indicating "strongly agree." We measured customer service performance using items modified from Chuang (2020) and Setia, Setia, Venkatesh, and Joglekar (2013). In particular, Setia et al. (2013) used items such as "retaining existing customers" and "attracting new customers" to measure customer service performance. These items reflect a firm's strengthened relationships with customers and are consistent with the item "My company has established good relationships with customers" from Chuang (2020). Therefore, this item was selected in our study to reflect enhanced customer-firm relationships as a measure of customer service performance.[2] We also used the item "My company has provided better customer service than ever" to represent overall customer service performance. This item is consistent with "achieving overall satisfaction" from Setia et al. (2013).

We adapted items measuring routine and innovative use of chatbots from Li et al. (2013) and modified them to fit our research context for chatbots. These items were selected because they reflected employees' actual usage behaviors. We used items that Akhtar et al. (2018) and Chuang (2020) designed to measure internal and external agility, with modifications to fit the current research context. These items were selected because they focused on the measurement of agility enabled by IT (e.g., social media). Adding "Because of the use of chatbots" to the questions ensured that participants focused on agility enabled by chatbots, also consistent with Chuang (2020). In other words, we were able to measure chatbot-enabled agility, rather than business agility in general. As such, it can provide further insights into the measures of business agility that is created by a particular type of IT. Removing this text would lead the items to measure general internal and external agility, which can be influenced by organizations' differing technologies.

4.3. Data analysis and results

We used SmartPLS 3.2.8, which offers the bootstrap resampling method (using 5000 samples), to test our model. Our measures were not normally distributed (i.e., Shapiro–Wilk tests were significant). Following Hair, Hult, Ringle, and Sarstedt (2016), it is appropriate to analyze unusually distributed data with PLS. Further, PLS focuses on predicting and maximizing explained variance (Henseler, Ringle, & Sarstedt, 2015), consistent with our aim of predicting customer service

[2] We thank one reviewer for providing very helpful comment regarding the measures of customer service performance.

performance. Last, PLS requires a smaller sample size (Henseler et al., 2015) and would therefore allow us to conduct post-hoc analysis with subsamples (Henseler et al., 2015). Therefore, we chose SmartPLS for this study.

4.3.1. Measurement model testing

We assessed the measurement model using both convergent and discriminant validity criteria for the variables. First, the loadings of each item placed above.70. Items also had acceptable reliabilities and the average variance extracted (AVE) for each construct exceeded.50 (Table 3), both supporting convergent validity. Second, as shown in Table 4, the square root of each variable's AVE exceeded correlations between that variable and all other variables, which supports discriminant validity. In addition, all the correlations between constructs fell below the quality criterion of 0.85, further confirming the discriminate validity of our measurement model (Brown, 2015). We conducted additional analyses by assessing cross loadings and the heterotrait–monotrait ratio of correlations. Again, the results (Appendix B) supported discriminant validity. Last, we calculated variance inflation factors (VIF). The values were 1.74 and 2.86 for routine/innovative use and internal/external agility, respectively. All values were below the threshold of 3.3 (Petter, Straub, & Rai, 2007), so multicollinearity was not an issue. Thus, this study had acceptable psychometric properties.

4.3.2. Structural model testing

We assessed path coefficients and R^2 and tested our hypotheses. The results appear in Fig. 2. They support H1, which states that internal agility is positively related to customer service performance ($\beta = 0.20$, $p < .05$). H2, which states that external agility is positively related to customer service performance, is also supported ($\beta = 0.65$, $p < .001$). H3a proposes that the routine use of chatbots is positively related to internal agility. This hypothesis is also supported ($\beta = 0.23$, $p < .001$). H3b, arguing that the routine use of chatbots is positively related to external agility, is supported as well ($\beta = 0.22$, $p < .001$). H4a states that the innovative use of chatbots is positively related to internal agility. This hypothesis is supported ($\beta = 0.53$, $p < .01$). The innovative use of chatbots is also positively related to external agility, as stated in H4b, which is also supported ($\beta = 0.53$, $p < .001$). The two types of chatbot use explain 49.37% of the variance based on internal agility and 48.79% of the variance based on external agility. The two types of agility explain 66.68% of the variance from the perspective of customer service performance.

Furthermore, the results are robust after controlling for firm size. After adding firm size as the control variable and testing the hypotheses, the effects of both internal ($\beta = 0.17$, $p < .05$) and external agility ($\beta = 0.61$, $p < .001$) remain significant, and the firm size has a positive effect on customer service performance ($\beta = 0.12$, $p < .05$). Overall, these results provide strong support for our model.

Finally, we tested the mediating effects of internal and external agility on bootstrapping by using the PROCESS macro (Hayes, 2017). Constructed scores generated from SmartPLS were used to conduct the analysis. When zero was not within the 95% confidence interval, the indirect effects were significant (i.e., the mediating effects were significant). The results (Table 5) show that external chatbot agility mediated the relationship between routine use of chatbots and customer service performance. Both internal and external chatbot agility mediated the relationship between innovative use of chatbots and customer service performance. These results further support our model.

Table 3
Item descriptive statistics.

Construct	Item	Mean	SD	Loading	Alpha	CR	AVE
Routine use of chatbots (Mean: 5.40; SD: 1.09)	RTN1	5.42	1.15	0.89	0.88	0.92	0.80
	RTN2	5.35	1.18	0.89			
	RTN3	5.43	1.28	0.91			
Innovative use of chatbots (Mean: 5.18; SD: 1.23)	INV1	5.15	1.33	0.90	0.86	0.92	0.78
	INV2	5.22	1.36	0.89			
	INV3	5.19	1.43	0.86			
Internal agility (Mean: 5.27; SD: 1.08)	IA1	5.22	1.25	0.89	0.90	0.93	0.77
	IA2	5.35	1.18	0.86			
	IA3	5.22	1.30	0.87			
	IA4	5.32	1.24	0.88			
External agility (Mean: 5.26; SD: 1.13)	EA1	5.26	1.22	0.88	0.90	0.93	0.78
	EA2	5.28	1.24	0.89			
	EA3	5.22	1.30	0.86			
	EA4	5.32	1.32	0.89			
Customer service performance (Mean: 5.43; SD: 1.16)	CSP1	5.47	1.25	0.94	0.87	0.94	0.88
	CSP2	5.41	1.23	0.94			

Table 4
Correlation between constructs and square root of AVEs (on Diagonal).

	1	2	3	4	5
1 Routine use of chatbots	**0.90**				
2 Innovative use of chatbots	0.65	**0.89**			
3 Internal agility	0.58	0.68	**0.88**		
4 External agility	0.57	0.68	0.81	**0.88**	
5 Customer service performance	0.59	0.64	0.72	0.81	**0.94**

4.3.3. Common method bias

We also assessed common method bias (CMB) (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) because all the variable collection occurred in one survey. First, the results of Harman's single factor analysis showed three factors, and the first of these explained 39.64% of the total variance. Second, we created a common method factor including all items (Podsakoff et al., 2003). We then calculated the variance explained by both the focal factor and the method for each item following (Liang, Saraf, Hu, & Xue, 2007). The results show that the average variance explained by the focal factor was.78, whereas the variance explained by the method factor was.003, with a ratio of 281:1. Lastly, we assessed variance inflation factors (VIFs). According to one study (Kock, 2015), CMB could be an issue when VIFs are greater than 3.3. Our analyses revealed that the VIFs for routine and innovative use were both 1.74, and the VIFs for internal and external chatbot agility were both 2.86. All of these values were below 3.3. Therefore, CMB seemed unlikely to be a concern and unlikely to influence the research results of this study.

4.3.4. Post-hoc analysis

Because firms of different sizes may have different business processes and different approaches to the use of chatbots, we divided our sample into two subsamples based on firm size. This post-hoc analysis provided further insights for our research aims and helped us understand whether the strengths of the relationships presented in our model differed across firm sizes. Seven participants did not report their firm sizes and were dropped from this analysis. According to one study (Dilger, 2017), firms with fewer than 500 employees are typically considered small-to-medium firms. Therefore, we chose to divide our sample into small-to-medium firms with fewer than 500 employees and large firms with 500 or more employees. We reran our model and compared the path coefficients between two subsamples following Keil et al. (2000), using the following formula to calculate the t-value and evaluate the

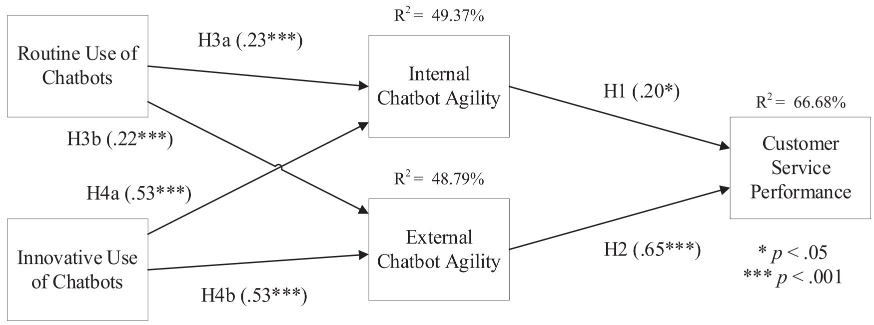

Fig. 2. Model Results.

Table 5
The mediating effect of internal and external agility.

Independent variable	Mediator	Dependent variable	Bootstrap analysis		
			Indirect effect	Percentile confidence	
				Lower	Upper
Routine use of chatbots	Internal chatbot agility	Customer service performance	0.08	−0.01	0.18
	External chatbot agility		0.34	0.23	0.46
	Total		0.42	0.32	0.53
Innovative use of chatbots	Internal chatbot agility	Customer service performance	0.10	0.01	0.23
	External chatbot agility		0.40	0.27	0.54
	Total		0.50	0.37	0.65

significance levels of the differences:

$$t = \frac{\text{Path coefficient}_{\text{Group1}} - \text{Path coefficent}_{\text{Group2}}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} \times SE^2_{\text{Group1}} + \frac{(n-1)^2}{(m+n-2)} \times SE^2_{\text{Group2}}}\right] \times \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

where SE_{Groupi} is the standard error of path in the structural model of group i, m is the sample size of Group 1 and n is the sample size of Group 2. In the existing literature, this approach has been demonstrated as a valid technique for testing subsample differences (e.g., Chiu, Wang, Fang, & Huang, 2014; Lin & Wang, 2020; Zhang, Ma, Xu, & Xu, 2019).

The results (Table 6) show that all hypotheses were still significant except for H1 for small-to-medium firms. Internal chatbot agility had a stronger effect on customer service performance for large firms, whereas external chatbot agility had a greater effect on small-to-medium firms. Routine use of chatbots produced stronger effects on internal/external chatbot agility for small-to-medium firms, whereas innovative use of chatbots had greater effects on large firms. These research findings offered some interesting insights into the use of chatbots and the impacts across firms of different sizes. Nevertheless, the effects of routine and innovative use on internal and external agility were significantly different when comparing small-to-medium firms and large firms. Future studies could further examine these differences.

Table 6
Post-hoc analysis (small-to-medium versus large firms).

Hypothesis	Small-to-Medium Firms ($N = 110$)	Large Firms ($N = 177$)	*T-value*	Diff. Sig.?
H1: Internal chatbot agility → Customer service performance	0.18	0.24**	− 4.58	< ***
H2: External chatbot agility → Customer service performance	0.67***	0.61***	5.33	> ***
H3a: Routine use of chatbots → Internal chatbot agility	0.37***	0.17*	18.51	> ***
H3b: Routine use of chatbots → External chatbot agility	0.37**	0.17*	17.38	> ***
H4a: Innovative use of chatbots → Internal chatbot agility	0.41***	0.58***	− 16.88	< ***
H4b: Innovative use of chatbots → External chatbot agility	0.41**	0.58***	− 14.95	< ***

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, Diff. Sig. = different significantly.

4.4. Additional exploratory research

To test and substantiate the proposed research model with some additional insights, we gave participants an opportunity to express their views about the use of chatbots and its impacts through open-ended questions. Below we summarize some responses and our interpretation.

Two respondents remarked:

> *Chatbots share some counterwork. For example, they provide customers with precise and personalized consulting services, which not only greatly saves the labor cost of the call center but also makes use of autonomous learning technology to analyze users' preferences and habits, actively seek and identify potential needs, and improve user engagement and conversion rate.*

> *The data provided by Chatbot will also be used as an aspect of the company's business reference. Managers will need this data to do business scheduling analysis through the data.*

The responses indicate that routine business processes incorporate chatbots (i.e., routine use of chatbots, as defined in the Section 2.3 Routine Versus Innovative Use), which can enhance business agility. Respondents also highlighted the role of the innovative use of chatbots in creating agility. For example, one participant highlighted the following:

> *Compared with the traditional marketing methods, we can understand the users' feedback through the data and call recording after natural language processing and constantly optimize the marketing scheme, which is very good.*

This response further confirms that data collected by chatbots can be analyzed by advanced methods to help identify new marketing opportunities (i.e., innovative use of chatbots as defined in the Routine Versus Innovative Use section).

Regarding the impacts of agility on customer service performance, one participant stated the following:

For mobile banking and credit-card-exclusive software, it not only could do the company's business but also bring it to more areas that can be consumed with the chat robot, increasing customer experience, cohesion, and loyalty.

Another participant also highlighted the following:

In the initial stage of product promotion, users can be effectively maintained, the retention rate of users can be improved, and the experience of users can be improved.

These responses helped to explain the important role of chatbots in improving customer service performance. In summary, the responses highlighted how the use of chatbots can improve firms' flexibility (i.e., enhance agility) in responding to customers' requirements and to marketing changes, which would, in turn, improve customer service performance.

5. Discussion

This study aimed to examine the effects of chatbot-enabled business agility by exploring its antecedents and consequences. We identified two antecedents: routine and innovative use of chatbots. We explained how these two types of chatbot use could create business agility, consisting of internal and external agility. In addition, we argued that both internal and external agility can improve customer service performance. Based on the survey data collected from 294 employees, our results provide strong support for our model.

Our results show that both the routine and the innovative use of chatbots increase business agility. Roberts et al. (2016) reported that the innovative use of decision support systems enhances managers' sensing abilities, which refers to the capacity to identify opportunities for organizational innovation. Altschuller, Gelb, and Henry (2010) also reported that innovative investment and use of IT can enhance firm performance. These studies provided insights into how traditional IS could bring benefits to business; however, they cannot be generalized to newly developed IS such as those that use AI. In our study, the focus on chatbot context allowed us to develop an understanding (Hong, Chan, Thong, Chasalow, & Dhillon, 2014) of how emerging AI tools can enhance business agility and thus benefit businesses. Our study also extends the reach of the literature by demonstrating additional benefits such as agility, which is an essential digitally enabled capability for business sustainability in the era of competitive marketing (Ashrafi, Ravasan, Trkman, & Afshari, 2019; Kappelman et al., 2019).

In addition, Roberts et al. (2016) reported that routine use of decision support systems does not enhance managers' sensing abilities. However, our study shows that routine use of chatbots can increase internal and external agility, although its effects are smaller than those brought by the innovative use of chatbots. In other words, once integrated into marketing employees' work processes, chatbots can help employees understand market changes and provide offers efficiently. Therefore, it is possible that the effect of the routine use of IS could evolve as long as the technology advances (Petter et al., 2012). In the context of traditional IT, routine use may not be a good approach for improving business operation and outcomes because of its relatively limited capabilities. Emerging technologies empowered by new features and functions, such as AI, are likely to address those issues and can thus change the way information systems are used as a routine process for achieving business benefits. The results of this study support this idea. As such, our study expands the literature by clarifying how different types of IT use increase internal and external agility in newly developed IT such as AI. This is also consistent with the research of Sambamurthy, Bharadwaj, and Grover (2003), which showed that IT investment and capabilities can enhance organizations' agility.

Our post-hoc analysis further showed that the effect of routine versus innovative use on internal and external agility differs across firm sizes. The effect of routine use is stronger for small-to-medium firms than large firms, whereas the effect of innovative use is greater for large firms than for small-to-medium firms. It is possible that the business processes of small-to-medium firms are simpler due to having few resources; therefore, there are not many options for chatbots to integrate into these businesses. In contrast, larger firms have more complex business processes and can implement innovative ways to use chatbots. Because our analysis was exploratory, future studies are needed to further examine how firms of different sizes adopt chatbots.

Last, our results reveal that internal and external agility can ultimately improve customer service performance. This is consistent with the findings of Chuang (2020), who reported that social media agility is positively related to the strength of customer–firm relationships. Customer service is a primary element in business sustainability (Huang, Niu, & Pan, 2021). Our study provides further insights into how customer service can be enhanced by digitally enabled agility created by emerging AI tools. Our research results support this relationship between agility and customer service based on data collected from marketing employees who are knowledgeable about customer service. Our post-hoc analysis further showed that internal chatbot agility has a stronger effect on customer service performance for large firms than for small-to-medium firms, whereas external chatbot agility has a greater effect on small-to-medium firms than on large firms. Small-to-medium firms, which have fewer resources, become more vulnerable to market changes, so increased external agility would greatly improve their ability to respond to market changes and serve customers. On the other hand, larger firms usually follow standardized procedures to deal with customers, so internal agility, which better supports these standardized procedures, would tremendously enhance customer services for large firms. Our findings entail important theoretical and practical implications, which are presented below.

5.1. Theoretical implications

Our study is among the very first studies to contribute to the literature of emerging AI by exploring employees' use of chatbots and related outcomes. This study makes two primary theoretical contributions. First, it describes the effect of chatbot use on business agility. Based on the literature (Li et al., 2013; Roberts et al., 2016), we argued that employees can engage in both routine and innovative use of chatbots. Our study thus extends the literature of routine and innovative use to the context of chatbots. Such conceptualization is important to help explain how chatbots can be used in organizations. Further, Helfat and Martin (2015) summarized that dynamic capabilities rely on managerial cognition, social capital, and human capital. By showing that IT can also contribute to agility, our study extends the literature on the DCV and highlights an additional avenue for the development of dynamic capabilities.

Although both routine and innovative use of chatbots can increase both internal and external agility, our results show that innovative use of chatbots plays a more important role in creating agility than does routine use. Our results highlight the importance of innovative use in creating business agility in the context of advanced technologies. The literature has suggested that individuals can vary regarding how they use this technology (e.g., features utilized, time invested) after technology adoption (Nambisan et al., 1999). Thus, innovative use is often proactive and initiated by employees, a finding consistent with the perspective that innovation is a human-driven phenomenon (Jerónimo, Henriques, de Lacerda, da Silva, & Vieira, 2020; Lee & Raschke, 2020). As such, innovative use is vital because it allows companies to gain additional benefits from their IT investment (Venkatesh, Brown, Maruping, & Bala, 2008) that cannot be achieved through routine use (Roberts et al., 2016). Failure to engage in innovative use could thus result in the underutilization of IT (Venkatesh et al., 2008), preventing companies from achieving the full potential value of IT. Our study has therefore highlighted the essential role of the innovative use of chatbots in reaping business benefits (i.e., business agility) as well as the role of the routine use of chatbots. It has also further confirmed the importance of conceptualizing different types of use of newly developed IT tools, such as AI, which requires further attention. Overall, our study contributes to the literature by explaining how chatbot uses lead to chatbot-enabled business agility.

Besides this, our study extends the agility concept to the emerging context of AI by conceptualizing chatbot-enabled agility using two dimensions: internal and external chatbot agility. This is a valuable contribution because agility plays a critical role in identifying new ways that IT can support business strategies and improve performance (Karahanna, Xu, Xu, & Zhang, 2018; Queiroz et al., 2018). An enhanced understanding of chatbot agility could provide insight into how the intersection of business strategies and advanced technology can create value. It could also help us rethink the advantages of technological advances, thus motivating the design and deployment of emerging technologies and changing the landscape of IT use within organizations (Petter et al., 2012).

Second, our results highlight the fact that chatbot-enabled business agility can significantly improve customer service performance. These findings suggest that chatbot-enabled agility is critical for companies to create sustained competitive advantages through responding to customer preference and market change (e.g., Chuang, 2020). Therefore, this study brings new insights into IT-enabled business agility and allows future studies to explore the role of emerging technologies in business (e.g., Nishant, Kennedy, & Corbett, 2020; Sipior, 2020). For example, future studies could explore how innovative and routine use of chatbots (or other AI tools) can lead to different organizational outcomes (e.g., Gursoy, Chi, Lu, & Nunkoo, 2019).

5.2. Practical implications

Our study also has important practical implications. First, our study shows that both internal and external chatbot agility relate to customer service performance. This finding provides practitioners with an enhanced understanding of the important role of chatbot-enabled agility in improving customer service. As consumers spend more time in digital environments facilitated by AI, companies are investing heavily in the development of AI tools and moving into this new environment (Ameen et al., 2021). As such, our study could assist business leaders with improving customer service via leveraging chatbots into business operations and creating business agility.

Based on the relationships validated in this study, business leaders may develop or choose efficient chatbot tools that enable them to create an innovative digital environment wherein they can better interact with customers, identify customer demand, and respond to market changes. Businesses can thus improve their customer service performance, which is likely to promote their sustainability and produce many long-term benefits for them (Lee & Raschke, 2020). For example, to improve customer experience and satisfaction, companies could choose chatbots that create internal agility through features such as automatically answering customers' questions, resolving customers' problems, and identifying customers' preferences. To better serve customers and remain competitive, companies could choose chatbots that create external agility with data analysis to identify changes in customer demand and the market. These practical approaches help managers determine the type of chatbot agility needed.

In addition, the results of our study indicate external agility has a larger effect on customer service performance than internal agility. Some companies may want to focus more on external agility and utilize chatbots to interpret market changes, especially whether marketing changes are what hinder the company in establishing excellent customer services performance. These benefits provide meaningful reasons for business leaders to incorporate chatbots into business strategies and maximize their competitive advantages. Alternatively, the research results of this study could provide initial implications for businesses to leverage other AI tools in business practices.

Our study also highlights the fact that both routine and innovative use of chatbots can enhance agility. Therefore, firms should not only require marketing employees to integrate chatbots into standardized marketing processes, but also encourage them to try new approaches to use chatbots to generate new insights about customers. Since routine use of chatbots can enhance agility, companies should integrate chatbots into routine processes of customer services. For example, chatbots can answer common questions from customers and collect their feedback to help identify customers' needs and market changes. Firms can also encourage employees to use chatbots innovatively to generate further insights from their interactions with the chatbots and customers. Our results show that innovative use has a stronger effect than routine use. Therefore, innovative use should be more emphasized when chatbots are incorporated to support employees' jobs and business operations. For example, firms can allow marketing employees to hold regular meetings and discuss different approaches to chatbot use, which will generate new insights and allow for the learning of new usage methods from peers. The literature has also found that intrinsic motivation can support innovative use (Li et al., 2013). Therefore, managers need to support employees' intrinsic motivation. For example, managers can help employees set up reasonable performance objectives for customer service. They can also allow some autonomy and encourage employees to try different features or approaches to the analysis of customers' data. The purpose of this would be to support employees to go beyond routine chatbot use to achieve further benefits for the company.

Although our results show that the effect of innovative use is weaker for small-to-medium firms, we hesitate to suggest that small-to-medium firms should focus less on innovative use. It is possible that small-to-medium firms have simpler business processes and fewer resources; therefore, they may find it difficult to use chatbots innovatively. Such innovative use, however, may have tremendous impact once identified because the literature has shown that innovative use can allow firms to generate further benefits from IT (Venkatesh et al., 2008). Therefore, we suggest that even small-to-medium firms try to explore innovative approaches to using chatbots.

5.3. Limitations and suggestions for future studies

Our study has several limitations. First, a survey company recruited our sample. Although our participants came from different companies, it is still possible that our sample was biased. Second, we focused on U.S. employees, so it is possible that the results might not be generalizable to other cultural backgrounds. For example, employees of certain backgrounds might be more likely than those from the U.S. to strictly follow orders from supervisors and thus engage in only the routine use of chatbots. By focusing on routine and innovative use of chatbots, our study captures the uniqueness of chatbots because varied types of technology are used differently. For example, unless combined with chatbots or other service assistants, social media cannot automatically answer consumers' standard questions. Nevertheless, future studies could examine how specific features of chatbots lead to agility and improve customer service.

Our paper used items focusing on enhanced customer-firm relationships and overall performance to measure customer service performance. This could be a limitation as they do not capture all aspects of customer service performance (Setia et al., 2013). In future studies, researchers could consider adopting more comprehensive items for measuring customer service performance when assessing chatbots and other AI tools. Future studies could also attempt to create new scales for measuring customer services for different contexts.

In our study, we focused on marketing employees who used chatbots to interact with customers. Unlike customers, who use chatbots to receive service, marketing employees use chatbots to provide customer service. Therefore, it was appropriate to collect data from marketing employees because they understand how product offers are provided and to what extent chatbots enhance customer service performance.

Customers could provide another perspective to understand the effectiveness of chatbot services, and we suggest that future studies examine this important issue.

Future studies could extend our study in several ways. First, future studies could test our model with different types of chatbots to assess which type of chatbot is more effective in other contexts, such as human resource management. For example, chatbots that support employees and those that support customers will probably be used in different ways. Second, field experiments could be conducted in future studies to examine the optimal combination of chatbot use contexts and its effect on chatbot agility. Third, other consequences of the use of chatbots could be examined. For example, future studies could examine firm performance or employee productivity. Fourth, studies could examine how certain variables (e.g., organizational culture) moderate the relationship between chatbot use and its consequences. Last, future studies could also examine factors that influences continuance intention in the context of chatbot use.

6. Conclusion

Chatbots have been increasingly used to support customer service. This study aimed to examine how chatbot-enabled agility improved customer service performance and to explore the antecedents of chatbot-enabled agility. The data collected came from a survey of 294 marketing employees who had experience with the use of chatbots within organizations. The results show that the effect of innovative use on internal and external agility is stronger than that of routine use. Further, both internal and external agility enhance customer service performance. Our results demonstrate how companies can achieve business agility by effectively integrating chatbots into business operations based on different types of use. Our study thus provides useful insights regarding ways of achieving business benefits (i.e., enhanced customer service) through the incorporation of chatbots into business operations. Future studies could extend our work regarding how certain organizational variables could moderate the relationship between chatbot use and its outcomes. Future studies could also examine work- versus non-work-related benefits for employees and additional business outcomes resulting from the use of chatbots within organizations.

CRediT authorship contribution statement

Xuequn Wang: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, **Xiaolin Lin:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, **Bin Shao:** Conceptualization, Writing – original draft, Writing – review & editing.

Appendix A. Measures

Routine Use of Chatbots (Li et al., 2013)	
RTN1	The use of chatbots has been incorporated into our regular business operations.
RTN2	The use of chatbots is pretty much integrated as part of our normal business operations.
RTN3	The use of chatbots is now a normal part of our business operations.
Innovative Use of Chatbots (Li et al., 2013)	
INV1	My company has discovered new uses of chatbots to enhance business operations.
INV2	My company has used chatbots in novel ways to support business operations.
INV3	My company has developed new applications, based on chatbot use, to support business operations.
Internal Chatbot Agility (Akhtar et al., 2018; Chuang, 2020)	
	Because of the use of chatbots in my company, the following is true:
IA1	The reliability of my company's offerings (i.e., products and services) has increased.
IA2	My company's day-to-day operations have been flexible for customized demand.
IA3	My company's offerings (i.e., products and services) have been more cost efficient than those of our competitors.
IA4	My company has delivered our offerings (i.e., products and services) more quickly.
External Chatbot Agility (Akhtar et al., 2018; Chuang, 2020)	
	Because of the use of chatbots in my company, the following is true:
EA1	My company has responded very reliably to market changes.
EA2	My company has had greater flexibility in our offerings to adapt to market changes.
EA3	My company has efficiently redesigned our offerings to adapt to market changes.
EA4	My company has been very quick to adapt to market opportunities.
Customer Service Performance (Chuang, 2020) (Setia et al., 2013)	
	Because of the use of chatbots in my company, the following is true:
CSP1	My company has established good relationships with customers.
CSP2	My company has provided better customer service than ever.

Appendix B. Additional analysis of discriminant validity

See Appendix Tables B1 and B2.

This appendix presents additional analysis results. Table B1 shows that all loadings are higher than cross-loadings. Table B2 shows that all values of Heterotrait-Monotrait ratio of correlations are below 0.90 (Teo, Srivastava, & Jiang, 2008). These results provide additional support for discriminant validly.

Table B.1
Loadings and cross-loading.

	Routine Use of Chatbots	Innovative Use of Chatbots	Internal Chatbot Agility	External Chatbot Agility	Customer Service Performance
RTN1	**0.89**	0.54	0.49	0.50	0.53
RTN2	**0.89**	0.62	0.53	0.51	0.51
RTN3	**0.91**	0.58	0.53	0.52	0.56
INV1	0.59	**0.90**	0.61	0.61	0.61
INV2	0.57	**0.89**	0.59	0.60	0.56
INV3	0.56	**0.86**	0.60	0.59	0.54
IA1	0.52	0.63	**0.89**	0.73	0.68
IA2	0.52	0.58	**0.86**	0.67	0.60
IA3	0.48	0.60	**0.87**	0.72	0.61
IA4	0.49	0.57	**0.88**	0.70	0.63
EA1	0.50	0.58	0.70	**0.88**	0.70
EA2	0.52	0.55	0.74	**0.89**	0.72
EA3	0.47	0.59	0.68	**0.86**	0.70
EA4	0.51	0.66	0.72	**0.89**	0.72
CSP1	0.54	0.60	0.70	0.76	**0.94**
CSP2	0.57	0.61	0.65	0.76	**0.94**

Table B.2
Heterotrait-monotrait ratio of correlations.

	1	2	3	4	5
1 Routine use of chatbots					
2 Innovative use of chatbots	0.75				
3 Internal agility	0.65	0.77			
4 External agility	0.64	0.77	0.88		
5 Customer service performance	0.61	0.66	0.69	0.88	

References

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

Akhtar, P., Khan, Z., Tarba, S., & Jayawickrama, U. (2018). The Internet of Things, dynamic data and information processing capabilities, and operational agility. *Technological Forecasting and Social Change, 136*, 307–316.

Altschuller, S., Gelb, D. S., & Henry, T. F. (2010). IT as a resource for competitive agility: an analysis of firm performance during industry turbulence. *Journal of International Technology and Information Management, 19*(1), 39–59.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114*, Article 106548. https://doi.org/10.1016/j.chb.2020.106548

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*, Article 101473. https://doi.org/10.1016/j.tele.2020.101473

Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management, 47*, 1–15.

Bae, S.-M. (2017). The relationship between the type of smartphone use and smartphone dependence of Korean adolescents: National survey study. *Children and Youth Services Review, 81*, 207–211.

Benner, M. J., & Tushman, M. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly, 47*(4), 676–707.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2020). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management, 57*, Article 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research*. Guilford Publications,.

Chiu, C., Wang, E., Fang, Y., & Huang, H. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal, 24*(1), 85–114.

Chiu, M.-C., & Chuang, K.-H. (2021). Applying transfer learning to achieve precision marketing in an omni-channel system–a case study of a sharing kitchen platform. *International Journal of Production Research*, 1–16.

Chuang, S.-H. (2020). Co-creating social media agility to build strong customer-firm relationships. *Industrial Marketing Management, 84*, 202–211.

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.

Claessen, V., Schmidt, A., & Heck, T. (2017). Virtual Assistants-A Study on the Usability and User Perception of Customer Service Systems for E-Commerce. Paper presented at the ISI.

Coombs, C. (2020). Will COVID-19 be the tipping point for the intelligent automation of work? A review of the debate and implications for research. *International Journal of Information Management, 55*, Article 102182.

Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: a technological diffusion approach. *Management Science, 36*(2), 123–139.

Da Silveira, G., Borenstein, D., & Fogliatto, F. S. (2001). Mass customization: Literature review and research directions. *International Journal of Production Economics, 72*(1), 1–13.

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

Dilger, R. J. (2017). Small Business Size Standards: A Historical Analysis of Contemporary Issues. *Congressional Research Service, July, 21*, 7–5700.

Duan, J., Faker, P., Fesak, A., & Stuart, T. (2013). Benefits and drawbacks of cloud-based versus traditional ERP systems. *Proceedings of the 2012–13 course on Advanced Resource Planning*.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Etemad-Sajadi, R., & Ghachem, L. (2015). The impact of hedonic and utilitarian value of online avatars on e-service quality. *Computers in Human Behavior, 52*, 81–86.

Gao, P., Zhang, J., Gong, Y., & Li, H. (2020). Effects of technical IT capabilities on organizational agility: The moderating role of IT business spanning capability. *Industrial Management & Data Systems, 120*(5), 941–961.

Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2020a). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management, 90*, 581–592.

Gupta, S., Meissonier, R., Drave, V. A., & Roubaud, D. (2020b). Examining the impact of Cloud ERP on sustainable performance: A dynamic capability view. *International Journal of Information Management, 51*, Article 102028.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.

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,.

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach*. Guilford Publications,.

He, W., Zhang, Z. J., & Li, W. (2021). Information technology solutions, challenges, and suggestions for tackling the COVID-19 pandemic. *International Journal of Information Management, 57*, Article 102287.

Helfat, C. E., & Martin, J. A. (2015). Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *Journal of Management, 41*(5), 1281–1312.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Holmqvist, M., & Pessi, K. (2006). Agility through scenario development and continuous implementation: a global aftermarket logistics case. *European Journal of Information Systems, 15*(2), 146–158.

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.

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management, 56*, Article 102250.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.

Huang, P.-Y., Niu, B., & Pan, S. L. (2021). Platform-based customer agility: An integrated framework of information management structure, capability, and culture. *International Journal of Information Management, 59*. https://doi.org/10.1016/j.ijinfomgt.2021.102346

Hui, S. C., Fong, A., & Jha, G. (2001). A web-based intelligent fault diagnosis system for customer service support. *Engineering Applications of Artificial Intelligence, 14*(4), 537–548.

Huo, B., Gu, M., & Wang, Z. (2018). Supply chain flexibility concepts, dimensions and outcomes: an organisational capability perspective. *International Journal of Production Research, 56*(17), 5883–5903.

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.

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.

Jerónimo, H. M., Henriques, P. L., de Lacerda, T. C., da Silva, F. P., & Vieira, P. R. (2020). Going green and sustainable: The influence of green HR practices on the organizational rationale for sustainability. *Journal of Business Research, 112*, 413–421.

Kappelman, L., Torres, R., McLean, E., Maurer, C., Johnson, V., & Kim, K. (2019). The 2018 SIM IT issues and trends study. *MIS Quarterly Executive, 18*(1), 7.

Karahanna, E., Xu, S. X., Xu, Y., & Zhang, N. A. (2018). The needs–affordances–features perspective for the use of social media. *MIS Quarterly, 42*(3), 737–756.

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*, 299–325.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec), 11*(4), 1–10.

Lalicic, L., & Weismayer, C. (2021). Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents. *Journal of Business Research, 129*, 891–901.

Lee, M. T., & Raschke, R. L. (2020). Innovative sustainability and stakeholders' shared understanding: The secret sauce to "performance with a purpose". *Journal of Business Research, 108*, 20–28.

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.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS Quarterly, 31*(1), 59–87.

Lin, X., & Wang, X. (2020). Examining gender differences in people's information-sharing decisions on social networking sites. *International Journal of Information Management, 50*, 45–56.

Lokshin, B., Belderbos, R., & Carree, M. (2008). The productivity effects of internal and external R&D: Evidence from a dynamic panel data model. *Oxford Bulletin of Economics and Statistics, 70*(3), 399–413.

Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly*, 931–954.

Mathiassen, L., & Pries-Heje, J. (2006). Business agility and diffusion of information technology. *European Journal of Information Systems, 15*(2), 116–119.

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), Article 103434.

Mordor Intelligence, 2021, Chatbot market - growth, trends, COVID-19 impact, and forecasts (2021–2026). ⟨https://www.mordorintelligence.com/industry-reports/chatbot-market⟩, Accessed on September 20, 2021.

Nambisan, S., Agarwal, R., & Tanniru, M. (1999). Organizational mechanisms for enhancing user innovation in information technology. *MIS Quarterly, 23*(3), 365–395.

Ngai, E. W., Chau, D. C., & Chan, T. (2011). Information technology, operational, and management competencies for supply chain agility: Findings from case studies. *The Journal of Strategic Information Systems, 20*(3), 232–249.

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management, 53*, Article 102104.

Nold, H., Anzengrubcr, J., Woclfle, M., & Michel, L. (2018). Organizational agility-testing, validity, and reliability of a diagnostic instrument. *Journal of Organizational Psychology, 18*(3), 104–117.

Overby, E., Bharadwaj, A., & Sambamurthy, V. (2006). Enterprise agility and the enabling role of information technology. *European Journal of Information Systems, 15*(2), 120–131.

Petter, S., DeLone, W., & McLean, E. R. (2012). The past, present, and future of "IS success". *Journal of the Association for Information Systems, 13*(5), 341–362.

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

Phansalkar, S., Kamat, P., Ahirrao, S., & Pawar, A. (2019). Decentralizing AI applications with block chain. *International Journal of Scientific & Technology Research, 8*(9), 362–370.

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.

Queiroz, M., Tallon, P. P., Sharma, R., & Coltman, T. (2018). The role of IT application orchestration capability in improving agility and performance. *The Journal of Strategic Information Systems, 27*(1), 4–21.

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

Roberts, N., Campbell, D. E., & Vijayasarathy, L. R. (2016). Using information systems to sense opportunities for innovation: Integrating postadoptive use behaviors with the dynamic managerial capability perspective. *Journal of Management Information Systems, 33*(1), 45–69.

Rosenthal, R., & Rosnow, R. L. (2008). *Essentials of Behavioral Research: Methods and Data Analysis, 3rd ed.* Boston: McGraw-Hill,.

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

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly, 27*(2), 237–263.

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.

Setia, P., Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance. *MIS Quarterly*, 565–590.

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

Sipior, J. C. (2020). Considerations for development and use of AI in response to COVID-19. *International Journal of Information Management, 55*, Article 102170.

Tallon, P. P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. *MIS Quarterly, 35*(2), 463–486.

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.

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review, 58*(4), 13–35.

Teo, T. S., Srivastava, S. C., & Jiang, L. (2008). Trust and electronic government success: An empirical study. *Journal of Management Information Systems, 25*(3), 99–132.

Trischler, J., Johnson, M., & Kristensson, P. (2020). A service ecosystem perspective on the diffusion of sustainability-oriented user innovations. *Journal of Business Research, 116*, 552–560.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly, 32*(3), 483–502.

Watson, H. J. (2019). Update tutorial: Big Data analytics: Concepts. *Technology, and Applications Communications of the Association for Information Systems, 44*(1), 364–379.

Weber, Y., & Tarba, S. Y. (2014). Strategic agility: A state of the art introduction to the special section on strategic agility. *California Management Review, 56*(3), 5–12.

Williams, R., 2019, Study: Chatbots to drive $112B in retail sales by 2023. ⟨https://www.mobilemarketer.com/news/study-chatbots-to-drive-112b-in-retail-sales-by-2023/554416/⟩, Accessed on May 24, 2021.

Zhang, X., Ma, L., Xu, B., & Xu, F. (2019). How social media usage affects employees' job satisfaction and turnover intention: An empirical study in China. *Information & Management, 56*(6), Article 103136. https://doi.org/10.1016/j.im.2018.12.004

Zhang, Y., Qu, T., Ho, O. K., & Huang, G. Q. (2011). Agent-based smart gateway for RFID-enabled real-time wireless manufacturing. *International Journal of Production Research, 49*(5), 1337–1352.

Xuequn (Alex) Wang is a Senior Lecturer in Edith Cowan University. He received his Ph. D. in Information Systems from Washington State University. His research interests include social media, privacy, e-commerce, and human-computer interaction. His research has appeared in MIS Quarterly, Information Systems Journal, Information & Management, Communications of the ACM, ACM Transactions, and Communications of the Association for Information Systems, among others.

Xiaolin Lin is currently assistant professor of management information systems in the college of business at California State University, Sacramento. Prior to that, he was an assistant professor of computer information systems in the Paul and Virginia Engler College of Business at West Texas A&M University. He received his Ph.D. in management information systems from Washington State University. His research focuses on the implications of IT in e-commerce and healthcare, human-AI interaction, cyber security, and gender differences in IT behavioral research. He has published papers in premier journals such as Journal of Business Ethics, European journal of Information Systems, Decision Sciences, Information & Management, International Journal of Electronic Commerce, Journal of the Association for Information Science and Technology, and International Journal of Information Management, among others. He has also presented numerous papers at international and national conferences.

Bin Shao is a professor of decision management & Terry Professor of Business in the Department of Computer Information and Decision Management, Paul and Virginia Engler College of Business, West Texas A&M University. She earned her Ph.D. from University of Illinois at Urbana-Champaign. Her current research interests are mainly in the interdisciplinary areas of information systems, decision management, and marketing. Her works have been published in International Advances in Economic Research, International Journal of Applied Management Science, Journal of Supply Chain and Operations Management, Journal of Management Information and Decision Sciences, and many others.