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Understanding virtual agents' service quality in the context of customer service: A fit-viability perspective

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ABSTRACT

Virtual agents, a prevalent application of artificial intelligence, significantly enhance e-commerce customer service (i.e., online interactions that address customers' concerns). This creates an innovative service model aiming to meet diverse customer demands and create value for enterprises. However, understanding the factors driving the performance of virtual agents, especially in terms of service quality, remains a gap. Expanding the fit-viability model (FVM), this study investigates the drivers and mechanisms influencing virtual agents' service quality, considering the matching of technology, service scenarios, and individual readiness. Surveying 399 respondents experienced in virtual agent service within e-commerce, the findings reveal that personalization negatively impacts response speed but positively influences response accuracy. Technology readiness positively affects convenience and accessibility. Overall, service quality is positively influenced by response speed, response accuracy, convenience, and accessibility. This study extends the fit-viability model to virtual agent service literature, providing practitioners with a fresh perspective to enhance e-commerce customer service.

1. Introduction

With the rapid development of artificial intelligence, virtual agents are widely used to reform the business operations model of e-commerce customer service in various contexts, such as the tourist industry, banking, and retailing (Das et al., 2023; DATA CONOMY, 2022). Specifically, virtual agents are programs capable of providing customer service through simulated conversation, leveraging artificial intelligence (e.g., natural language processing and self-learning) to achieve automation and intelligence. They can handle multiple tasks simultaneously and provide personalized and real-time information and solutions to customers, thus improving service efficiency and consumers' experience, strengthening customer relationships, and reducing enterprise operating costs (Radziwill and Benton, 2017; Wirtz et al., 2018). Virtual agents have proved to have the potential to bring new value to business organizations. For example, Servion (2020) forecasted that virtual agents would drive 95% of consumer interactions within firms by 2025. Furthermore, Statista (2021) predicted that the market value of virtual agents in banking, retailing, financial services, and insurance will reach 6.83 billion U.S. dollars by 2030.

Although virtual agents have significant market potential, consumers hold inconsistent assessments of the service quality of virtual agents, and most of them are dissatisfied with these agents (UJET, 2022). In fact, service quality is the core of performing e-commerce customer service and determines the true success of virtual agents. High service quality directly enhances consumer experience, which helps improve consumer satisfaction and loyalty (Wang et al., 2019; Kasiri et al., 2017). Moving into the context of the e-commerce customer service delivered by virtual agents, the positive relationships are also verified (Behera et al., 2021; Ashfaq et al., 2020). Thus, how to enhance service quality of virtual agents has become a key focus and challenge for practitioners.

Though service quality is important, less attention was paid to exploring its antecedents. Very few studies examined the drivers of service quality from the perspective of technology features (Chung et al., 2020; Haugeland et al., 2022). However, virtual agents providing customer service are a process of human–computer interaction. Consumers' perception of virtual agents can be affected not only by technical characteristics but also by environmental support factors, such as individual-related factors (Rapp et al., 2021) and availability (Ashfaq et al., 2020). Therefore, it is crucial to understand the drivers of virtual agents' service quality in e-commerce customer service from a comprehensive perspective.

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Even though previous studies have explored the comprehensive factors (e.g., service per se, technical characteristics, and personal ability) that influenced service quality provided by traditional agents (e.g., human employees, websites, and self-service) (Brady and Cronin, 2001; Blut, 2016; Kim and Chen, 2023), we cannot directly apply the results to the context of virtual agents. This is because virtual agents, as new agents, are different from traditional agents. Virtual agents integrate human attributes and technical capacity and replace humans to provide service information and solve questions. They possess the abilities of big data analysis and deep learning and surpass traditional agents, enabling them to offer personalized services that cater to the diverse needs and preferences of consumers. It is essential to focus on the extent to which virtual agents meet consumer needs in customer service to understand how these factors influence service quality in the context of virtual agents.

Given the practical and research gaps, we have posed the following research questions (RQs): *RQ1*: What factors drive service quality of virtual agents from the perspective of the matching of technology, service, and consumer? *RQ2*: How do these drivers affect virtual agents' service quality? In order to fill the research questions, based on the fit-viability model (FVM), we propose the drivers of service quality from fit which measures the match between technical characteristics and service requirements of tasks (i.e., personalization, response speed, and response accuracy), and viability which measures the match between application of technology and its associated consumer (i.e., technology readiness, accessibility, and convenience). We also examine the influence of personalization (technology readiness) on response speed and response accuracy (accessibility and convenience).

This study makes several contributions. First, it identifies several antecedents of virtual agents' service quality in the context of e-commerce customer service by considering the roles of technology, service scenario, and individual readiness. It provides a comprehensive angle for understanding how virtual agents create value for customers in e-commerce and extends the understanding of virtual agent services. Second, the FVM is applied in this new scenario to understand consumer perceptions of service quality and examine the correlation of variables within the fit and viability dimensions, extending the application scope of the model. Furthermore, this study provides practitioners with suggestions on how to design and improve virtual agents' performance, enhancing the development of e-commerce.

The rest of this paper is structured as follows. Section 2 reviews the literature on virtual customer service agents, service quality and its antecedents, and the FVM, then establishes the proposed model. Section 3 presents the hypotheses. Section 4 reports the research method. Section 5 details the results. Finally, we discuss the findings, contributions, additional implications, and limitations.

2. Literature review

2.1. Virtual agents for e-commerce customer service

Virtual agents, which have changed the platform business model by creating more value for customers and enterprises, have been widely used for e-commerce customer service. As conversational service tools, they provide customers with recommendations and decision aids to meet customers' needs by artificial intelligence technology (Chen et al., 2021b). Virtual agents play a vital role in facilitating customer engagement, enhancing the user experience through real-time and more human-like interactions (Chung et al., 2020; Scherer et al., 2015). Virtual agents have numerous advantages over traditional agents. First, they can provide 24/7 and real-time online customer service, which can improve service providers' responsiveness and product conversion rate. Radziwill and Benton (2017) verified that virtual agents can provide uninterrupted and time-to-response customer service, increasing customer satisfaction and engagement. Second, virtual agents have unique capabilities and can provide personalized service by analyzing and learning consumer data (e.g., history information and preferences). Third, virtual agents can help companies reduce customer service operation costs. For example, virtual agents can process multiple session windows at the same time without limitations of location or knowledgeable staff (Wu et al., 2020). Finally, virtual agents do not have negative human emotions like impatience or fatigue. Time after time, they can engage in friendly conversation based dynamically on consumer inputs (Adam et al., 2021). Thus, practitioners and researchers are interested in how to enhance the performance of customer service virtual agents.

Previous studies have paid attention to acceptance (Zhang et al., 2021; Rese et al., 2020), customer experience and satisfaction (Araujo, 2018; Pizzi et al., 2021; Sands et al., 2021), and engagement (Kull et al., 2021; Schuetzler et al., 2020) of virtual agents in the e-commerce customer service context. Meanwhile, some studies also examined the consequences (e.g., customer experience and satisfaction) of virtual agents' service quality (Behera et al., 2021). For example, Ashfaq et al. (2020) identified that service quality positively influenced consumers' satisfaction and predicted continuance intention. Very few studies explored the drivers of virtual agents' service quality in e-commerce customer service (Baabdullah et al., 2022). For example, Haugeland et al. (2022) focused on the roles of two interaction design features (i.e., topic-led conversations and task-led conversations, free text interaction and button interaction) in enhancing the service quality of customer service virtual agents. These studies illustrated the importance of service quality from the perspective of technology features, neglecting the degree to which technological features meet the customer service tasks, and the support from environmental factors. Therefore, we need to identify the drivers of virtual agents' service quality through the fit-viability model.

2.2. Service quality and its antecedents

Service quality was formally proposed by Grönroos (1984) and has been recognized as an important construct to measure consumers' perception of service performance. Previous research has examined different service agents in the context of marketing and identified the drivers of service quality from various perspectives (see Table 1). The earliest research focused on human employee service in face-to-face encounters, which identified service per se, human employee's expertise, and environment as vital factors driving service quality. For instance, Brady and Cronin (2001) proposed a classical model of service quality with three dimensions: outcome, interaction, and environmental quality. This model demonstrated and verified that attitude, behavior, expertise, ambient conditions, design, social factors, waiting time, tangibles, and valence play important roles in assessing the quality of human employee service.

With the development of information technology, customers can access services through websites. Studies have investigated factors influencing service quality by considering technology-related factors, such as website availability, and how websites meet customer service requirements. For instance, the e-service quality model (eTailQ model) is commonly used to predict web service quality based on dimensions such as website design, customer service, fulfillment, and security/privacy (Wolfinbarger and Gilly, 2003; Blut, 2016). Huang et al. (2019) found that accessibility and ease of use are important antecedents of online customer service quality.

Moreover, with the rise of e-commerce, consumers can complete the entire service process online by interacting with self-service technology, placing them in a dominant position in the service. Individual initiative can significantly affect the user experience; therefore, individuals' ability (e.g., attitude and control) to use technology is also considered. For example, Pooya et al. (2020) illustrated that technology readiness has a positive significant effect on consumers' perception of service quality toward self-service banking.

Although previous studies on traditional agents have enhanced our

Table 1
Literature on drivers of service quality in different contexts of agents.

Types of agents	Sources	Research perspectives	Drivers
Human employee	(Brady and Cronin, 2001)	Outcome quality, interaction quality, environmental quality	Attitude, behavior, expertise, ambient conditions, design, social factors, waiting time, tangibles, valence
	(Kasiri et al., 2017)	-	Standardization, customization
Online human employee	(Wang et al., 2004)	SERVQUAL model	Tangibles, reliability, responsiveness, assurance, and empathy, network quality
Website	(Wolfinbarger and Gilly, 2003)	E-service quality model (eTailQ model)	Website design, customer service, fulfillment/reliability, security/privacy
	(Lee and Lin, 2005)	SERVQUAL model	Website design, reliability, responsiveness, trust
	(Fassnacht and Koese, 2006)	-	Reliability, functional benefit, emotional benefit, attractiveness of selection, information quality, ease of use, technical quality, graphic quality, clarity of layout
	(Blut, 2016)	eTailQ model	Website design: information quality, website aesthetics, purchase process, website convenience, product selection, merchandise availability, price offerings, website personalization, and system availability; Fulfillment: delivery timeliness, order accuracy, and delivery condition; Customer service: service level and return handling/policies; Security/Privacy: security and privacy
Self-service technology	(Dabholkar et al., 1996)	Attribute-based model, overall affect model	Speed of delivery, reliability, enjoyment, ease of use, control, attitude toward using technological products, need for interaction with service employee
	(Shamdasani et al., 2008)	Self-service quality framework, the technology acceptance model	Speed of service, ease of use, reliability, enjoyment, control
	(Kallweit et al., 2014)	Technology acceptance model	Adequacy of information, usefulness of content, perceived ease of use, attitude towards usage
	(Pooya et al., 2020)	-	Technology readiness
	(Kim and Chen, 2023)	-	Consumer empowerment
Virtual agent	(Baabdullah et al., 2022)	Technology interactivity model	Personalisation, responsiveness, ubiquitous connectivity, readability, transparency
	(Haugeland et al., 2022)	Interaction design features	Interaction style: topic-led conversations, task-led conversations; conversation types: free text interaction, button interaction
	(Chung et al., 2020).	Technical features	Interaction, entertainment, trendiness, customization, problem-solving
	(Song et al., 2022)	Type of service agent	Type of service agent (chatbot/human)

understanding of antecedents of service quality by considering service-related, technology-related, and individual-related factors, it is not appropriate to translate them directly to the context of virtual agent services. This is because the existing antecedents are based on specific encounter types, such as human employee service, website service, or self-service. Virtual agent services have some unique interaction styles. Firstly, unlike human employees, virtual agents provide service through an artificial intelligence (e.g., big data analysis and natural language processing) system. Secondly, compared with website service or self-service, virtual agent service is based on interactive conversations. These unique interaction styles determine that the key to the successful provision of customer service by virtual agents lies in virtual agents' ability to match service and consumer. Currently, only a limited amount of research has begun to explore the service quality determinants of virtual agents from the perspective of technical characteristics. Hence, a new model is needed to comprehensively understand the virtual agent service context adequately by combining the match between technology, service, and consumer.

2.3. Fit-viability model

The fit-viability model was developed by Liang and Wei (2004) to assess the success of mobile commerce applications from an organizational perspective. It originated from a two-dimensional matrix (i.e., fit and viability) (Tjan, 2001) and then became a guideline to evaluate the performance of adopting technologies via fit and viability dimensions (Liang et al., 2007). Fit measures the match between technologies and the requirements of tasks (Liang et al., 2007); viability refers to the extent to which the environment or organization is ready for a given application (Liang et al., 2007), which generally has three aspects: economic feasibility, technical infrastructure, and users' readiness to use. This model has already been adopted to explain the performance of new technology applications in many contexts (Larosiliere and Carter, 2016; Liang et al., 2021; San Martin et al., 2012). For example, Larosiliere and Carter (2016) used the FVM to evaluate antecedents of e-government maturity at the country level.

There are three critical reasons for adopting the FVM as our theoretical framework. First, the FVM is utilized to assess the performance of new technology applications, and virtual agents fall into this category. In this study, our focus is on exploring the performance, specifically the service quality, of virtual agents in customer service. Thus, the FVM aligns with our research goals. Second, service quality is influenced not only by technical attributes satisfying consumer needs (Grönroos, 1984) but also by the way consumers obtain services (Zeithaml et al., 2002). As mentioned above, in the context of virtual agents, we should explore drivers of service quality by considering the matching of technology, service, and consumer. These aspects align with the two dimensions of the FVM: fit and viability. Third, the FVM has been applied in the assessment from the perspective of individual consumers. For example, Zhang et al. (2020) applied the FVM to assess how mobility affects social media advertising effectiveness from the consumer standpoint. It thus can be equally applicable to our research context.

2.4. Proposed model

2.4.1. Contextualization of the fit dimension

In the fit dimension, we contextualize and identify personalization, response speed, and response accuracy as the drivers of service quality. Consistent with the fit dimension of the FVM, in this study, fit measures the alignment between the technical characteristics of virtual agents and customer service requirements (Liang et al., 2007). First, efficiency and automation are primary reasons organizations use virtual agents for customer service tasks (Li et al., 2020; Selamat and Windasari, 2021). In other words, virtual agents can provide consumers with real-time and accurate services, such as information and solutions. Additionally, virtual agents possess big data analysis and deep learning capabilities, enabling them to offer personalized services (Chung et al., 2020). Thus, providing real-time, accurate, and personalized customer services are technical features of virtual agents. Second, speed and accuracy of performing tasks are considered two fundamental requirements of online customer service. Previous research has identified that responsiveness and reliability are vital factors affecting service performance

(Palese and Usai, 2018; Parasuraman et al., 1988). Considering the match between technical features of virtual agents and the requirements of customer service (Goodhue and Thompson, 1995), we argue that personalization, response speed, and response accuracy influence service quality.

Furthermore, virtual agents, powered by big data and artificial intelligence, can provide unique services tailored to the needs of different customers based on preferences, demand backgrounds, and contextual information. Because of this personalized service, virtual agents can respond faster and identify consumer needs more accurately during service interactions (Baabdullah et al., 2022). Therefore, we posit that personalization influences response speed and response accuracy.

2.4.2. Contextualization of the viability dimension

Within the FVM, viability reflects the extent to which the organizational environment is ready for the application, encompassing general economic feasibility, technical infrastructure, and social readiness (Liang et al., 2007). We abstract convenience, accessibility, and technology readiness from the viability dimension after analyzing environmental support for the process of consumer interaction with virtual agents. First, economic feasibility includes economic costs and benefits (Liang and Wei, 2004). Compared with using other agents for customer service, consumers do not need to cover costs and efforts associated with choosing the place or time. Conversely, consumers can initiate an interaction with virtual agents at any time and anywhere. This provides convenient conditions for consumers to encounter services. Thus, we regard convenience as the general economic feasibility of using a virtual agent. Second, technical infrastructure denotes technical environment support, providing the necessary foundation to support technological operations. Virtual agents facilitate the accessibility of information or services for the consumer. When a new virtual agent is easy to access, this indicates that the new service agent is ready and able to perform service delivery (Cheng and Jiang, 2021); that is, it indicates that the technical environment of the service encounter is feasible. Thus, we abstract accessibility to measure technical infrastructure in the context of virtual agent services. Finally, the readiness of the individual is another crucial supporting factor for the success of the system. Consumers' technology readiness for virtual agents, involving experiences, beliefs, and technical abilities, is a key factor affecting the consumer experience (Roy et al., 2018) and service quality (Zeithaml et al., 2002). Thus, we abstract technology readiness as another variable in the viability dimension.

Moreover, consumers' abilities and attitudes toward technology influence their perceptions of using the technology. Consumers with some degree of knowledge and a positive attitude toward new technologies are more likely to adapt to the interface and functionality of virtual agents, making it easier for them to navigate and interact with virtual agents seamlessly. Additionally, if consumers are ready to use virtual agents, they are more likely to initiate services as needed, rather than waiting for human employee services, making the overall experience more convenient. Thus, we argue that technology readiness influences convenience and accessibility.

2.4.3. Research model

By comparing virtual agents to traditional agents, we discovered that virtual agents possess unique interaction styles, which determine that factors influencing service quality should consider the matching of technology, service, and consumer. Therefore, we proposed the FVM, which evaluates technology performance by examining the match between technology, service scenario, and user readiness, as a suitable framework for exploring service quality. With the assistance of the FVM, we integrated the technical characteristics of virtual agents with customer service scenarios to abstract the fit dimension (i.e., personalization, response speed, and accuracy) in the "Contextualization of the fit dimension" section. Additionally, we considered the match between the application of virtual agents and its associated consumer to abstract the viability dimension (i.e., technology readiness, convenience, and accessibility) in the "Contextualization of the viability dimension" section. We propose a model to elucidate the driving mechanism of virtual agents' service quality in customer service settings (see Fig. 1). In the model, we examine the relationship between fit, viability, and service quality. Furthermore, we also propose the internal relationships between personalization (technology readiness) and response speed/ response accuracy (convenience/accessibility). Then, we regard service quality as the measure of virtual agents' performance.

3. Hypotheses

3.1. Response speed

Response speed refers to the time consumers perceive it takes to actively complete services via virtual agents (Collier and Sherrell, 2010). Response speed is one of the major considerations when introducing virtual agents into customer service settings (Binder et al., 2017; Chen et al., 2021a). For instance, in an online shopping context, when a consumer needs more information than the web display provides, they try to use the dialog window to consult a sales agent for more information. Once the consult button is triggered, virtual agents need to respond to the consumer's requirements quickly (Cheng and Jiang, 2021), and their quick response speed can enhance the customer's experience and perception of service quality. Accordingly, Brandtzaeg and Folstad (2017) found that more consumers tend to use virtual agents if virtual agents help consumers obtain information quickly, and a survey found that more than half of baby boomers and millennials state that virtual agents should provide instant responses to their questions (Sweezey, 2018). In the context of customer service provided by virtual agents, we hypothesize that:

H1: Response speed has a positive influence on virtual agents' service quality.

3.2. Response accuracy

In the context of virtual agents for customer service, response accuracy is defined as the extent to which a consumer perceives a virtual agent service provides precise information or services that suit consumers' needs (Lee and Benbasat, 2011; Chan et al., 2021). If virtual agents can offer accurate information or services that satisfy consumers' needs, consumers will perceive less uncertainty and obtain required services or solve their problems efficiently, which would increase consumers' perceived value. Consistent with this view, reliability, reflecting the ability to perform the promised service dependably and accurately, is one of the most important constructs for predicting an individual's perception of service quality (Parasuraman et al., 1988). In the domain of e-government service, Chan et al. (2021) also identified accuracy as an important factor influencing service quality. Thus, we hypothesize:

H2: Response accuracy has a positive influence on virtual agents' service quality.

3.3. Personalization

Personalization reflects the degree to which the virtual agents' offerings are tailored to meet heterogeneous customers' needs and preferences (Coelho and Henseler, 2012). A synonym for personalization is customization. Personalization is the most important advantage of the virtual agent in customer service. Alt et al. (2019) indicated that during customer service, the supply side (virtual agents) and demand side (customers) should be matched, projecting customer-oriented service as the future pathway for improving service. In contrast with human employees, virtual agents use natural language processing technology to provide personalized services based on the user's input information or personal portrait. These personalized services can help consumers find the proper products or information in a timely manner, increasing their

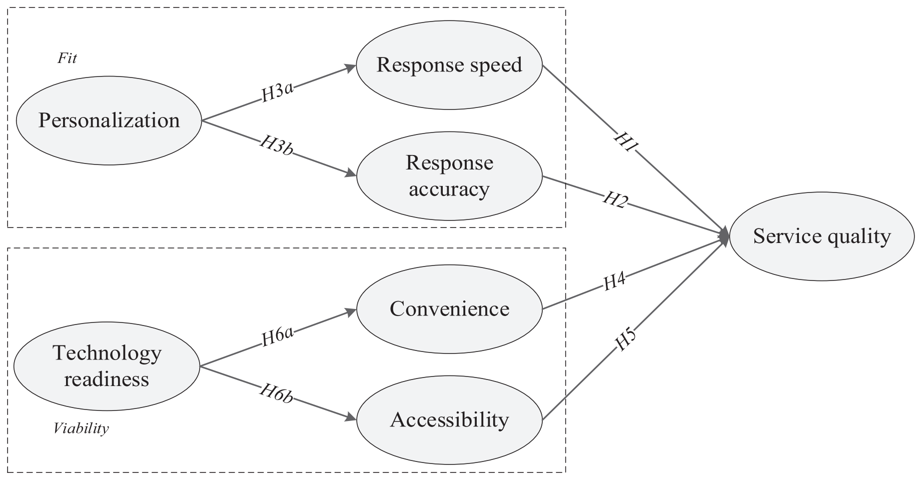

Fig. 1. Research model.

perception of speed. As Radziwill and Benton (2017) indicated, virtual agents can meet diverse needs and have been used by companies to reduce time-to-response. Thus, we speculate that personalization is related to the response speed of virtual agents. Therefore, we hypothesize:

H3a: Personalization has a positive influence on response speed.

Personalization afforded by virtual agents provides consumers with more valuable information or services (Cheng and Jiang, 2021). For instance, using consumers' browsing history or purchase history, virtual agents can access individuals' preferences and recommend products or after-sale services to them. Previous studies have consistently found that such personalization of virtual agents has a positive effect on the accuracy of communication (Chung et al., 2020). Therefore, we hypothesize:

H3b: Personalization has a positive influence on response accuracy.

3.4. Convenience

In this study, convenience refers to consumers' perceived time and effort required to find and facilitate the use of virtual agents for customer service (Collier and Sherrell, 2010). It also reflects the customer's ability to dictate the service experience. Virtual agents usually have preset procedures and Q&As contributing to solving customers' problems. For example, through operation procedures or recommendations, virtual agents can deliver information or services that aid consumers in decision-making. The convenience of virtual agents thus enhances the customer's experience of obtaining a helpful response. Previous research has found that convenience significantly influences service quality in the e-business environment (Srinivasan et al., 2002; Udo et al., 2010). Convenience is also regarded as a critical driver of a virtual agent's performance (Jang et al., 2021). Thus, it is hypothesized that:

H4: Convenience has a positive influence on virtual agents' service quality.

3.5. Accessibility

Accessibility refers to the ease with which information and services can be accessed through virtual agents in the customer service context (Wixom and Todd, 2005). Accessibility is a key driver of the successful use of a new system or technology. If the system or technology is easy to access, individuals are likely to use it successfully. When a virtual agent with a simple operation process increases service accessibility, the consumer has a positive communication and interaction experience. Previous research has indicated that the accessibility of a virtual agent is a key dimension of its communication quality and thus influences its performance (Cheng and Jiang, 2021). Chan et al. (2021) also revealed that accessibility is a vital factor that facilitates service perception and has a positive effect on service quality in e-government services. Thus, we hypothesize that:

H5: Accessibility has a positive influence on virtual agents' service quality.

3.6. Technology readiness

In this study, technology readiness not only reflects the consumer's ability to use the virtual agent but also includes the consumer's beliefs or attitudes about virtual agents. We conceptualize technology readiness as the extent to which a consumer has the ability and propensity to use virtual agents for customer services (Parasuraman, 2000; Venkatesh and Bala, 2012). It also reflects an individual's feelings or beliefs about high-tech products and services and their ability to use them. Technology readiness is conducive to a consumer's use of a virtual agent to achieve a task, and it offers them convenience. For example, if a consumer is ready to use a virtual agent and views it as an efficient tool to gain information or solve a problem, they are more inclined to choose a virtual agent. They can then communicate with the virtual agent at a convenient time and place, which can save them time and effort and lead them to perceive that the customer service they received was convenient. Previous research has revealed that technology readiness influence consumers' cognitive capability, leading them to take advantage of new technologies to acquire necessary services conveniently (Ferreira et al., 2014; Roy et al., 2018). Previous research has also demonstrated that technology readiness (i.e., personal computer skills) plays a vital role in service convenience (Udo et al., 2010). Thus, we hypothesize:

H6a: Technology readiness has a positive influence on convenience.

When a consumer is ready to adopt new technology, they can deal with challenges and discomforts that may arise during technology use. Thus, high levels of technology readiness make it easier for consumers to access technology (Jin, 2020). When considering service quality delivery through websites, technology readiness was identified as one customer-specific construct to understand customer behaviors (Zeithaml et al., 2002). In the context of virtual agents, technology readiness affords consumers the capability of understanding the functions of virtual agents and how a virtual agent can help them accomplish their shopping goals and tasks. This capability makes it easier for consumers to access virtual agents for information or services (Roy et al., 2018). Thus, it is hypothesized that:

H6b: Technology readiness has a positive influence on accessibility.

4. Methodology

4.1. Samples and data collection

As our study focuses on virtual agents in customer service, we chose a context in which virtual agents provide customer service on Chinese e-commerce platforms (e.g., Taobao, JD.com, Suning). First, the respondents on those platforms are representative, as the number of online shopping platform users in China reached 840 million as of June 2022 (CNNIC, 2022). Second, the respondents are familiar with the research context, as 42.3% of Chinese e-commerce platform users used virtual agents for customer service in this context in 2021 (iiMedia Research, 2021).

An online survey was performed to collect data through Sojump (http://www.sojump.com). We targeted people who have experienced customer services through virtual agents. To encourage all respondents to actively and seriously participate in the investigation, we provided those who successfully completed the questionnaire with an opportunity to win a power bank worth RMB 49. Data were collected in China from March 18 to April 15, 2021, and 427 completed responses were obtained. After we eliminated questionnaires completed in under 60 seconds and failed to recognize the reverse items, 399 valid responses were retained for use in the analysis. Sample demographics are shown in Table 2. Of the respondents, 219 (54.89%) were female and 180 (45.11%) were male. The largest age group was 25-34 years (177, 44.36%), followed by the 35-45 age group (103, 25.81%). The gender and age distributions are similar to that of CNNIC (2022). In terms of frequency of virtual agent use, 38.35% (153) of the respondents used virtual agents 1-2 times per month.

4.2. Response bias and common variance bias

The time trend method was used to check for non-response bias. Thus, we used the first 50 and the last 50 observations to assess the difference. The results showed that the significant value in all variables exceeds 0.05, which means there is no statistically significant difference between early and late participants and indicates that the issue of non-response bias is not a serious concern.

Considering that our data were self-reported by individuals and gathered at the same point in time, two methods were utilized to check for common method variance (CMV). First, Harman's single-factor test was used to examine common method bias (Malhotra et al., 2006). The results showed that all the scale items are classified into seven factors with eigenvalues greater than 1.0, and the cumulative variance explanation rate is 76.66%. Unrotated principal components analysis showed the variance explanation rate of the first factor is 27.31%, which is far less than the threshold of 50% (Podsakoff et al., 2003). These results showed that common method bias is also not a serious concern in this study. Second, we employed the unmeasured latent method construct (ULMC) approach to examine the potential impact of CMV on the observed relationships among the indicators of the measurement models (Richardson et al., 2009). Two models were constructed in Mplus software: the baseline model and the ULMC model. The findings showed that fit indices of the ULMC model were not significantly different compared to the baseline model ($\Delta\chi 2 = 4.886$, $\Delta df = 8$, $p > 0.05$, $\Delta RMSEM = - 0.009$, $\Delta CFI = 0.008$, $\Delta TLI = 0.012$), indicating that there is no serious common method bias.

Table 2
Sample characteristics.

Variable	Value	Frequency (N= 399)	Percentage (%)
Gender	Female	219	54.89
	Male	180	45.11
Age	Below 25	99	24.81
	25–34	177	44.36
	35–45	103	25.81
	More than 45	20	5.02
Frequency of using virtual agents (per month)	[1, 2] times	153	38.35
	[3, 5] times	133	33.33
	[6, 10] times	89	22.31
	More than 10 times	24	6.01

4.3. Development of measurement instrument

All survey items were measured using a 7-point Likert scale ranging from "strongly disagree (1)" to "strongly agree (7)." All measures were based on existing validated scales and were modified to fit the research context. The measurement of response speed was derived from Collier and Sherrell's (2010) research. A four-item scale taken from Lee and Benbasat (2011) was used to measure response accuracy. Personalization was assessed with a three-item scale extracted from Gattiker and Goodhue (2005) and Coelho and Henseler (2012). Convenience was tested using a scale proposed by Collier and Sherrell (2010). A three-item scale proposed by Wixom and Todd (2005) was adopted to measure accessibility. The two items for technology readiness were adapted from Venkatesh and Bala (2012), and another item that reflected consumers' technology propensity was added. The measurement of service quality of virtual agents consisted of four items from Taylor and Baker (1994).

To ensure the reliability and validity of the measure, we conducted multiple rounds of assessments before the formal survey. First, we asked two professors, two Ph.D. candidates, and three potential respondents to evaluate the understandability and clarity of the modified items. Then, all items were translated from English to Chinese using the back-translation technique (McGorry Susan, 2000), and minor adjustments were made to ensure they would be easily and accurately understood. Second, a pilot test was conducted with thirty students experienced in virtual agent services. After analyzing the data, the results demonstrated that the scales obtained acceptable reliability and validity. During this process, we also assessed the respondents' process of answering the survey, checking whether there were any steps or questions that might have caused confusion or distress. The items are shown in Appendix 1.

5. Results

5.1. Measurement model

Confirmatory factor analysis was used to establish a seven-factor correlated measurement model by using MPLUS 7.0. An inspection of the model showed good overall fit indexes ($\chi 2$ (384.384)/df (254) = 1.513, CFI = 0.978, TLI = 0.974, RMSEA = 0.036 and SRMR = 0.045), indicating an acceptable fit to the data. The internal reliability, convergent validity, and discriminant validity were demonstrated by the measurement model. As shown in Table 3, Cronbach's α of each scale and the composite reliability (CV) of variables exceed the suggested threshold of 0.7 (Hair et al., 2012), indicating that all scales are internally consistent and reliable. The convergent validity was assessed by examining the standardized factor loadings and average variance extracted (AVE). Table 3 indicates that each factor loading of the items with the underlying constructs is greater than 0.6 and significant at the 0.001 level. The values of AVE from each construct are all greater than the recommended 0.5 (Fornell and Larcker, 1981; Sparkman, 1979). Thus, convergent validity is established among these constructs. In addition, to examine discriminant validity, we compared the root of AVE values and correlation analysis results. As Table 4 shows, the discriminant validity is confirmed, as the square root of AVE for each construct exceeds the correlations between the construct and other constructs (Fornell and Larcker, 1981).

Table 3
Cronbach's alpha, composite reliability, factor loading, and average variance extracted.

Construct	Item	Mean	S.D.	Factor loading[a]	Average variance extracted	Cronbach's α	Composite reliability
Response speed (RS)	RS1	3.125	1.389	0.898	0.769	0.929	0.930
	RS2	3.143	1.383	0.903			
	RS3	3.130	1.419	0.890			
	RS4	3.241	1.294	0.814			
Response accuracy (RA)	RA1	3.985	1.354	0.714	0.507	0.802	0.804
	RA2	4.271	1.281	0.744			
	RA3	3.466	1.295	0.722			
	RA4	3.576	1.442	0.665			
Personalization (PER)	PER1	4.697	1.455	0.791	0.699	0.873	0.875
	PER2	4.900	1.468	0.860			
	PER3	4.960	1.431	0.856			
Convenience (CON)	CON1	5.574	1.470	0.782	0.649	0.880	0.881
	CON2	4.982	1.395	0.761			
	CON3	5.271	1.417	0.830			
	CON4	5.165	1.413	0.847			
Accessibility (ACC)	ACC1	4.506	1.274	0.732	0.673	0.857	0.860
	ACC2	4.594	1.362	0.887			
	ACC3	4.556	1.344	0.834			
Technology readiness (TR)	TR1	4.732	1.296	0.833	0.729	0.890	0.890
	TR2	4.779	1.321	0.846			
	TR3	4.987	1.337	0.881			
Service quality (SQ)	SQ1	4.341	1.475	0.871	0.668	0.887	0.889
	SQ2	4.386	1.487	0.855			
	SQ3	4.025	1.553	0.809			
	SQ4	4.436	1.430	0.726			

Note: a. χ^2 (384.384) / df (254) =1.513, CFI = 0.978, TLI = 0.974, and RMSEA = 0.036, SRMR = 0.045;b. ***p <0.001

Table 4
Discriminant validity.

Construct	1	2	3	4	5	6	7
Response speed	**0.877**						
Response accuracy	*-0.120*	**0.712**					
Personalization	-0.347	0.374	**0.836**				
Convenience	-0.236	0.232	0.315	**0.806**			
Accessibility	-0.253	0.181	0.255	0.265	**0.820**		
Technology readiness	-0.257	0.359	0.320	0.441	0.346	**0.854**	
Service quality	0.069	0.471	0.273	0.406	0.307	0.282	**0.817**

Note(s): The figures in the subdiagonal are correlation coefficients, which except for the italic figures are all significant at the 0.010 level, and the bold figures in the diagonal represent the square root of the average variance extracted (AVE).

5.2. Structural model assessment

A structural equation model was applied to test the hypotheses in MPLUS 7.0. It generated a satisfactory model fit with $\chi2$ (449.217)/df (266) = 1.689, CFI = 0.969, TLI = 0.965, RMSEA = 0.042, and SRMR = 0.081. The fit index, explanatory power, standardized path coefficients, and associated T-values of the structural model are reported in Fig. 2.

We observe that response speed ($\beta = 0.240$, $p < 0.001$) and response accuracy ($\beta = 0.402$, $p < 0.001$) are positively associated with service quality. Thus, H1 and H2 are supported. Personalization significantly and positively influences response accuracy ($\beta = 0.391$, $p < 0.001$) while it significantly and negatively influences response speed ($\beta =$ - 0.351, $p < 0.001$); thus, H3a is not supported and H3b is supported. Convenience ($\beta = 0.326$, $p < 0.001$) and accessibility ($\beta = 0.223$, $p < 0.001$) are positively associated with service quality, supporting H4 and H5. Finally, technology readiness is positively related to both convenience ($\beta = 0.452$, $p < 0.001$) and accessibility ($\beta = 0.358$, $p < 0.001$), indicating that H6a and H6b are supported.

To test the robustness of the results, we added control variables (i.e., gender, age, and frequency of using virtual agents) to the model. The subsequent analysis indicated that gender, age, and frequency of using virtual agents had no statistically significant influences on service quality, and the identified hypothesized relationships remained significant. It strengthened the overall credibility and generalizability of our findings.

5.3. Mediation examinations

To analyze the mediating role of response speed, response accuracy, convenience, and accessibility, we followed a procedure proposed by Baron and Kenny (1986) and built parallel multiple mediator models using MPLUS 7.0 (Hayes, 2018) (see Table 5). First, the results of model 1 indicate the significant effects of personalization (technology readiness) (independent variable (IV)) on service quality (dependent variable (DV)). After adding response speed and response accuracy (convenience and accessibility) (mediating variable (MV)), the coefficient value between personalization (technology readiness) and service quality (DV) decreases and is not significant (see model 2), while the 95% confidence intervals of indirect effects based on bootstrap samples do not include zero (see model 3). Therefore, the relationship between personalization (technology readiness) and service quality is fully mediated by response speed and response accuracy (convenience and accessibility).

6. Discussion

6.1. Major findings

This study examined the antecedents and mechanisms of virtual agents' service quality in the context of e-commerce customer service, thus enhancing the understanding of the new service model afforded by virtual agents. Our findings showed that response speed, response accuracy, convenience, and accessibility have direct influences on service

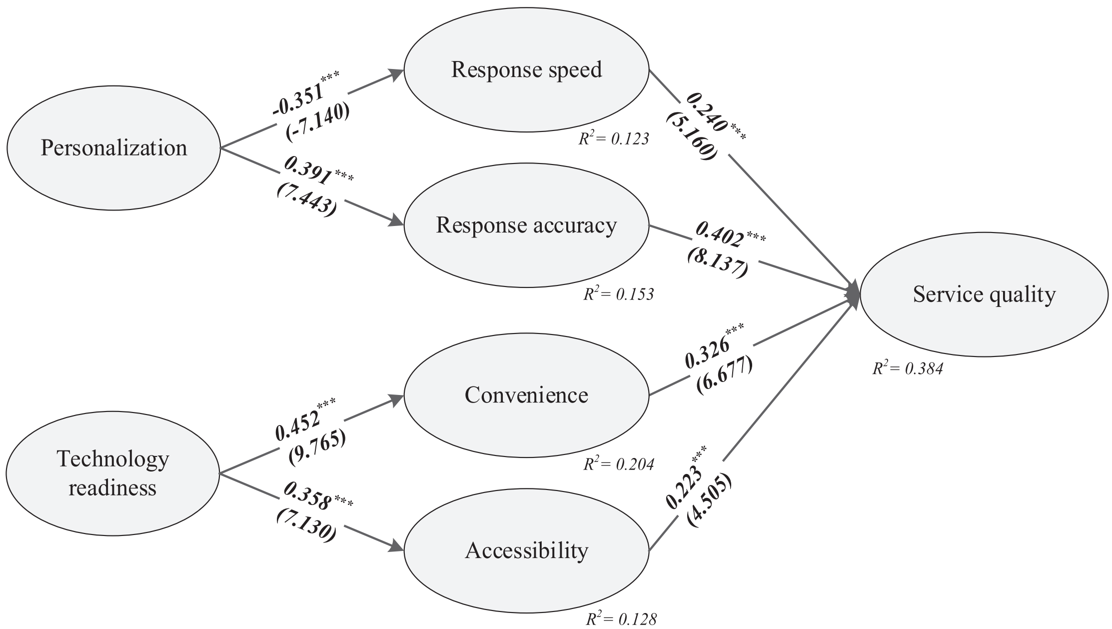

Fig. 2. Results of the structural model.

Table 5
Results of the mediation effects.

Construct	Model 1	Model 2	Indirect effect of IV→MV→DV		
	IV→DV	IV+MV→DV	Index	BootLLCI	BootULCI
Personalization	0.201***	0.080	Fully mediated		
Technology readiness	0.217***	-0.018	Fully mediated		
Response speed		0.263***	-0.093***	-0.133	-0.052
Response accuracy		0.369***	0.142***	0.083	0.201
Convenience		0.309***	0.143***	0.091	0.195
Accessibility		0.211***	0.078**	0.037	0.119
χ2	32.087	384.384	446.970		
df	32	254	264		
χ2/df	1.003	1.513	1.693		
CFI	0.999	0.978	0.969		
TLI	0.999	0.974	0.965		
RMSEA	0.003	0.036	0.042		
SRMR	0.024	0.045	0.080		

Note(s): a. IV=independent variable, MV=mediating variable, DV=dependent variable; b. ***p < 0.001, **p < 0.01; c. Indirect effect is generated by Model 3 with IND command; d. Number of bootstrap samples for bias corrected bootstrap confidence intervals is 5,000.

quality, and personalization and technology readiness are indirectly related to service quality. These findings provide empirical evidence to verify that it is appropriate to understand the antecedents of service quality from the dimensions of fit and viability. First, two variables (response speed and response accuracy) from the fit dimension have positive influences on service quality of virtual agents. It means that when virtual agents satisfy consumers' service requirements quickly and accurately, consumers will think highly of such services provided by virtual agents. These results are close to those of Baabdullah et al. (2022), who proved the significant role of responsiveness in customers' experience with chatbots. These findings indicate that service speed and accuracy are the same key factors of the new service model as the traditional service model (especially driven by human staff) (Luo et al., 2019).

Secondly, the findings demonstrate that personalization is positively associated with response accuracy, while it exerts reversed influences on response speed. Specifically, the positive relationship between personalization and response accuracy indicates that personalized agents enhance communication accuracy, supporting previous research in the context of retail marketing (Chung et al., 2020). It also suggests that virtual agents utilizing data analysis and deep learning technology have the potential to rival human employees in providing personalized services, thereby increasing response accuracy (Song et al., 2022). However, the hypothesis regarding the positive relationship between personalization and response speed is not supported; instead, personalization has a significant and negative influence on response speed. A possible reason for this may be that current technology has not yet reached the stage of "strong artificial intelligence" (Huang and Rust, 2018). In order to better satisfy consumer needs, virtual agents may require more time to analyze and match data to provide personalized solutions, consequently reducing consumers' perception of speed. These findings reveal that personalization implemented by virtual agents is a double-edged sword, requiring more attention when increasing the level of personalization.

Thirdly, the findings elucidate the direct and indirect relationships between constructs in the viability dimension and service quality. Specifically, convenience and accessibility exhibit direct positive influences on the service quality of virtual agents in e-commerce customer service.

This emphasizes the critical role of environmental factors in promoting service operability, affirming that service availability contributes to service quality, whether conducted by new agents (i.e., virtual agents) or traditional agents (Stamenkov and Dika, 2019; Zeithaml et al., 2002). Moreover, the findings indicate that technology readiness influences accessibility and convenience. This implies that customers who actively embrace new technology and possess the capability to adopt it are more likely to leverage the feasible conditions offered by virtual agents. These findings align closely with those of Roy et al. (2018), indicating that consumers, when ready and capable of using networks of smart or intelligent objects and devices for retail services, perceive greater ease of use. Additionally, mediation effects of convenience and accessibility suggest that individuals' technology readiness influences service quality through their perceptions of operational conditions, extending the research conducted by Goutam et al. (2022), which only explored the direct relationship between technology readiness and service quality.

6.2. *Theoretical contributions*

This study offers several significant theoretical contributions. First, it is one of the earlier studies that pioneered the idea of the service quality of virtual agents as a new kind of service principal in the context of e-commerce. Diverging from prior studies that predominantly focused on examining antecedents of acceptance, customer experience, satisfaction, and engagement (Zhang et al., 2021; Araujo, 2018; Schuetzler et al., 2020), this study significantly contributes by placing a greater emphasis on service quality with virtual agents. This enriches the literature on virtual agents and enhances the understanding and optimization of the new service model afforded by virtual agents. This study also opens up a novel avenue for researchers to advance the effectiveness of virtual agent applications.

Secondly, this study enhances the understanding of the service quality of customer service virtual agents from a new perspective. In contrast to a few studies that solely examined drivers of service quality from the perspective of technical features, neglecting process factors and available resources (Chung et al., 2020; Haugeland et al., 2022), this study identifies the antecedents of service quality by integrating technology, service scenario, and individual readiness in the context of customer service virtual agents. It provides a vital supplement to promote the understanding of service quality.

Thirdly, the exploration of internal relationships among service quality antecedents contributes to a deeper understanding of theoretical mechanisms and pathways of service quality. Previous research has primarily focused on the parallel effects of agent service characteristics, technological availability, and consumer individual factors on service quality, neglecting to delve into the internal relationships. This study explores the relationship between personalization and response speed and accuracy. Additionally, it emphasizes the influence of technology readiness on convenience and accessibility. By revealing the complex relationships among antecedent variables, this study provides insights into service quality theory and advances theoretical development.

Fourthly, this study extends the application scope of FVM by exploring the antecedents of service quality of virtual agents in e-commerce customer service. By applying FVM as the theoretical foundation, this study contextualizes the fit and viability dimensions to elucidate the drivers of performance (i.e., service quality) (Liang et al., 2007; Zhang et al., 2020). The findings indicate that the FVM can be a suitable framework to verify the importance of the degree to which the technical characteristics meet customer service tasks and the individual environment is ready for applications in the customer service context. Similar to the research of Zhang et al. (2020), this study also enriches the application of FVM at the consumer level.

6.3. *Practical implications*

This study is conducive to understanding and improving virtual agents' service quality in the context of e-commerce. First, managers and operators should pay attention to response speed, response accuracy, convenience, and accessibility when assessing virtual agents' performance, especially the service quality of the new business model. They should take care of customers' experience by reducing consumer waiting time, improving the accuracy of services, and providing a convenient and accessible operating environment when embedding virtual agents into the service delivery process. Second, organizations and developers should note the complex effects of personalized service strategies. On one hand, service providers can leverage more advanced artificial intelligence technologies to enhance the responsiveness of virtual agent services. On the other hand, personalization may reduce consumers' perception of service response speed to avoid misleading customers. A trade-off between speed and accuracy should be made when increasing the level of personalization. Third, consumers' readiness for virtual agents should be emphasized. Operators and developers can provide more guiding or explanatory language for virtual agents to increase consumers' levels of optimism and familiarity toward the new agents. Thus, virtual agents can become more readily accepted in customer service settings.

6.4. *Limitations and future research*

Despite this study's numerous significant contributions, it is essential to recognize its limitations, offering avenues for consideration in future research. The first limitation is the low level of external validity due to the sample composition (i.e., it comprises only consumers in China). Further research is necessary to verify the results obtained in different cultures and countries. Second, this study only obtained cross-sectional data. Future longitudinal study designs can lead to a better understanding of the influencing factors of service quality in different use stages. Third, the antecedents in this study explain 38.4% of the variance in service quality. Future research could examine more potential variables (e.g., anthropomorphism, customer interaction) that may drive the service quality of virtual agents in the customer service context.

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CRediT authorship contribution statement

Yanping Zhang: Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Changyong Liang:** Supervision, Project administration, Conceptualization. **Xiaodong Li:** Writing – review & editing, Validation, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix 1. . Factor items

Construct	Item	References
Response speed	1. I interact with virtual agents without spending too much time. 2. Virtual agents respond to my request quickly. 3. Virtual agents complete an interaction quickly. 4. It is efficient to interact with virtual agents.	(Collier and Sherrell, 2010)
Response accuracy	1. The answers/services provided by virtual agents suit my requirements. 2. The answers/services provided by virtual agents best match my needs. 3. The answers/services provided by virtual agents do not match my requests. (R) 4. I agree with and choose answers/services provided by virtual agents.	(Lee and Benbasat, 2011)
Personalization	1. Virtual agents can offer me the information/services that satisfy my specific needs. 2. Virtual agents are altered to improve their fit with me. 3. Virtual agents can't provide personalized information or services for my personal needs. (R)	(Gattiker and Goodhue, 2005), (Coelho and Henseler, 2012)
Convenience	1. Virtual agents allow me to initiate an interaction whenever I choose. 2. Virtual agents allow me to initiate an interaction at a convenient place. 3. I value the ability to initiate an interaction that is comfortable to me. 4. I like the ability to initiate an interaction conveniently.	(Collier and Sherrell, 2010)
Accessibility	1. Virtual agents allow information/services to be readily accessible to me. 2. Virtual agents make information/services very accessible. 3. Virtual agents make information/services easy to access.	(Wixom and Todd, 2005)
Technology readiness	1. I am ready to embrace interaction with virtual agents. 2. I have the IT infrastructure that I need to interact with virtual agents. 3. I have enough expertise to interact with virtual agents.	(Venkatesh and Bala, 2012)
Service quality	1. I believe that the general service quality of virtual agents is high. 2. Overall, I consider virtual agents' services to be excellent. 3. The service quality of virtual agents is generally excellent. 4.The service quality of virtual agents is generally poor (R).	(Taylor and Baker, 1994)

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