Journal of Business Research 156 (2023) 113526

Contents lists available at ScienceDirect

Journal of Business Research

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

Are AI chatbots a cure-all? The relative effectiveness of chatbot ambidexterity in crafting hedonic and cognitive smart experiences

Hua Fan [a], Wei Gao [b,*], Bing Han [c]

[a] School of Business and Management, Shanghai International Studies University, 550 Dalian Road (W), Shanghai, China
[b] College of Economics and Management, Southwest University, 2 Tiansheng Rd. Chongqing, China
[c] School of Management, Shanghai University of International Business and Economics, 1900 Wenxiang Road, Songjiang District, Shanghai, China

ARTICLE INFO

Keywords:
Chatbot ambidexterity
Smart experiences
Dual process models
Polynomial regression
Response surface analysis

ABSTRACT

Whether AI chatbots improve smart experiences and generate revenue is an under-researched topic. This study fills this research gap by investigating and comparing the effects of the full range of chatbot ambidexterity on smart experiences. Using empirical data from 1,026 customers, the results indicate that chatbot ambidexterity is not a cure-all. Only efficiency-flexibility ambidexterity benefits smart experiences and customer patronage, while service-sales ambidexterity is detrimental to the creation of smart experiences. Furthermore, high service-low sales (vs low service-high sales) ambidexterity has a stronger impact on hedonic smart experiences but a weaker influence on cognitive smart experiences. Low efficiency-high flexibility and low existing-high new product selling ambidexterity outperform high efficiency-low flexibility and high existing-low new product selling ambidexterity, respectively, in crafting either hedonic or cognitive smart experiences. The results also reveal that hedonic smart experiences have a stronger impact on customer patronage than cognitive smart experiences. This study contributes to the literature on smart experiences and chatbot ambidexterity and provides fruitful and meaningful guidance for service providers regarding the deployment of AI chatbots in the frontline interface.

1. Introduction

"Smart experiences" refer to the emotional and cognitive responses of customers to smart technologies (Gao et al., 2022). Powered by artificial intelligence (AI), chatbots are a popular new technology with unprecedented business potential and are gradually taking over frontline interfaces (Larivière et al., 2017; Xiao & Kumar, 2021). Service providers rely heavily on AI chatbots to deliver smart experiences to improve word-of-mouth, customer attitude and patronage, and sales performance (Fan et al., 2022a; Gao et al., 2022; Mishra et al., 2022). The COVID-19 pandemic has especially created the need for no-touch customer service, and the market size of AI chatbots has increased rapidly, from US$250 million in 2017 to a predicted value of more than US$1.34 billion in 2024 (Luo et al., 2019). Therefore, examining the effectiveness of AI chatbots is important for crafting smart experiences.

There are three research gaps in the literature on smart experiences (see Table 1). First, smart experiences have been investigated in the contexts of online and omnichannel retailing, branded app services, and augmented/virtual reality (AR/VR) services (Fan et al., 2020; Herrando et al., 2019; Japutra et al., 2021; Kumar & Srivastava, 2022), but only a few studies have examined smart experiences created by AI chatbots (e.g., Fan et al., 2022a; Gao et al., 2022). Despite the changes brought about by AI technology in frontline service (Belanche et al., 2019; Henkel et al., 2020), limited attention has been paid to how to optimize smart experiences through AI chatbots (Research Gap 1).

Second, studies have revealed the influence of AI features, such as AI technology stimuli (Gao et al., 2022) and AI chatbots' service-sales ambidexterity (Fan et al., 2022a), on smart experiences. Although it is well acknowledged that AI chatbots can pursue seemingly conflicting goals simultaneously (de Ruyter et al., 2020; Fan et al., 2022b), the literature has not recognized the full range of chatbot ambidexterity (i.e., *service-sales ambidexterity*, *efficiency-flexibility ambidexterity*, and *existing-new product selling ambidexterity*) as the potential antecedents of smart experiences (Research Gap 2).

Third, service providers usually have limited resources to satisfy the multiple needs of customers (Fan et al., 2022c; Liu et al., 2020) and, therefore, have to focus on a sub-dimension of smart experiences. Various taxonomies have been used to define the dimensionality of

* Corresponding author.
E-mail address: gaoweibaggio@qq.com (W. Gao).

https://doi.org/10.1016/j.jbusres.2022.113526
Received 25 March 2022; Received in revised form 27 November 2022; Accepted 29 November 2022
Available online 6 December 2022
0148-2963/

smart experiences, among which "hedonic" and "cognitive experiences" are the most frequently mentioned (e.g., Barhorst et al., 2021; Lee et al., 2020; Molinillo et al., 2022, 2020; Qing & Haiying, 2021; Tyrväinen et al., 2020). Although scholars have explored the antecedents and consequences of hedonic/cognitive experiences, no one has attempted to investigate the relative effectiveness of different antecedents in crafting hedonic and cognitive smart experiences (Research Gap 3).

To fill these research gaps, this study builds on dual process models to scrutinize the relative effectiveness of AI chatbot ambidexterity in influencing smart experiences and customer patronage. We seek to answer the following question: What kind of chatbot ambidexterity should service providers deploy to cultivate an optimal hedonic/cognitive smart experience? In answering this research question, this study contributes to the literature in three ways. First, it contributes to smart experience research by taking a multi-dimensional view of AI chatbot services. Studies on AI chatbots have conceptualized smart experiences as either a holistic construct (Fan et al., 2022a) or a unidimensional cognitive construct (Gao et al., 2022). By uncovering the effects of chatbot ambidexterity on different dimensions of smart experiences, this study extends that of Gao et al. (2022) and considers more elements (e.g., emotion and behavior) in smart experience research. Second, it adds to the AI chatbot literature by examining the effects of the full range of ambidexterity. The literature on smart experiences has only investigated the triggering role of AI chatbots' service-sales ambidexterity (Fan et al., 2022a). By integrating AI chatbots' efficiency-flexibility (i.e., service) and existing-new product selling (i.e., sales) ambidexterity, this study extends that of Fan et al., (2022a) and estimates the effectiveness of different types of chatbot ambidexterity. Third, it enriches dual process models by offering a fresh perspective on the effects of chatbot ambidexterity. By comparing the different effects of chatbot ambidexterity on hedonic and cognitive smart experiences, this study responds to the call of Gao et al. (2021) to validate the multi-dimensional experience scale in different situations and that of Pertusa-Ortega et al. (2021) to examine additional outcomes of ambidexterity. The findings of this study also provide practical guidance to service providers for designing and deploying AI chatbots in frontline human–machine interactions.

2. Literature review

2.1. Smart experiences

Customer experience describes a customer's interactions with a firm's products, personnel, services, and/or shopping environment (Gao et al., 2021). Over the last decade, customer experience has been a popular research topic, as it is essential for a service provider's success (see De Keyser et al., 2020 for a review). By extending customer experience research to the context of smart services, Roy et al. (2019) defined smart experiences as customers' subjective and internal responses to their encounters with smart technologies. Smart experiences have become a primary focus in marketing research due to the ubiquity of smart technologies, such as electronic commerce, smartphone apps, and AR/VR (Fan et al., 2020; Herrando et al., 2019; Japutra et al., 2021; Kumar & Srivastava, 2022).

The latest trend in smart experience research is to study AI chatbots (e.g., Fan et al., 2022a; Gao et al., 2022). AI technologies, such as natural language processing and machine learning, can analyze customer feedback and sentiment at scale and with speed and precision (Ameen et al., 2021). Therefore, AI represents an updated stream of smart

Table 1
An Overview of Selected Empirical Studies on Smart Experiences.

Research Context	Studies	Antecedents	Sub-dimensions of Smart Experience: Hedonic/ Affective	Cognitive/ Utilitarian	Other dimensions
Online and omnichannel retailing	Lambillotte et al. (2022)	Website content congruence	✔	✔	Behavioral
	Cocco & Demoulin (2022)	Omnichannel integration	✔	✔	
	Gao et al. (2021)	Omnichannel integration	✔	✔	
	Tyrväinen et al. (2020)	Hedonic motivation, personalization	✔	✔	
	Bleier et al. (2019)	Webpage design elements	✔	✔	Social, sensorial
	Herrando et al. (2019)	Hedonic and utilitarian stimulus			Flow experience
Branded app services	Molinillo et al. (2022)	–	✔	✔	Relational, sensorial
	Ameen et al. (2021)	Trust, perceived sacrifice, relationship commitment	✔		Recognition
	Japutra et al. (2021)	–	✔		Sensory, interactivity, relative advantage
	Molinillo et al. (2020)	–	✔	✔	
	Roy et al. (2019)	Smart servicescape, interaction with employees	✔	✔	Social, personal, pragmatic, economic
AR/VR services	Kumar & Srivastava (2022)	Augmentation, flow experience	✔		Perceived risk
	Barhorst et al. (2021)	Flow experience	✔	✔	Learning
	Jung et al. (2021)	Presence, spatial ability, conceptual understanding			Education, aesthetic, entertainment, escape
	Qing & Haiying (2021)	Hedonic and utilitarian motives	✔	✔	
	Fan et al. (2020)	Environmental embedding, simulated physical control		✔	
	Lee et al. (2020)	Telepresence	✔	✔	
AI chatbot service	Gao et al. (2022)	AI technology stimuli		✔	Interactivity, relative advantage
	Fan et al. (2022a)	AI chatbot sales-service ambidexterity			Single dimension
	This study	**Full range of chatbot ambidexterity**	✔	✔	
Research Gap 1 *Cultivate a multi-dimensional smart experience via an AI chatbot service*		***Research Gap 2*** *Full range of frontline ambidexterity performed by AI chatbots*	***Research Gap 3*** *Relative effectiveness of distinct AI chatbot ambidexterity in crafting hedonic and cognitive smart experiences*		

technologies, and AI-based chatbots can become a vital tool for service providers to establish and maintain their competitive advantage (Keeling et al., 2010). AI chatbots have been extensively deployed in various industries (e.g., airports, restaurants, retail, hotels, and travel planning) to improve smart experiences (Fan et al., 2022b; Hughes & Ogilvie, 2020).

However, the literature lacks consensus on the conceptualization of smart experiences and different taxonomies have been used to measure smart experiences. In their seminal work, Roy et al. (2019) established a huge framework to define smart experiences, with six sub-dimensions: hedonic, cognitive, social, personal, pragmatic, and economic. Although some scholars have concentrated on either hedonic (Ameen et al., 2021; Japutra et al., 2021; Kumar & Srivastava, 2022) or cognitive experiences (Fan et al., 2020; Gao et al., 2022), researchers have widely recognized both dimensions of smart experiences (see Table 1).

Hedonic experience captures a mental process and includes emotions, moods, and attitudes (Molinillo et al., 2020). It occurs when the purchasing process evokes a positive mood, thus emphasizing the entertainment and pleasure derived by customers from shopping (Barari et al., 2020; Japutra et al., 2021). Therefore, an AI chatbot can create hedonic smart experiences by offering flexible and customized services that bring enjoyment (Fan et al., 2022a). Similarly, cognitive experience captures a mental process and involves perception, problem-solving, and abstract thinking (Ameen et al., 2021). It is created when functional information (e.g., product/service price and quality) is timely provided, thus emphasizing the efficiency and functionality of obtaining services and products (Gao et al., 2021; Keiningham et al., 2017). Therefore, an AI chatbot can create cognitive smart experiences by offering efficient service and adequate information (Gao et al., 2022).

2.2. Chatbot ambidexterity

Ambidexterity refers to a frontline employee's simultaneous pursuit of seemingly conflicting goals, such as service and sales, service efficiency and flexibility, and sale of existing and new products (Hughes & Ogilvie, 2020; Pertusa-Ortega et al., 2021). The literature has identified the salient role of the ambidexterity of human employees, such as in personal selling (Hughes & Ogilvie, 2020), supply chain management (Van der Borgh & Schepers, 2018), air services (Kao & Chen, 2016), patient care (Yu et al., 2020), and project management (Sun et al., 2020). However, there is limited evidence of the frontline ambidexterity of virtual employees (i.e., AI chatbots).

Using natural language processing tools, real-time access to databases and sophisticated computing power, AI chatbots can easily handle ambidextrous frontline tasks without getting frustrated or tired like human employees (de Ruyter et al., 2020). AI chatbots can implement three types of ambidextrous tasks: (1) *service-sales ambidexterity*, which refers to an AI chatbot's ability to conduct customer service and cross-selling simultaneously (Fan et al., 2022a). AI chatbots can rely on standardized programs to accomplish repetitious service requests and identify a cross-selling opportunity by analyzing conversational patterns (Singh et al., 2019). (2) *Efficiency-flexibility (service) ambidexterity*, which refers to an AI chatbot's ability to provide frontline services that are simultaneously efficient and flexible (Fan et al., 2022b). By searching information databases and matching current offerings to customer needs, AI chatbots can facilitate information exchange at a much higher efficiency level and flexibility (de Ruyter et al., 2020). (3) *Existing-new product selling (sales) ambidexterity*, which refers to the ability to concurrently pursue the sale of existing and new products in a firm's product portfolio (Van der Borgh et al., 2017). AI chatbots can scan customers' digital footprints on accessible platforms and detect their preferences for a firm's existing and new products or competitors' products (Agnihotri, 2021).

2.3. Dual process models

Dual process models (e.g., elaboration likelihood model, heuristic-systematic model) have been widely applied to understand the formation of customer experiences (Kang, 2016; Lee et al., 2019). Dual process theorists posit that customers use two information processing modes—*affective-based processes* and *cognitive-based processes*—to make purchase decisions (Lee et al., 2019). *Affective-based processes* are automatic, heuristic, less analytical, and demand fewer cognitive resources (Breves, 2021). When information is irrelevant to personal interest (i.e., low customer involvement), customers tend to process information using peripheral and heuristic cues (Petty & Cacioppo, 1986). In contrast, *cognitive-based processes* are deliberate, reflective, effortful, and require more cognitive resources (Breves, 2021). When customers elaborately process information (i.e., high customer involvement), they tend to follow central and systematic cues (Petty & Cacioppo, 1986).

In addition, the two information processing modes can operate in parallel, indicating that customers can focus on both irrational and rational information comprehensively (Kang, 2016). Therefore, when interacting with an AI chatbot, if the content of the interaction is routine and repetitious, customers can process the interaction peripherally or heuristically (i.e., affective-based processes) by devoting fewer cognitive resources and attention. In contrast, if the content of the interaction is high in personal relevance, customers may engage in thoughtful and elaborate processing (i.e., cognitive-based processes) by devoting more cognitive resources and effort (Breves, 2021; Lee et al., 2019). Therefore, dual process models appear to be the most suitable for exploring how different forms of chatbot ambidexterity have different effects on hedonic/cognitive smart experiences (as illustrated in Fig. 1).

3. Hypothesis development

We propose a two-by-two matrix (see Fig. 2) that juxtaposes the extent (high vs low) of chatbot ambidexterity with its type (service vs sales, efficiency vs flexibility, selling existing vs new products) to better interpret the diverse configurations of chatbot ambidexterity. We use the dual process models to first differentiate between ambidextrous component fit (quadrants 1 and 2 of Fig. 2) and misfit (quadrants 3 and 4 of Fig. 2). However, from a resource-based view (Fan et al., 2022c; Liu et al., 2020), companies often have limited resources to deploy a chatbot that can perform equally well in service and sales, service efficiency and flexibility, and sales of existing and new products. Therefore, we compare the two quadrants within the misfit diagonal (quadrant 3 vs quadrant 4 of Fig. 2).

3.1. Service-sales ambidexterity and smart experiences

Service-sales ambidexterity drives both hedonic and cognitive smart experiences because an AI chatbot's service provision and cross-selling facilitate customers' affective- and cognitive-based processes, respectively. First, high-quality service comes from the service history data of similar customers (Fan et al., 2022a). Such a database provides information to chatbots to address certain problems (de Ruyter et al., 2020), thus requiring fewer cognitive resources (i.e., affective-based processes) from customers to answer their questions. Second, high-quality sales imply that an AI chatbot can use its algorithm to provide an optimal cross-sell offer (de Ruyter et al., 2020). As customers evaluate whether the additional product information fulfills their needs, they have to process the information more deliberately and effortfully (i.e., cognitive-based processes). Therefore, service-sales ambidexterity improves both hedonic and cognitive smart experiences.

There are two plausible outcomes when considering organizational resource constraints: high service-low sales (quadrant 4 of Fig. 2) and low service-high sales (quadrant 3 of Fig. 2) ambidexterity. According to dual process models, low (high) customer involvement causes individuals to process information using an affective-based (cognitive-

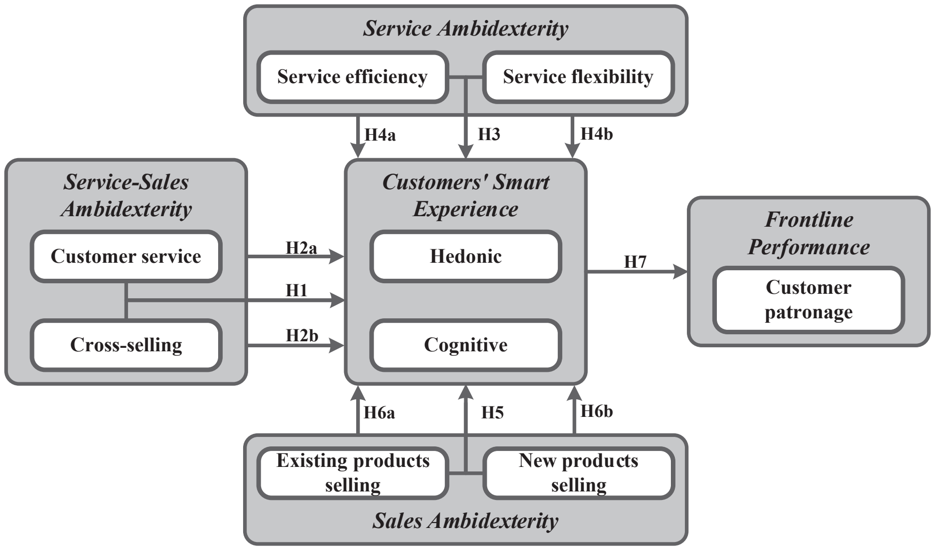

Fig. 1. Theoretical Framework.

		Service/Efficiency/Existing Product Selling	
		High level ● Frequent service interactions ● Customers rate service efficiency as high quality ● Frequent sales interactions relevant to existing products	**Low level** ● Occasional service interactions ● Customers rate service efficiency as low quality ● Occasional sales interactions relevant to existing products
Sales/Flexibility/Selling New Products	**High level** ● Frequent sales interactions ● Customers rate service flexibility as high quality ● Frequent sales interactions relevant to new products	**Ambidextrous component fit** Equivalent high levels of service-sales ambidexterity, efficiency-flexibility ambidexterity, and existing-new product selling ambidexterity (*Quadrant 1*)	**Ambidextrous component misfit** Low service-high sales ambidexterity, low efficiency-high flexibility ambidexterity, and low existing-high new products selling ambidexterity (*Quadrant 3*)
	Low level ● Occasional sales interactions ● Customers rate service flexibility as low quality ● Occasional sales interactions relevant to new products	**Ambidextrous component misfit** High service-low sales ambidexterity, high efficiency-low flexibility ambidexterity, and high existing-low new product selling ambidexterity (*Quadrant 4*)	**Ambidextrous component fit** Equivalent low levels of service-sales ambidexterity, efficiency-flexibility ambidexterity, and existing-new product selling ambidexterity (*Quadrant 2*)

Fig. 2. Two-by-Two Matrix Juxtaposing Extent with Types of Ambidextrous Components.

based) approach (Breves, 2021; Lee et al., 2019). Service provision relies on more standardized processes to resolve customer problems than cross-selling (Mullins et al., 2020). A service dialogue between an AI chatbot and a customer thus involves a low level of customer involvement and creates the customer's hedonic (vs cognitive) smart experience. In contrast, cross-selling requires a frontline employee to leverage dispersed information to form an in-depth understanding of customer needs (Evans et al., 1999). As an AI chatbot provides customers with more accurate, appropriate, and personalized product information in a sales dialogue (de Ruyter et al., 2020), it requires a high level of customer involvement and easily creates the customer's cognitive (vs hedonic) smart experience. Therefore, we propose the following hypotheses based on dual process models (e.g., Kang, 2016; Lee et al., 2019; Petty & Cacioppo, 1986):

H1: AI chatbots' service-sales ambidexterity increases (a) hedonic and (b) cognitive smart experiences.

H2: AI chatbots' high service-low sales (vs low service-high sales) ambidexterity triggers (a) more hedonic and (b) less cognitive smart experiences.

3.2. Efficiency-flexibility ambidexterity and smart experiences

Efficiency-flexibility ambidexterity also drives smart experiences. Hedonic smart experience reflects the entertainment and pleasure of shopping (Barari et al., 2020; Japutra et al., 2021), while cognitive smart experience mirrors the efficiency of service (Gao et al., 2021; Keiningham et al., 2017). An AI chatbot can provide flexible service by delivering the best quality care and ensuring maximum customer satisfaction (Fan et al., 2022b), which greatly facilitates customers' affective-based processes. An AI chatbot can also provide efficient service by cutting costs and improving efficiency (Fan et al., 2022b), which enables customers' cognitive-based processes. According to dual process models (Breves, 2021), an AI chatbot's efficiency-flexibility (service) ambidexterity enables customers' affective- and cognitive-based processes, thus improving both hedonic and cognitive smart experiences.

There are two plausible organizational practices when considering resource constraints: high efficiency-low flexibility (quadrant 4 of Fig. 2) and low efficiency-high flexibility (quadrant 3 of Fig. 2) ambidexterity. On the one hand, AI chatbots can take on routine service requests and accomplish a range of functionalities based on historical data (de Ruyter et al., 2020). These convenient actions cater to customers' cognitive-based processes that emphasize the efficiency of obtaining services (Gao et al., 2021). On the other hand, AI chatbots can offer more flexible services, such as suggesting questions, providing timely information, and personalized costs (de Ruyter et al., 2020). This type of customized service accommodates customers' affective-based processes. Therefore, an AI chatbot focusing on flexible service (low efficiency-high flexibility ambidexterity) fosters hedonic experiences (Fan et al., 2022a), whereas an AI chatbot focusing on efficient service (high efficiency-low flexibility ambidexterity) creates cognitive experiences (Gao et al., 2022). Accordingly, we propose the following hypotheses:

H3: AI chatbots' efficiency-flexibility ambidexterity increases (a) hedonic and (b) cognitive smart experiences.

H4: AI chatbots' high efficiency-low flexibility (vs low efficiency-high flexibility) ambidexterity triggers (a) less hedonic and (b) more cognitive smart experiences.

3.3. Existing-new product selling ambidexterity and smart experiences

Existing-new product selling ambidexterity only drives cognitive smart experiences, as sales attempts by AI chatbots have a stronger influence on cognitive-based processes than on affective-based processes. The sale of existing or new products shows the proactivity of salespeople in revenue generation (Van der Borgh & Schepers, 2017). AI chatbots' proactive delivery of functional content can increase the total amount and benefit of information exchange in dyadic communication (Köhler et al., 2011). According to dual process models, when product information is highly relevant to customers' personal interests, customers allocate more cognitive effort and time to process the information elaborately (Lee et al., 2019). Given that cognitive smart experiences focus on the functional information received by customers (Gao et al., 2022; Roy et al., 2019; Verleye, 2015), an AI chatbot's existing-new product selling (sales) ambidexterity benefits cognitive smart experiences.

There can be two business practices when considering resource constraints: high existing-low new (quadrant 4 of Fig. 2) and low existing-high new (quadrant 3 of Fig. 2) product selling ambidexterity. Companies may prefer to focus on existing products first because the information related to existing products is less risky (Van der Borgh & Schepers, 2018). As a result, customers may be less influenced, maintain the status quo, and devote less cognitive effort. In contrast, customers may prefer to have access to new products, as new information represents novel and customized solutions for their different needs (Van der Borgh et al., 2017). An AI chatbot can leverage smart technologies to provide timely, accurate, and relevant information about how the new product addresses customer needs. Therefore, pragmatic information about new products sheds more light on customers' affective- and cognitive-based processes than information about existing products. According to dual process models, such information processes increase the persuasiveness of AI chatbots and create smart experiences (Breves, 2021; Lee et al., 2019). Accordingly, we propose the following hypotheses:

H5: AI chatbots' existing-new product selling ambidexterity increases (a) cognitive but not (b) hedonic smart experiences.

H6: AI chatbots' high existing-low new (vs low existing-high new) product selling ambidexterity triggers (a) less hedonic and (b) less cognitive smart experiences.

3.4. Smart experiences and customer patronage

Customer patronage refers to a customer's positive attitude toward and their patronage of a brand/firm (Fan et al., 2022a). In general, patronage is characterized by reciprocity between partners in a dyadic relationship, whereby a salesperson offers services to a customer and, in return, the customer adopts a positive attitude and behavior toward the salesperson (Blut et al., 2018). A high perception of a smart experience is one in which customers obtain multiple benefits (Verleye, 2015) and derive satisfaction and happiness from these experiences (Buonincontri et al., 2017). In return for these superior functional and relational values created by an AI chatbot, customers are more likely to spread positive word-of-mouth and spend more for the service provider (Buonincontri et al., 2017; Roy et al., 2019). In contrast, if an AI chatbot fails to meet customers' needs for hedonic and cognitive benefits during frontline interactions, customer satisfaction decreases along with their patronage intentions (Gao et al., 2021). Therefore, we propose that customer patronage is an important consequence of customers' perception of smart experience.

H7: Smart experiences positively affect customer patronage.

4. Material and methods

4.1. Research setting

The setting of this study was a large e-bike sharing company (hereafter, Company J) with headquarters in Shanghai and a yearly net income of more than US$2 million. E-bike sharing provides considerable convenience to users while traveling, but there are many service problems, such as location and capability of stations, repositioning of vehicles, functioning of bike-sharing systems, and parking issues. Most customer requests are regular and repetitive, making the deployment of service chatbots essential and economic. Therefore, Company J outsourced its call center to an AI-based service system provider to cut operating costs. Each customer service request is routed to an AI chatbot first, which can perform both customer service provision and cross-selling tasks. Only unsolved problems are transferred to human frontline employees recruited by Company J.

The AI chatbot's customer service provision includes daily conversations, such as weather reports, normal greetings, and informal chats, and order-related solutions, such as parking area navigation, vehicle location services, and vehicle return guidance. Cross-selling includes the sale of rental packages, a joint product with a bank, a joint product with an online video platform, and a joint product with a car-hailing app. During the cross-selling process, the AI chatbot can randomly introduce a new rental package based on a user's historical riding data, recommend the joint product with a bank to a user who often pays bills via their bank account, recommend the joint product with an online video platform to a user who often rides to subway stations, or recommend the joint product with a car-hailing app to a user who often returns the e-bike to a rural place. To date, Company J has over 30,000 registered users.

4.2. Data collection

Field data were collected in three stages during 2021. In Stage 1, together with Company J and the service system provider, we formed a research team to collect customer scores on service efficiency and flexibility, smart experience, and several other background variables through an online questionnaire. The questionnaire was developed in English and translated into Chinese to ensure that the participants understood the questions. It was then back-translated into English and checked against the original English version for accuracy. The questionnaire was then sent to 11,470 registered users of Company J through the mobile app, along with an incentive of a rental coupon. To ensure that the participants had some experience with the AI chatbot, we only targeted users who had interacted with the AI chatbot in the previous 6 months. At the end of Stage 1, 1,091 registered users completed the questionnaire.

In Stage 2, we matched the participants with the service system provider's database of all frontline conversations between the AI chatbot and customers. Each conversation was classified as service provision or cross-selling, and each cross-selling conversation was categorized as selling existing products or new products. The employees of Company J affiliated with our research team undertook the process of coding man–machine interactions (customer service, sale of existing products, or sale of new products). Over 12,000 dialogues were recorded from the 1,091 registered users who completed the questionnaire, indicating that each user had about 11 conversations on average with the AI chatbot in the previous 6 months. Among the conversations, 50.2 % were categorized as service provision, 25.1 % as cross-selling of existing products, and 24.7 % as cross-selling of new products. We invited four independent judges (customer-contact managers with extensive frontline service experience) to validate the classification method. They coded a random sample of 300 conversations from the sample pool. Cohen's kappa was 0.86 on average, suggesting good interrater agreement.

In Stage 3, we matched the 1,091 accounts to Company J's financial database for their customer patronage measures. The account IDs were sent back to Company J for collecting these users' actual expenditures in the previous 6 months. We only collected expenditures from the link displayed by the chatbot to ensure that user patronage occurred after talking to the AI chatbot. Not every user had purchased a rental package or a joint product through the chatbot; therefore, we dropped 65 accounts from the sample pool, leaving 1,026 accounts with archival financial data for direct customer patronage measures in the final stage.

4.3. Measures

Following Köhler et al. (2011), we differentiated service provision from cross-selling. Man–machine interactions involve daily conversations, order-related services, sale of rental packages, and sale of joint products. We classified an interaction as customer service (SE) when the conversation was about the underlying services (e.g., daily conversations, order-related issues). Therefore, we measured the extent to which the chatbot implements customer service as the number of interactions that are service-dominant and irrelevant to product sales. We classified an interaction as cross-selling (SA) when the chatbot intended to harvest a purchase (e.g., recommendation of rental packages or joint products). Therefore, we measured the extent to which the AI chatbot implements cross-selling as the number of sales-related interactions. Furthermore, among the cross-selling interactions, we classified an interaction as selling new products (NE) when a product link was displayed to a customer for the first time and as selling existing products (EX) if a product link had been displayed to the customer before.

Service efficiency and flexibility and smart experiences were measured by well-established scales from the literature (see the appendix). Service efficiency (EF) and flexibility (FL) were both measured by three items on a 7-point scale, asking users' opinions about the activities that the chatbot engaged in. Following Fan et al. (2022a, 2022b) and Yu et al. (2020), we created three multiplicative interaction terms to interpret the levels of service-sales ambidexterity, efficiency-flexibility ambidexterity, and product selling ambidexterity. Hedonic (HD) and cognitive (CG) smart experiences were both measured by three items on a 7-point scale, focusing on customers' emotional and cognitive responses to the chatbot service. Customer patronage (PT) was measured by the archival data of Company J, as an accurate indicator of how much a customer uses the chatbot for purchases (Köhler et al., 2011).

The final dataset comprised 1,026 customers who had at least one man–machine interaction during our observation period. The conversations between the customers and the AI chatbot provided 10,876 dialogues, of which 5,458 focused on customer service provision (SD = 0.91), 2,688 promoted existing products (SD = 0.47), and the remaining 2,730 were new product sales (SD = 0.47). On average, a customer spent USD38.63 (SD = 33.12) after the chatbot interaction. The final sample included 58 % women, with an average age of 31 years. Customers' monthly income was evenly distributed between less than USD400 and more than USD1,200, and 72 % of them had a bachelor's degree. Table 2 shows the descriptive statistics and correlations among the variables.

5. Results

5.1. Measurement validation

We first performed a confirmatory factor analysis for the online survey data. The measurement model had a good model fit ($\chi^2 = 257.11$, df = 48, RMSEA = 0.07, CFI = 0.96, TLI = 0.95, SRMR = 0.03). We then evaluated the reliability and validity of the data (see the appendix). Cronbach's alpha and composite reliability values all exceeded the cutoff of 0.70, reflecting adequate reliability. The average variance extracted (AVE) for each construct was greater than the cutoff of 0.50, indicating high convergent validity. The square root of each AVE exceeded all correlations, indicating discriminant validity (Fornell & Larcker, 1981). These results suggested that all of the constructs were reliable and valid. Last, to prevent common method bias, we checked the variance inflation factor (VIF) values using a full multicollinearity test (Molinillo et al., 2022). The VIF values (SE → HD/CG = 2.17; SA → HD/CG = 2.09; EF → HD/CG = 1.85; FL → HD/CG = 2.57; EX → HD/CG = 2.10; NE → HD/CG = 2.14; HD/CG → PT = 1.89) were below the suggested maximum of 3.33 (Kumar & Srivastava, 2022; Qing & Haiying, 2021).

5.2. Hypothesis testing

We used polynomial regression analyses to test the effects of chatbot ambidexterity, as this approach provides more nuanced findings on ambidextrous component fit and misfit (Liu et al., 2020). As Table 3 shows, three dependent variables (HD, CG, and PT) were regressed on the control variables, scale-centered ambidextrous components (SE, SA, EF, EL, EX, NE), and nine higher-order effects (SE^2, $SE \times SA$, SA^2, EF^2, $EF \times FL$, FL^2, EX^2, $EX \times NE$, NE^2). The coefficients of the polynomial terms were used to calculate the slope (SE – SA, EF – FL, and EX − NE) and curvature ($SE^2 - SE \times SA + SA^2$, $EF^2 - EF \times FL + FL^2$, and $EX^2 - EX \times NE + NE^2$) along the misfit lines. We included response surfaces (see Fig. 3), illustrating the predicted values of the dependent variables for different ambidexterity configurations, to interpret the three-dimensional relationships more clearly. As Fig. 3 shows, the misfit lines (dashed lines) lie along the floor of each graph, from the point where SE/EF/EX is low and SA/FL/NE is high to the point where SE/EF/EX is high and SA/FL/NE is low.

There was a significant ambidextrous component fit effect (H1, H3, H5) when the curvature along the misfit line was significant and negative. For service-sales ambidexterity, the surfaces of HD and CG were convex with a positive curvature of the misfit lines (HD = 0.08, [0.01, 0.08], CG = 0.03, [−0.07, 0.14]), indicating that smart experiences decreased as service-sales configurations shifted to ambidexterity. As Panels A and B of Fig. 3 show, service-sales ambidexterity of AI chatbots did not improve smart experiences; thus, neither H1a nor H1b was supported. One possible explanation for this is that service provision triggers customers' affective-based processes, whereas cross-selling activates cognitive-based processes. Such excessive information processing tasks push customers to allocate more cognitive effort to make decisions, thus jeopardizing their satisfaction and experience (Lee et al., 2019).

However, the slopes of the misfit lines and further comparison with

Table 2
Summary Statistics.

A: Definitions and Summary Statistics of Variables

Variables	Definitions	Mean	S.D.	Percentage (%)			
1.Gender	User gender reported (1: female, 0: male)	0.58	0.49	1: 58	0: 41		
2.Age	User age reported	31.17	8.51	≤25: 27	26–30: 21	31–35: 30	≥36: 22
3.Monthly income	Monthly income reported (in USD, h: hundred)	2.83	1.15	≤4h: 13	4 h-8 h: 29	8 h-12 h:29	≥12 h: 29
4.Education level	Education level (1: High school, 2: College, 3: Bachelor, 4: Master)	3.76	0.73	1: 8	2: 13	3: 72	4: 7
5.Customer service	Number of dialogues irrelevant with products selling	5.32	0.91	≤4: 18	5: 35	6: 39	≥7: 8
6.Cross-selling	Number of dialogues involve products selling	5.28	0.96	≤4: 20	5: 34	6: 40	≥7: 6
7.Efficiency	Perceived dedication to minimize time cost, improve operational efficiency	5.48	0.83	≤4: 6	4.3–5: 27	5.3–6: 47	≥6.3: 20
8.Flexibility	Perceived dedication to improve service quality, ensure higher satisfaction	5.23	1.09	≤4: 17	4.3–5: 26	5.3–6: 36	≥6.3: 21
9.Existing products selling	Number of dialogues involve products that had been showed before	2.66	0.47	1: 2	2: 31	3: 66	4: 1
10.New products selling	Number of dialogues involve products that were showed for the first time	2.62	0.47	1: 1	2: 37	3: 61	4: 1
11.Hedonic SX	Perceived benefits related with pleasurable experiences	5.25	1.09	≤4: 14	4.3–5: 27	5.3–6: 38	≥6.3: 21
12.Cognitive SX	Perceived benefits related with new knowledge/skills	5.24	1.11	≤4: 16	4.3–5: 24	5.3–6: 40	≥6.3: 20
13.Customer patronage	Amount of money a user topped up via the AI chatbot (in USD)	38.63	33.12	≤20: 34	21–30: 20	31–40: 14	≥41: 32

B: Correlation Matrix of Variables

	1	2	3	4	5	6	7	8	9	10	11	12
1.Gender	NA											
2.Age	-0.16**	NA										
3.Monthly income	-0.15**	0.27**	NA									
4.Education level	0.07*	-0.12**	0.33**	NA								
5.Customer service	-0.10**	0.12**	0.15**	0.12**	NA							
6.Cross-selling	-0.12**	0.08*	0.14**	0.17**	0.64**	NA						
7.Efficiency	-0.08**	0.05	0.19**	0.17**	0.58**	0.57**	0.83					
8.Flexibility	-0.09**	0.10**	0.16**	0.08*	0.72**	0.69**	0.54**	0.85				
9.Existing products selling	-0.10**	0.11**	0.19**	0.10**	0.57**	0.66**	0.60**	0.64**	NA			
10.New products selling	-0.07*	0.10**	0.21**	0.12**	0.54**	0.65**	0.62**	0.62**	0.79**	NA		
11.Hedonic SX	-0.06*	0.14**	0.19**	0.09**	0.70**	0.65**	0.52**	0.73**	0.56**	0.56**	0.85	
12.Cognitive SX	-0.12**	0.12**	0.18**	0.11**	0.60**	0.67**	0.56**	0.70**	0.62**	0.66**	0.69**	0.86
13.Customer patronage	-0.08*	0.10**	0.21**	0.14**	0.61**	0.61**	0.57**	0.64**	0.63**	0.63**	0.69**	0.65**

Notes: *p <.05. **p <.01. SX = Smart experience. NA = not applicable. The numbers on the diagonal are the square roots of the AVE values.

the standardized path coefficients indicated that customer service had a stronger effect on HD (vs CG) ($t_{spooled} = 79.27$) and cross-selling had a stronger effect on CG (vs HD) ($t_{spooled} = -28.31$). Panels A and B of Fig. 3 also show dissymmetric misfit effects whereby high service-low sales ambidexterity was more (less) effective than low service-high sales ambidexterity in creating hedonic (cognitive) smart experiences; therefore, H2a and H2b were supported.

For efficiency-flexibility ambidexterity, the surface of HD was concave (HD = −0.25, [−0.37, −0.13]) and the surface of CG was saddle-shaped (CG = −0.16, [−0.28, −0.05]) with a significant and negative curvature of the misfit lines. These results showed that both hedonic and cognitive smart experiences increased as efficiency-flexibility configurations shifted to ambidexterity; therefore, both H3a and H3b were supported.

In addition, the slopes of the misfit lines (HD = −0.14, [−0.23, −0.05], CG = −0.19, [−0.28, −0.10]) and a comparison of the path coefficients indicated that chatbot service flexibility had a stronger effect on both HD ($t_{spooled} = -70.03$) and CG ($t_{spooled} = -107.59$) than efficiency. Panels C and D of Fig. 3 also show dissymmetric misfit effects whereby high efficiency-low flexibility ambidexterity was less effective than low efficiency-high flexibility ambidexterity in creating smart experiences, supporting H4a but not H4b. One possible explanation for rejecting H4b is that cognitive experiences focus on both the efficiency and functionality of obtaining services and products (Ameen et al., 2021). Although AI chatbots are able to offer efficient services by adhering to established procedures, chatbot flexibility is better than chatbot efficiency at solving unforeseen problems and offering functional services (Fan et al., 2022b). Therefore, low efficiency-high flexibility ambidexterity outperforms high efficiency-low flexibility ambidexterity in crafting either hedonic or cognitive smart experiences.

For existing-new product selling ambidexterity, the surface of HD was significantly saddle-shaped (HD = 0.46, [0.12, 0.83]), while the surface of CG was significantly concave (CG = −0.71, [−1.23, −0.09]). As Panels E and F show, HD (CG) decreased (increased) as AI chatbots' product sales became ambidextrous, supporting H5. In addition, the slopes of the misfit lines and a comparison of the path coefficients indicated that chatbot sales of new products had a stronger effect on HD ($t_{spooled} = -33.33$) and CG ($t_{spooled} = -125.02$) than chatbot sales of existing products. Panels E and F of Fig. 3 also show dissymmetric misfit effects whereby high existing-low new product selling ambidexterity was less effective than low existing-high new product selling ambidexterity in creating smart experiences, supporting H6a and H6b.

Both HD and CG had a positive and significant influence on PT, supporting H7. In addition, a simple comparison of the path coefficients ($t_{spooled} = 130.06$) revealed that HD had a stronger effect on improving PT than CG. These findings are in line with findings from the service management literature that emotional attachment leads to customer retention and loyalty more effectively than cognition (Jaakkola et al., 2015). These findings also confirm that smart experiences are critical for success in e-business settings, as they make it easier for customers to purchase the virtual service.

5.3. Post hoc analyses

Following Fan et al., (2022a), we located the stationary point, which provided the maximum, minimum, or saddle points of the surface to explore the optimal chatbot ambidexterity configuration for each dimension of smart experiences (HD and CG). For service-sales ambidexterity (i.e., Fig. 3, Panels A and B), the surface of HD was convex with the stationary point at $X = 0.22$ and $Y = 8.56$ (moderate service-high sales), and the surface of CG was also convex with the stationary point at $X = -0.66$ and $Y = 2.44$ (moderate service-high sales). For a convex surface, the stationary point represents the surface minimum (Fan et al., 2022a), which indicated that smart experiences were minimized when

Table 3
Polynomial Regression Results.

Variables	Hedonic SX		Cognitive SX		Patronage		Acceptance/ rejection
	β	S.E.	β	S.E.	β	S.E.	
Intercept	-0.05	0.25	0.08	0.27	-0.11	0.18	
Controls							
Gender	0.06	0.04	-0.08*	0.04	0.01	0.03	
Age	0.01	0.01	0.01	0.01	0.01	0.01	
Monthly income	0.06**	0.02	0.02	0.02	0.01	0.02	
Education level	-0.01	0.04	0.01	0.04	0.05*	0.03	
Polynomial effects							
Customer service (SE)	0.32**	0.04	0.09*	0.04	0.02	0.03	
Cross-selling (SA)	0.18**	0.04	0.14**	0.04	0.06*	0.03	
SE^2	0.05*	0.03	0.05	0.04	-0.01	0.03	
SE × SA	-0.04	0.03	-0.01	0.04	0.01	0.03	
SA^2	-0.01	0.02	-0.03	0.02	-0.01	0.02	
Efficiency (EF)	0.13**	0.04	0.17**	0.04	0.05	0.04	
Flexibility (FL)	0.27**	0.05	0.36**	0.04	0.08*	0.04	
EF^2	-0.04	0.04	-0.04	0.04	-0.07*	0.04	
EF × FL	0.11*	0.04	0.10*	0.04	0.15**	0.05	
FL^2	-0.11**	0.03	-0.03	0.02	-0.03	0.02	
Existing products selling (EX)	-0.02	0.10	-0.03	0.08	0.07	0.07	
New products selling (NE)	0.12*	0.09	0.44**	0.09	0.20**	0.07	
EX^2	-0.03	0.13	-0.24	0.20	-0.34*	0.18	
EX × NE	-0.24*	0.12	0.28	0.17	0.39**	0.14	
NE^2	0.25*	0.11	-0.19*	0.11	-0.13	0.13	
Hedonic SX					0.45**	0.05	H7: accepted
Cognitive SX					0.19**	0.04	
R^2	0.63		0.61		0.77		
$t_{spooled}$ (SE-SA)	79.27		−28.31				H2: accepted
$t_{spooled}$ (EF-FL)	−70.03		−107.59				H4: partially accepted
$t_{spooled}$ (EX-NE)	−33.33		−125.02				H6: accepted
Misfit line (SE = -SA)							
Slope	0.14**		-0.04		-0.04		
	[0.05, 0.24]		[-0.14, 0.07]		[-0.11, 0.04]		
Curvature	0.08*		0.03		-0.02		H1: rejected
	[0.01, 0.18]		[-0.07, 0.14]		[-0.10, 0.06]		
Misfit line (EF = -FL)							
Slope	-0.14**		-0.19**		-0.03		
	[-0.23, -0.05]		[-0.28, -0.10]		[-0.11, 0.06]		
Curvature	-0.25**		-0.16*		-0.25**		H3: accepted
	[-0.37, -0.13]		[-0.28, -0.05]		[-0.39, -0.11]		
Misfit line (EX = -NE)							
Slope	-0.14		-0.47**		-0.13		
	[-0.40, 0.15]		[-0.71, -0.22]		[-0.33, 0.08]		
Curvature	0.46**		-0.71*		-0.85**		H5: accepted
	[0.12, 0.83]		[-1.23, -0.09]		[-1.28, -0.34]		

Notes: *p <.05, **p <.01. $t_{spooled} = (\beta_1 - \beta_2)/SQR[(S.E._1^2 + S.E._2^2)/n]$. SX = Smart experience,β = path coefficient, S.E. = standard error. 90 % BC-CIs were reported.

chatbot service was at a moderate level and chatbot sales were at a high level in this study.

For service ambidexterity, the surface of HD was concave (i.e., Fig. 3, Panel C) with the stationary point at $X = 10.60$ and $Y = 6.53$ (high efficiency-high flexibility). For a concave surface, the stationary point represents the surface maximum (Fan et al., 2022a), which indicated that hedonic smart experiences were maximized when chatbot service efficiency and flexibility were both at a high level. The surface of CG was saddle-shaped (i.e., Fig. 3, Panel D) with the stationary point at $X = -8.88$ and $Y = -8.81$ (low efficiency-low flexibility). For a saddle-shaped surface, we identified the slopes of two perpendicular principal axes, reflecting the line with the maximum curvature (Fan et al., 2022a). The slopes of the first and second principal axes ($p_{11} = 1.10$; $p_{21} = -0.90$) indicated that cognitive smart experiences increased the fastest as the efficiency-flexibility configuration shifted to high/high and decreased the fastest as the AI chatbot shifted to efficiency-dominant behavior.

For sales ambidexterity, the surface of HD was saddle-shaped (i.e., Fig. 3, Panel E) with the stationary point at $X = 0.21$ and $Y = -0.14$ (moderate existing-moderate new product selling). The slopes of the first and second principal axes ($p_{11} = -2.70$; $p_{21} = 0.37$) indicated that hedonic smart experiences decreased the fastest as sales ambidexterity shifted to high/high or low/low and increased the fastest as the AI chatbot shifted to existing- or new-dominant product selling. The surface of CG was concave (i.e., Fig. 3, Panel F) with the stationary point at $X = 1.08$ and $Y = 1.95$ (moderate existing-moderate new product selling), indicating that cognitive smart experiences were maximized when existing product selling and new product selling were both at a moderate level.

6. Discussion and conclusions

Using empirical data from 1,026 observations of an e-bike sharing market, this study used dual process models to explore the relative effectiveness of different chatbot ambidexterity configurations in crafting smart experiences and customer patronage. The results of this study showed that chatbot ambidexterity might not always be beneficial for smart experiences. Under the condition of ambidextrous component fit, chatbot service-sales ambidexterity worsened smart experiences (H1); existing-new product selling (sales) ambidexterity undermined hedonic but not cognitive smart experiences (H5); while only efficiency-flexibility (service) ambidexterity increased smart experiences (H3).

Under the condition of ambidextrous component misfit, high service-low sales (vs low service-high sales) ambidexterity had a stronger impact on hedonic smart experiences and a weaker impact on cognitive smart experiences (H2); low efficiency-high flexibility ambidexterity outperformed high efficiency-low flexibility ambidexterity in crafting

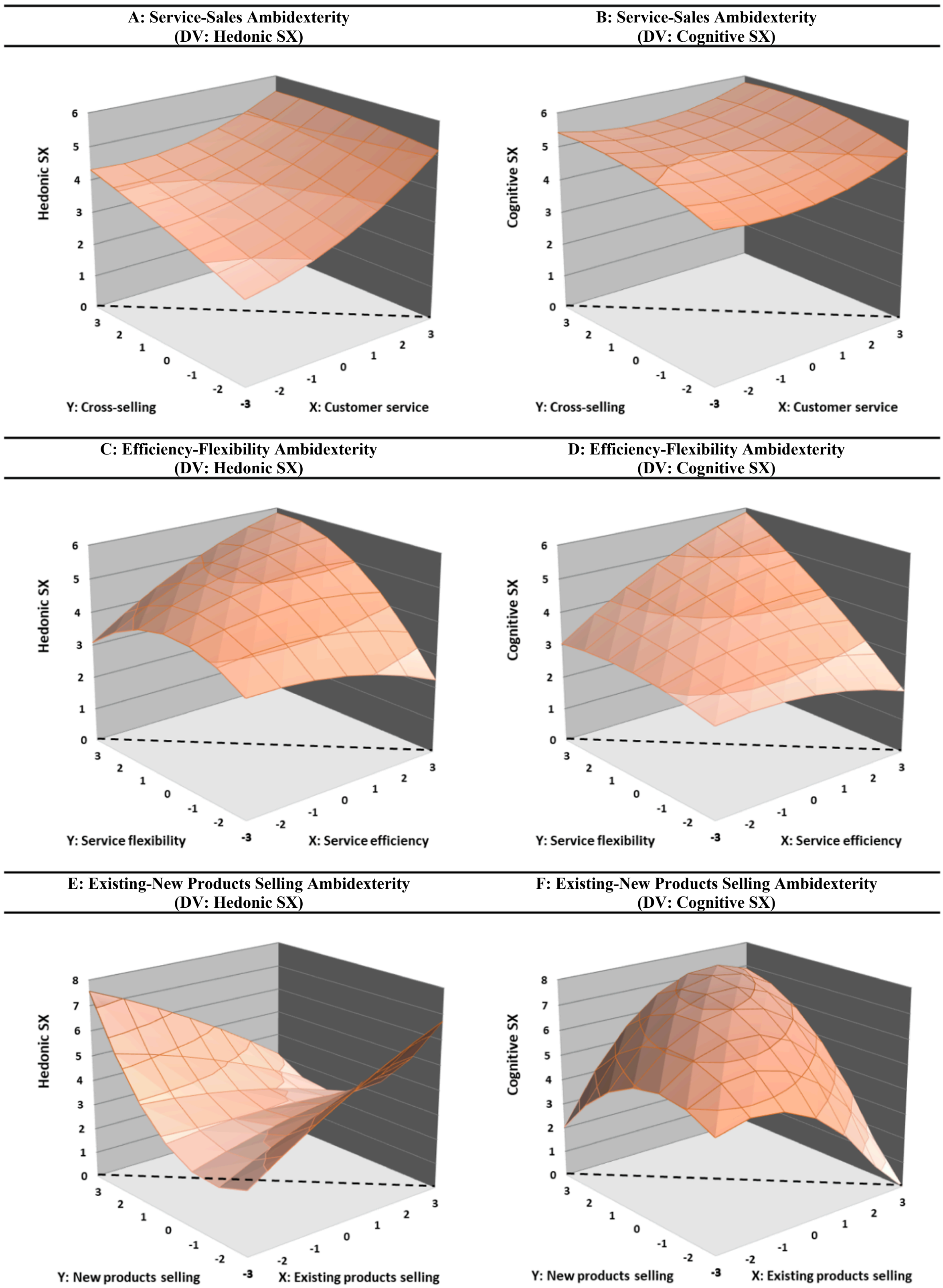

Fig. 3. Response Surfaces of Polynomial Regression Results.

hedonic or cognitive smart experiences (H4); and low existing-high new (vs high existing-low new) product selling ambidexterity was superior for creating both hedonic and cognitive smart experiences (H6). This study offers a more holistic view of smart experiences and opens a new avenue for investigating the effects of ambidextrous service implemented by virtual frontline employees (i.e., AI chatbots).

6.1. Theoretical implications

First, by examining the effectiveness of chatbot service in crafting customer smart experiences, this study bridges two research domains—AI services and smart experiences (addressing Research Gap 1 in Table 1). The literature has provided rich empirical and theoretical findings on customer experiences of smart technologies, such as online and omnichannel retailing, branded apps, and AR/VR services (see Table 1). However, only a few studies (Fan et al., 2022a; Gao et al., 2022) have shed light on the smart experiences created by AI chatbots. Using field data on chatbot interactions, customer survey data, and archival data from service providers, this study revealed that AI service is not a "one-size-fits-all" solution for crafting smart experiences (H1, H3, and H5). In doing so, this study adds to the understanding of smart experiences from an AI service perspective, thereby extending the work of Gao et al. (2022) by considering more elements in smart experience research.

Second, this study contributes to research on smart experiences by introducing three types of chatbot ambidexterity as important antecedents (addressing Research Gap 2). Studies have shed light on various determinants of smart experiences, such as website design (Bleier et al., 2019; Lambillotte et al., 2022), channel integration (Cocco & Demoulin, 2022; Gao et al., 2021), customer perceptions of branded apps (Ameen et al., 2021; Roy et al., 2019), and AR/VR characteristics (Fan et al., 2020; Jung et al., 2021; Kumar & Srivastava, 2022). Although Fan et al., (2022a) explained the creation of smart experiences facilitated by chatbot ambidexterity, they only examined a single type of service-sales ambidexterity. By investigating how to cultivate optimal smart experiences through a full range of chatbot ambidexterity (service-sales ambidexterity, efficiency-flexibility ambidexterity, and existing-new product selling ambidexterity), our study extends the work of de Ruyter et al. (2020) and Mullins et al. (2020) by exploring ambidexterity in AI-powered frontline interfaces and that of Fan et al., (2022a) by gauging the effectiveness of different types of chatbot ambidexterity.

Third, this study adds to dual process models by applying affective/cognitive-based processes to compare the relative effectiveness of chatbot ambidexterity in crafting smart experiences (addressing Research Gap 3). Studies have conceptualized smart experiences as a multi-dimensional construct but failed to compare the paths to influence different sub-dimensions (see Table 1). Our study first differentiated between ambidextrous component fit and misfit (quadrants 1 and 2 vs quadrants 3 and 4 of Fig. 2) and then compared two conditions of ambidextrous component misfit (quadrant 3 vs quadrant 4 of Fig. 2). Using dual process models and polynomial regressions and response surfaces, this study confirmed that customers' affective-based processes are more relevant to hedonic smart experiences, while cognitive-based processes lead to cognitive smart experiences. In doing so, this study extends the work of Roy et al. (2019) by validating the multi-dimensional smart experience scale in other research contexts.

6.2. Practical implications

First, both hedonic and cognitive smart experiences have a significant influence on customer patronage (see Table 3). We agree with Roy et al. (2019) that online service providers should pay more attention to smart experiences, as "the investment in the smart experience co-creation will result in a tangible return on investment" (p. 1503). However, if service providers have limited organizational resources to optimize both hedonic and cognitive smart experiences through AI chatbots, we suggest focusing on the hedonic dimension, as hedonic smart experiences are superior to the cognitive dimension ($t_{spooled}$ = 130.06, $\beta_{HD} = 0.45$, $\beta_{CG} = 0.19$) in generating customer patronage.

Second, the findings of our study offer counterintuitive yet reasonable guidance for implementing chatbot ambidexterity. According to Table 3, only efficiency-flexibility ambidexterity (−0.25, [−0.39, −0.11]) and existing-new product selling ambidexterity (−0.85, [−1.28, −0.34]) were beneficial for customer patronage, while service-sales ambidexterity was ineffective (−0.02, [−0.10, 0.06]). Worse still, service-sales ambidexterity hindered the creation of customers' smart experiences. As excessive information processing tasks can increase cognitive effort and undermine customer satisfaction (Lee et al., 2019), we suggest that service providers carefully gauge the effectiveness of AI chatbots' service-sales ambidexterity and avoid the blind pursuit of all types of frontline ambidextrous capabilities.

Third, if service providers cannot achieve ambidextrous component fit, our findings revealed that ambidextrous component misfit can still enrich smart experiences. As Table 3 shows, service provision, flexibility, and selling new products outperformed cross-selling, efficiency, and selling existing products, respectively, in improving hedonic smart experiences. Therefore, companies should rely on high service-low sales, low efficiency-high flexibility and low existing-high new product selling ambidexterity to provide enjoyment. Service providers could deploy AI chatbots to take on routine customer service requests, such as normal greetings, informal chats, and solving order-related issues. AI chatbots could also be programed to recommend new products from a new category. AI chatbots should be designed to be flexible, which necessitates the service provider to improve the customer database that allows its AI chatbots to timely incorporate profile information, review contact history, display information, and suggest questions.

The results in Table 3 also reveal that cross-selling, flexibility, and selling new products outperformed service provision, efficiency, and selling existing products, respectively, in driving cognitive smart experiences. Therefore, companies should rely on low service-high sales, low efficiency-high flexibility, and low existing-high new product selling ambidexterity to create functionality. During the cross-selling process, AI chatbots should focus on providing more functional and pragmatic information, including specific suggestions, information on product features, operating procedures, and after-sales service. We advise against blindly designing AI chatbots without a specific target. Companies that decide to use AI chatbots should allocate their limited resources purposefully to craft different aspects of smart experiences.

6.3. Limitations and future research

First, although we used data from multiple sources to validate the theoretical framework, our research design was cross-sectional in a highly specific context. Each customer touchpoint (dialogue with the chatbot) can lead to a different experience (De Keyser et al., 2020), and chatbot ambidexterity can change over time (Fan et al., 2022a). In this study, each customer had 11 dialogues with the chatbot on average, but smart experiences were measured only once. Chatbot service is a dynamic process in which ambidexterity evolves, but chatbot ambidexterity was also measured only once in a period (12 months). In addition, digital bike rental is a low-involvement, low-price service segment, in which customers usually have little need for interpersonal contact. Our sample from just one industry may undermine the generalizability of our findings. Future studies could involve other service contexts, different levels of customer involvement, and adopt a longitudinal research design to dynamically measure smart experiences and chatbot ambidexterity.

Second, although the empirical results of this study have fruitful and meaningful implications, we only included two dimensions of smart experiences (i.e., hedonic and cognitive), which are the most widely acknowledged by the literature (see Table 1). However, the effectiveness of other dimensions (e.g., social, personal, pragmatic, and economic) remains unclear. In addition, although we revealed the underlying mechanism of smart experiences, the relationship between chatbot ambidexterity and customer patronage is worth further exploration. For example, according to our results, existing-new product selling ambidexterity negatively affects hedonic experiences (0.46, [0.12, 0.83]) but positively influences cognitive experiences (−0.71, [−1.23, −0.09]), indicating the existence of other potential mediators. Future research would benefit from a better understanding of other conduits, as there is no one-size-fits-all approach to stimulating customer patronage from smart experiences.

Last, this study only focused on the role of AI chatbots in crafting smart experiences. In practice, chatbot service is different from human service, as "authentic human touch can help differentiate offerings in the marketplace and display unique brand-building behaviors" (Larivière et al., 2017, p. 241). AI chatbots are often deployed by companies as service assistants to human frontline employees. AI–employee collaboration has become a popular research topic in frontline service studies, as it is important to determine customers' emotional states (Henkel et al., 2020), firms' overall service quality (Fan et al., 2022c), and ultimate service failure and/or success (Belanche et al., 2019). Future studies could use human frontline employee data and explore the optimization of smart experiences from a customer–AI–employee triadic perspective.

CRediT authorship contribution statement

Hua Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Wei Gao:** Methodology, Data curation, Conceptualization. **Bing Han:** Writing – original draft.

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.

Acknowledgments

We acknowledge this research was supported by the National Natural Science Foundation of China [Grant numbers: 72202141, 72202185, 72202133]. The authors thank the Editor Professor Lauren Beitelspacher and two anonymous reviewers for their insightful comments and guidance.

Appendix. . Measurement scales

Construct	# of items	Reference	Adapted scale	α	CR	AVE
Service efficiency	3	Fan et al. (2022b)	During the last 12 months, the chatbot highly engaged in activities that can be characterized as: Increasing and improving interaction efficiency Cutting and lowering time costs Relying on automation and procedural responses	0.74	0.81	0.69
Service flexibility	3	Fan et al. (2022b)	During the last 12 months, the chatbot highly engaged in activities that can be characterized as: Delivering the best-quality service Ensuring the highest levels of customer satisfaction Using creative ways to satisfy its customers' needs.	0.81	0.89	0.72
Hedonic smart experience	3	Roy et al. (2019);Verleye (2015)	• I think the experience with the chatbot was nice I feel that the chatbot was fun I enjoyed the chatbot	0.81	0.89	0.73
Cognitive smart experience	3	Roy et al. (2019);Verleye (2015)	• I was able to improve my skills using the chatbot By using the chatbot, I feel I can gain new knowledge/expertise I was able to test my capabilities using the chatbot	0.82	0.90	0.74

α = Cronbach's alpha, CR = composite reliability, AVE = average variance extracted

References

Agnihotri, R. (2021). From sales force automation to digital transformation: How social media, social CRM, and artificial intelligence technologies are influencing the sales process. *A Research Agenda for Sales, 21–47*. https://doi.org/10.4337/9781788975315.00009

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

Barari, M., Ross, M., & Surachartkumtonkun, J. (2020). Negative and positive customer shopping experience in an online context. *Journal of Retailing and Consumer Services, 53*, Article 101985. https://doi.org/10.1016/j.jretconser.2019.101985

Barhorst, J. B., McLean, G., Shah, E., & Mack, R. (2021). Blending the real world and the virtual world: Exploring the role of flow in augmented reality experiences. *Journal of Business Research, 122*, 423–436. https://doi.org/10.1016/j.jbusres.2020.08.041

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7), 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*(2), 98–119. https://doi.org/10.1177/0022242918809930

Blut, M., Teller, C., & Floh, A. (2018). Testing retail marketing-mix effects on patronage: A meta-analysis. *Journal of Retailing, 94*(2), 113–135. https://doi.org/10.1016/j.jretai.2018.03.001

Breves, P. (2021). Biased by being there: The persuasive impact of spatial presence on cognitive processing. *Computers in Human Behavior, 119*, Article 106723. https://doi.org/10.1016/j.chb.2021.106723

Buonincontri, P., Morvillo, A., Okumus, F., & van Niekerk, M. (2017). Managing the experience co-creation process in tourism destinations: Empirical findings from Naples. *Tourism Management, 62*, 264–277. https://doi.org/10.1016/j.tourman.2017.04.014

Cocco, H., & Demoulin, N. T. (2022). Designing a seamless shopping journey through omnichannel retailer integration. *Journal of Business Research, 150*, 461–475. https://doi.org/10.1016/j.jbusres.2022.06.031

De Keyser, A., Verleye, K., Lemon, K. N., Keiningham, T. L., & Klaus, P. (2020). Moving the customer experience field forward: Introducing the touchpoints, context, qualities (TCQ) nomenclature. *Journal of Service Research, 23*(4), 433–455. https://doi.org/10.1177/1094670520928390

de Ruyter, K., Keeling, D. I., & Yu, T. (2020). Service-sales ambidexterity: Evidence, practice, and opportunities for future research. *Journal of Service Research, 23*(1), 13–21. https://doi.org/10.1177/1094670519878880

Evans, K. R., Arnold, T. J., & Grant, J. A. (1999). Combining service and sales at the point of customer contact: A retail banking example. *Journal of Service Research, 2*(1), 34–49. https://doi.org/10.1177/109467059921004

Fan, H., Han, B., Gao, W., & Li, W. (2022a). How AI chatbots have reshaped the frontline interface in China: Examining the role of sales–service ambidexterity and the personalization–privacy paradox. *International Journal of Emerging Markets, 17*(4), 967–986. https://doi.org/10.1108/IJOEM-04-2021-0532

Fan, H., Han, B., & Gao, W. (2022b). (Im) Balanced customer-oriented behaviors and AI chatbots' Efficiency-Flexibility performance: The moderating role of customers' rational choices. *Journal of Retailing and Consumer Services, 66*, Article 102937. https://doi.org/10.1016/j.jretconser.2022.102937

Fan, H., Gao, W., & Han, B. (2022c). How does (im) balanced acceptance of robots between customers and frontline employees affect hotels' service quality? *Computers*

in Human Behavior, 133, Article 107287. https://doi.org/10.1016/j.chb.2022.107287
Fan, X., Chai, Z., Deng, N., & Dong, X. (2020). Adoption of augmented reality in online retailing and consumers' product attitude: A cognitive perspective. *Journal of Retailing and Consumer Services, 53*, Article 101986. https://doi.org/10.1016/j.jretconser.2019.101986
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104
Gao, J., Ren, L., Yang, Y., Zhang, D., & Li, L. (2022). The impact of artificial intelligence technology stimuli on smart customer experience and the moderating effect of technology readiness. *International Journal of Emerging Markets, 17*(4), 1123–1142. https://doi.org/10.1108/IJOEM-06-2021-0975
Gao, W., Fan, H., Li, W., & Wang, H. (2021). Crafting the customer experience in omnichannel contexts: The role of channel integration. *Journal of Business Research, 126*, 12–22. https://doi.org/10.1016/j.jbusres.2020.12.056
Henkel, A. P., Čaić, M., Blaurock, M., & Okan, M. (2020). Robotic transformative service research: Deploying social robots for consumer well-being during COVID-19 and beyond. *Journal of Service Management, 31*(6), 1131–1148. https://doi.org/10.1108/JOSM-05-2020-0145
Herrando, C., Jiménez-Martínez, J., & Hoyos, M. D. (2019). Social commerce users' optimal experience: Stimuli, response and culture. *Journal of Electronic Commerce Research, 20*(4), 199–218.
Hughes, D. E., & Ogilvie, J. L. (2020). When sales becomes service: The evolution of the professional selling role and an organic model of frontline ambidexterity. *Journal of Service Research, 23*(1), 22–32. https://doi.org/10.1177/1094670519878882
Jaakkola, E., Helkkula, A., & Aarikka-Stenroos, L. (2015). Service experience co-creation: Conceptualization, implications, and future research directions. *Journal of Service Management, 26*(2), 182–205. https://doi.org/10.1108/JOSM-12-2014-0323
Japutra, A., Utami, A. F., Molinillo, S., & Ekaputra, I. A. (2021). Influence of customer application experience and value in use on loyalty toward retailers. *Journal of Retailing and Consumer Services, 59*, Article 102390. https://doi.org/10.1016/j.jretconser.2020.102390
Jung, T. H., Bae, S., Moorhouse, N., & Kwon, O. (2021). The impact of user perceptions of AR on purchase intention of location-based AR navigation systems. *Journal of Retailing and Consumer Services, 61*, Article 102575. https://doi.org/10.1016/j.jretconser.2021.102575
Kang, D. S. (2016). Turning inside out: Perceived internal branding in customer-firm relationship building. *Journal of Services Marketing, 30*(4), 462–475. https://doi.org/10.1108/JSM-07-2015-0229
Kao, Y. L., & Chen, C. F. (2016). Antecedents, consequences and moderators of ambidextrous behaviours among frontline employees. *Management Decision, 54*(8), 1846–1860. https://doi.org/10.1108/MD-05-2015-0187
Keeling, K., McGoldrick, P., & Beatty, S. (2010). Avatars as salespeople: Communication style, trust, and intentions. *Journal of Business Research, 63*(8), 793–800. https://doi.org/10.1016/j.jbusres.2008.12.015
Keiningham, T., Ball, J., Benoit, S., Bruce, H. L., Buoye, A., Dzenkovska, J., … Zaki, M. (2017). The interplay of customer experience and commitment. *Journal of Services Marketing, 31*(2), 148–160. https://doi.org/10.1108/JSM-09-2016-0337
Köhler, C. F., Rohm, A. J., De Ruyter, K., & Wetzels, M. (2011). Return on interactivity: The impact of online agents on newcomer adjustment. *Journal of Marketing, 75*(2), 93–108. https://doi.org/10.1509/jm.75.2.93
Kumar, H., & Srivastava, R. (2022). Exploring the role of augmented reality in online impulse behaviour. *International Journal of Retail & Distribution Management, 50*(10), 1281–1301. https://doi.org/10.1108/IJRDM-11-2021-0535
Lambillotte, L., Magrofuoco, N., Poncin, I., & Vanderdonckt, J. (2022). Enhancing playful customer experience with personalization. *Journal of Retailing and Consumer Services, 68*, Article 103017. https://doi.org/10.1016/j.jretconser.2022.103017
Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., … De Keyser, A. (2017). "Service Encounter 2.0": An investigation into the roles of technology, employees and customers. *Journal of Business Research, 79*, 238–246. https://doi.org/10.1016/j.jbusres.2017.03.008
Lee, H., Xu, Y., & Porterfield, A. (2020). Consumers' adoption of AR-based virtual fitting rooms: From the perspective of theory of interactive media effects. *Journal of Fashion Marketing and Management: An International Journal, 25*(1), 45–62. https://doi.org/10.1108/JFMM-05-2019-0092
Lee, M., Lee, S. A., & Koh, Y. (2019). Multisensory experience for enhancing hotel guest experience: Empirical evidence from big data analytics. *International Journal of Contemporary Hospitality Management, 31*(11), 4313–4337. https://doi.org/10.1108/IJCHM-03-2018-0263
Liu, Y., Chen, D. Q., & Gao, W. (2020). How does customer orientation (in) congruence affect B2B electronic commerce platform firms' performance? *Industrial Marketing Management, 87*, 18–30. https://doi.org/10.1016/j.indmarman.2020.02.027
Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192
Mishra, A., Shukla, A., & Sharma, S. K. (2022). Psychological determinants of users' adoption and word-of-mouth recommendations of smart voice assistants. *International Journal of Information Management, 102413*. https://doi.org/10.1016/j.ijinfomgt.2021.102413
Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Carvajal-Trujillo, E. (2022). The customer retail app experience: Implications for customer loyalty. *Journal of Retailing and Consumer Services, 65*, Article 102842. https://doi.org/10.1016/j.jretconser.2021.102842
Molinillo, S., Navarro-García, A., Anaya-Sánchez, R., & Japutra, A. (2020). The impact of affective and cognitive app experiences on loyalty towards retailers. *Journal of Retailing and Consumer Services, 54*, Article 101948. https://doi.org/10.1016/j.jretconser.2019.101948
Mullins, R., Agnihotri, R., & Hall, Z. (2020). The ambidextrous sales force: Aligning salesperson polychronicity and selling contexts for sales-service behaviors and customer value. *Journal of Service Research, 23*(1), 33–52. https://doi.org/10.1177/1094670519883344
Pertusa-Ortega, E. M., Molina-Azorín, J. F., Tarí, J. J., Pereira-Moliner, J., & López-Gamero, M. D. (2021). The microfoundations of organizational ambidexterity: A systematic review of individual ambidexterity through a multilevel framework. *BRQ Business Research Quarterly, 24*(4), 355–371. https://doi.org/10.1177/2340944420929711
Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1–24). New York, NY: Springer. https://doi.org/10.1007/978-1-4612-4964-1_1.
Qing, T., & Haiying, D. (2021). How to achieve consumer continuance intention toward branded apps—From the consumer–brand engagement perspective. *Journal of Retailing and Consumer Services, 60*, Article 102486. https://doi.org/10.1016/j.jretconser.2021.102486
Roy, S. K., Singh, G., Hope, M., Nguyen, B., & Harrigan, P. (2019). The rise of smart consumers: Role of smart servicescape and smart consumer experience co-creation. *Journal of Marketing Management, 35*(15–16), 1480–1513. https://doi.org/10.1080/0267257X.2019.1680569
Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., … Onyemah, V. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: Concepts, priorities, and questions. *Journal of Personal Selling & Sales Management, 39*(1), 2–22. https://doi.org/10.1080/08853134.2018.1557525
Sun, X., Zhu, F., Sun, M., Müller, R., & Yu, M. (2020). Facilitating efficiency and flexibility ambidexterity in project-based organizations: An exploratory study of organizational antecedents. *Project Management Journal, 51*(5), 556–572. https://doi.org/10.1177/8756972820912562
Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. *Journal of Retailing and Consumer Services, 57*, Article 102233. https://doi.org/10.1016/j.jretconser.2020.102233
Van der Borgh, M., de Jong, A., & Nijssen, E. J. (2017). Alternative mechanisms guiding salespersons' ambidextrous product selling. *British Journal of Management, 28*(2), 331–353. https://doi.org/10.1111/1467-8551.12148
Van der Borgh, M., & Schepers, J. (2018). Are conservative approaches to new product selling a blessing in disguise? *Journal of the Academy of Marketing Science, 46*(5), 857–878. https://doi.org/10.1007/s11747-017-0521-1
Verleye, K. (2015). The co-creation experience from the customer perspective: Its measurement and determinants. *Journal of Service Management, 26*(2), 321–342. https://doi.org/10.1108/JOSM-09-2014-0254
Xiao, L., & Kumar, V. (2021). Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research, 24*(1), 9–29. https://doi.org/10.1177/1094670519878881
Yu, T., Gudergan, S., & Chen, C. F. (2020). Achieving employee efficiency–flexibility ambidexterity. *The International Journal of Human Resource Management, 31*(19), 2459–2494. https://doi.org/10.1080/09585192.2018.1449762

Hua Fan is an associate professor in the School of Business and Management at the Shanghai International Studies University. He received his Ph.D. in Marketing from Shanghai Jiao Tong University. His research has been published in such journals as *Journal of Business Research*, *Computers in Human Behavior*, *Industrial Marketing Management*, *Journal of Retailing and Consumer Services*, *International Journal of Emerging Markets*. His current research interests include key account management, online communities, and business intelligence.

Wei Gao is an assistant professor of the College of Economics and Management at Southwest University. He received his Ph.D. in Business Administration from Shanghai Jiao Tong University. His research has been published in such journals as *Industrial Marketing Management*, *Journal of Business Research*, *Electronic Commerce Research and Applications*, *Journal of Retailing and Consumer Services*, *Computers in Human Behavior*, *Behavior and Information Technology*. His academic work focuses on omnichannel, B2B platform, and livestreaming.

Bing Han is an assistant professor in marketing at School of Management, Shanghai University of International Business and Economics. She received her Ph.D. in Business Administration from Shanghai Jiao Tong University. Her research has been published in such journals as *Journal of Advertising, Cornell Hospitality Quarterly*. Her current research interests include consumer behavior, brand scandal, and brand image.