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Out of the way, human! Understanding post-adoption of last-mile delivery robots

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ABSTRACT

The pace of technological development is exceeding expectations and transforming the landscape of last-mile delivery. This study investigates how users' post-adoption behavior in using delivery robots is formed. Based on the task-technology fit (TTF) model, we present a research model that includes both direct and indirect factors that have been previously overlooked in the literature. We collected data from 550 users of delivery robots. Our structural equation modelling results show that two hedonic- (i.e., gratification and anthropomorphism) and three utilitarian- (i.e., service quality experience, delivery task requirements, and user-facing technology performance) driven factors predict perceived TTF in using delivery robots. Value-in-use and trust have sequential mediating effects that connect perceived TTF and service reuse likelihood and word-of-mouth recommendation. Our findings suggest ways to improve last-mile delivery robot strategies and provide practical implications for the industry.

1. Introduction

"Envision a future in which a robot travels in the elevator through the block of your tower, knocks on your door, and delivers the package you ordered. That's the future of last-mile delivery."—The authors.

The logistics sector, a critical component of the global supply chain, is undergoing a significant transformation, spurred by technological innovations and evolving consumption trends. Central to this evolution is the concept of last-mile logistics, which refers to the final step of the delivery process where goods are transported from a transportation hub to the final delivery destination. This stage is crucial for customer satisfaction and has become increasingly complex in urban environments.

Last-mile delivery robots, a solution integrating advanced sensors, artificial intelligence (AI), and robotics, are redefining last-mile logistics by offering numerous benefits. They facilitate social (physical) distancing, a practice that became particularly vital during the COVID-19 pandemic, enhance delivery safety, reduce the environmental footprint of deliveries, and improve overall efficiency (Hwang et al., 2021; Mejia and Kajikawa, 2019; Montobbio et al., 2022; Shin, 2022). Major e-commerce players and retailers are rapidly adopting this technology. For example, Amazon's Scout and FedEx's Roxo robots have been operational in states like California, Texas, and Washington (Forbes, 2022). Nuro, a U.S.-based robotics company, has forged partnerships for driverless deliveries with various retailers. In China, Alibaba's Xiaomanlv robot has successfully completed millions of parcel deliveries (Alizila, 2022). The food delivery sector is not far behind, with innovations like Foodora's Doora robot (Delivery Hero, 2021).

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The onset of the COVID-19 pandemic has further highlighted the significance of delivery robots, with social (physical) distancing and remote operations becoming more prevalent (Lim, 2021, 2022). The market for ground delivery robots is expected to form a substantial segment of global autonomous last-mile delivery by 2027 (Grand View Research, 2020), and the overall market for delivery robots is projected to exceed $84 billion globally by 2031, growing at a rate of over 24 % (Allied Market Research, 2022). Despite their potential, the adoption of delivery robots is not without challenges. Scepticism among potential users, stemming from limited experience and confidence in this nascent technology, raises questions about the practicality and necessity of automated door-to-door deliveries (Peerless Research Group, 2022).

To address these concerns and ensure the long-term success of delivery robot initiatives, conducting post-adoption research is crucial. This research can provide valuable insights to the delivery robot industry, helping to overcome potential challenges and drop-out rates, while facilitating the seamless integration of these delivery robots into last-mile logistics. This, in turn, fosters a more sustainable and efficient delivery ecosystem. To uncover the key factors influencing users' perceptions and willingness to adopt and continue using delivery robots, this study is built upon two key research questions (RQs):

RQ1. What are the relevant characteristics of robot delivery, and how do users respond to them?

RQ2. What processes influence users' willingness to reuse the delivery robot and recommend it to others?

This study is grounded by the task-technology fit (TTF) model (Goodhue and Thompson, 1995). The model is ideal for identifying the alignment between technology and related tasks, a challenge highlighted by several information systems (IS) studies (Al-Emran, 2021; Zhong et al., 2020). The main goal of this study concentrates on the users' perspective, encompassing their experiences and interactions with delivery robots during the last-mile delivery process. Although the TTF model has been used to explore the motivations for adopting service robots in various contexts, such as airports (Hoang and Tran, 2022), hotels (Shin and Jeong, 2022), and restaurants (Hwang et al., 2020), limited research has comprehensively addressed the determinants influencing users' intention to reuse delivery robots. Hence, our study aims to bridge this gap and provide a holistic view of this critical aspect.

Our study offers notable contributions to the advancement of the current state-of-the-art in robotic technologies. We distinctly identify the attributes prompting the adoption of delivery robots in an industry traditionally characterised as "high-tech-and-low-touch." This is particularly relevant as autonomous robots become more prevalent in service provision. Our study considers both hedonic and utilitarian lenses to elucidate users' perceptions of such novel automated technologies and their assessment of the TTF of delivery robots. The hedonic perspective concentrates on users who gain immediate pleasure or satisfaction from technology use, while the utilitarian lens focuses on goal-driven users who leverage technology for efficient and effortless task completion. Both these motivations have been found to possess strong predictive power in influencing behavior (Chang et al., 2023).

From a hedonic standpoint, delivery robots offer distinctive experiences that cater to users' emotional needs, fostering a positive emotional experience during interactions with the innovation. Key hedonic factors contributing to enhanced enjoyment and pleasure in using service robots include interpersonal influence, gratification, and anthropomorphism (Gursoy et al., 2019). Adhering to group norms and forging an emotional bond with service robots are pivotal in fostering positive attitudes and influencing future behaviors (Borghi and Mariani, 2022; Pentina et al., 2023), whereas anthropomorphism augments the pleasure of use as it enables users to sense a deeper relationship and connection with service robots (Chiang et al., 2022; Kim and McGill, 2018).

From a utilitarian viewpoint, service quality is paramount in determining both users' responses and the profitability of businesses. Concerns often revolve around the ability of service robots to deliver timely and personalised services at a level comparable to human employees, leading to user hesitancy (Chandra et al., 2022b). Service failures, attributed to both hardware and software issues, combined with unpredictable interactions with the environment and human users, further result in users perceiving service robots as less competent, thereby diminishing their interest in utilising them (Liu et al., 2022a,Liu et al., 2022b; Song and Kim, 2022). Nonetheless, global events such as infectious disease outbreaks like COVID-19 have heightened the preference for methods that allow individuals to maintain safe distances from others and avoid services staffed by humans (Kim et al., 2021; Lim, 2021, 2022; Lim et al., 2023). This transition has accelerated the adoption of innovations in the Fourth Industrial Revolution (Ciasullo et al., 2023), seamlessly integrating technology-based tasks into daily routines (Sheth, 2020). While there have been numerous studies into the factors influencing the adoption of robotic services during the pandemic, there is limited research on users' reactions to technological functions and their degree of reliance on delivery robots. To bridge this research chasm, our study centres on three utilitarian-driven aspects: service quality experience, delivery task requirement, and user-facing technology performance, (Prentice and Nguyen, 2021; Wang et al., 2021b).

The concept of value-in-use is foundational within the technology-based services ecosystem, denoting how technologies can generate or enhance value for individuals (Bulawa and Jacob, 2021; Søraa et al., 2021; Tiberius et al., 2022; Tiitola et al., 2023). As services transition to the digital realm, it becomes vital to ensure that delivery robots can address users' needs and deliver a broad spectrum of values comparable to human employees. Wang et al., 2021a,Wang et al., 2021b posit that to enhance robot services, emphasis should be placed on the robot's ability to introduce new value propositions for long-term advantages. Scholars have further acknowledged that the value derived is the primary determinant guiding users' decisions to persist with a service technology (Fu et al., 2022; Li et al., 2022; Ofori et al., 2021). Yet, there exists a void in the literature regarding the influence of value-in-use on post-adoption behavior.

Trust is another pivotal element in adopting robotic technologies that handle users' sensitive personal data (Huang and Rust, 2021). This concept holds a central position in facilitating human-to-robot interactions and elucidating the nexus between individuals' convictions regarding technological attributes and their acceptance behavior (Hride et al., 2022; Liu and Tao, 2022; Liu et al., 2022a). This study endeavours to bridge these lacunae by probing the sequential mediation roles of value-in-use and trust in bolstering service reuse probability and word-of-mouth (WOM) recommendations for last-mile delivery robots.

To achieve the study's objectives, we collected empirical data in China. The commercial service robot market in China witnessed remarkable growth, with revenues soaring to RMB540 million in 2021 – a year-on-year increase of 110.4 %. This surge signals an impending boom (Global Times, 2022). Projections indicate that by 2023, the market value will approach RMB49.536 billion, and by 2025 it will surpass RMB100 billion. It is also estimated that around 50 million workers could be displaced or affected by the integration of service robots (Global Times, 2022). As such, understanding users' post-adoption behavior is of paramount importance, and the Chinese context provides a compelling example of the growth potential in using robots for last-mile delivery.

2. Literature review

2.1. Service reuse likelihood and word-of-mouth

In this study, our focus centred on service reuse likelihood and WOM as two principal outcome variables within the context of last-mile delivery robots. Several reasons underpin this emphasis. Firstly, the IS literature defines service reuse likelihood as the chance or probability that users will continue to employ a particular service or software component across different situations or for numerous tasks over time (Heller et al., 2021). This notion has attracted substantial attention in the domain of innovation development since it underscores the sustainability and ongoing use of a service or software element. A heightened service reuse likelihood suggests that users deem the service valuable, effective, and aptly tailored to their needs, leading to its recurrent usage and endorsement (Vakulenko et al., 2022).

Delving into *service reuse likelihood* concerning last-mile delivery robots is paramount. This importance arises from the pivotal role of services within last-mile delivery operations, which epitomises the final phase of delivering goods to a customer's doorstep. As a critical segment of the supply chain, services within this sphere are instrumental in guaranteeing efficient and timely delivery, thereby shaping a positive customer experience (Vassilakopoulou et al., 2023). Research conducted by Edrisi and Ganjipour (2022) accentuates that discerning the primary factors that sway users' propensity to reuse delivery robots permits service providers to cultivate enhanced strategies. These strategies can, in turn, refine the entirety of the delivery process, imbuing the last-mile delivery with greater economic feasibility. Moreover, the deployment of robotic technology within last-mile delivery entails notable initial expenditures, including robot acquisition, upkeep, staff training, and system amalgamation. Such a fiscal dimension further underlines the urgency for scholars to probe into users' reuse willingness. As elucidated by Ozcan et al. (2022), an augmented service reuse likelihood reflects users' discernment of value and efficacy in the innovative deployment, which translates to a heightened return on investment over extended periods. In a similar vein, evaluating the factors that mould users' choices to reuse delivery robots equips enterprises with the insights necessary to pinpoint and rectify potential challenges, thereby enhancing user satisfaction. This methodology, as spotlighted by Spencer et al. (2022), fosters the enhancement of robot functionalities rooted in user perspectives, resulting in a more streamlined and user-aligned delivery experience, further propelling users to continue using the service.

On the other hand, *WOM* refers to the process through which users share their experiences, opinions, and recommendations, in this case, about a particular technology, with others (Akbari et al., 2022; Rudeloff et al., 2022). Specifically, WOM involves informal communication between individuals, wherein they convey information or insights based on their personal experiences and perceptions (Chopra et al., 2024; Lim et al., 2022a; Xie and Lei, 2022). Positive WOM has consistently been found to influence users' intentions to adopt and utilize technology (Chen et al., 2023). When users share positive experiences and recommendations about delivery robots, it creates a ripple effect, generating increased interest among potential users. Moreover, WOM plays a crucial role in user acquisition and retention. Recent research, such as that conducted by Soren and Chakraborty (2023), has demonstrated that WOM referrals have a more significant impact on acquiring new users than traditional marketing efforts. These recommendations and feedback from satisfied users are found to be more persuasive, particularly in shaping the continued adoption of new innovations, such as last-mile delivery robots. Furthermore, understanding the factors driving positive WOM can act as a guiding force in developing more user-centric delivery robot solutions. Previous studies, such as those by Kautish et al. (2023) and Pal et al. (2023), underscore the importance of user experience and satisfaction in generating positive WOM. Therefore, uncovering the antecedents of WOM in the context of delivery robots provides valuable insights that profoundly affect technology acceptance and usage. This not only promotes broader acceptance and utilisation of delivery robots in last-mile operations but also lays the foundation for enhancing the success and sustainability of delivery robot initiatives in last-mile delivery.

2.2. The task-technology fit model

The theoretical model in the IS domain can be divided into three perspectives: technology diffusion, technology use, and IS success (Legris et al., 2003; Spies et al., 2020). First, the models of technology diffusion (e.g., innovation diffusion theory) typically focus on the acceptance and initial use of the system rather than the performance impacts. Second, the models of technology use (e.g., technology acceptance model, theory of planned behavior, social cognitive theory) are often used to examine the factors that influenced system use. Third, the models of IS success (e.g., elaboration likelihood model, expectation confirmation model) investigate how system use can influence personal or workplace-related performances. Although most models have been widely applied in various contexts, a limitation has been raised. As pointed out in Jeyaraj (2022) meta-study, in such models, tasks performed by users have largely been assumed but not modelled—i.e., there is no evaluation of the extent to which the technology fits the tasks, or how technology fit affects the system usage. Thus, this outlines a difference between the TTF model, which focuses on the 'fit' involving both tasks and technologies.

The TTF model was created to explain how technology can meet the task requirements of individuals (Goodhue and Thompson, 1995). The model suggests that technologies that fit user tasks are more likely to be used often and to have a greater impact on performance. The TTF model focuses mainly on task-related aspects and proposes that the fit between task and technology is essential. In other words, people may not use a technology solely based on task requirements but also on how well the technology suits the task (Goodhue and Thompson, 1995). Initially, the TTF model was used to understand the use of technologies in organisational work settings handled by employees such as business intelligence systems, decision support systems, and enterprise resource planning systems (Jaklič et al., 2018; Liu et al., 2011; Yang et al., 2013). Over time, the model has also been applied in non-work settings such as the use of intelligent agents, mobile devices, social media, and virtual reality (Chang, 2008; Zhang et al., 2017). However, little research has been done in the field of service robots, especially in the context of last-mile delivery robots.

The antecedents of the TTF model encompass technology and task characteristics, making it a suitable foundation for explaining users' behavior in using last-mile delivery robots for two major reasons. First, the usage of delivery robots is optional and relies on user perceptions of their impact on the task, alongside various social and contextual factors. In this regard, our research argues that delivery robots represent a convenient and innovative solution to address issues related to delayed and slow deliveries. Second, the TTF model aligns with the environment of delivery robots. As argued in Seddon (1997) study, the critical factor for measuring IS success is the net benefits derived from their use. A successful system should provide users with benefits such as increased efficiency in their work, completing more work in less time, and at the same quality as previous work. These ideas align with the success of delivery robots, which reduce user uncertainty and facilitate the efficient receipt of parcels. Given the above, the TTF model is considered apt for achieving the main goal of this study, as demonstrated in Fig. 1, which illustrates the hypothesised relationships reflecting the causes and effects of TTF, with more details for each hypothesis explained in the subsequent section.

3. Hypotheses development

The current study builds on the TTF model and Gursoy et al.'s (2019) arguments to propose that users' perceived fit level of delivery robots is predicted by a combination of hedonic- and utilitarian-driven factors, including interpersonal influence, gratification, anthropomorphism, service quality experience, delivery task requirement, and user-facing technology performance.

3.1. Hedonic-driven factors and perceived TTF

Interpersonal influence in the context of delivery robots refers to the impact of social norms and group conformity on individuals' perceptions of the appropriateness and acceptance of using a delivery robot (Zonca

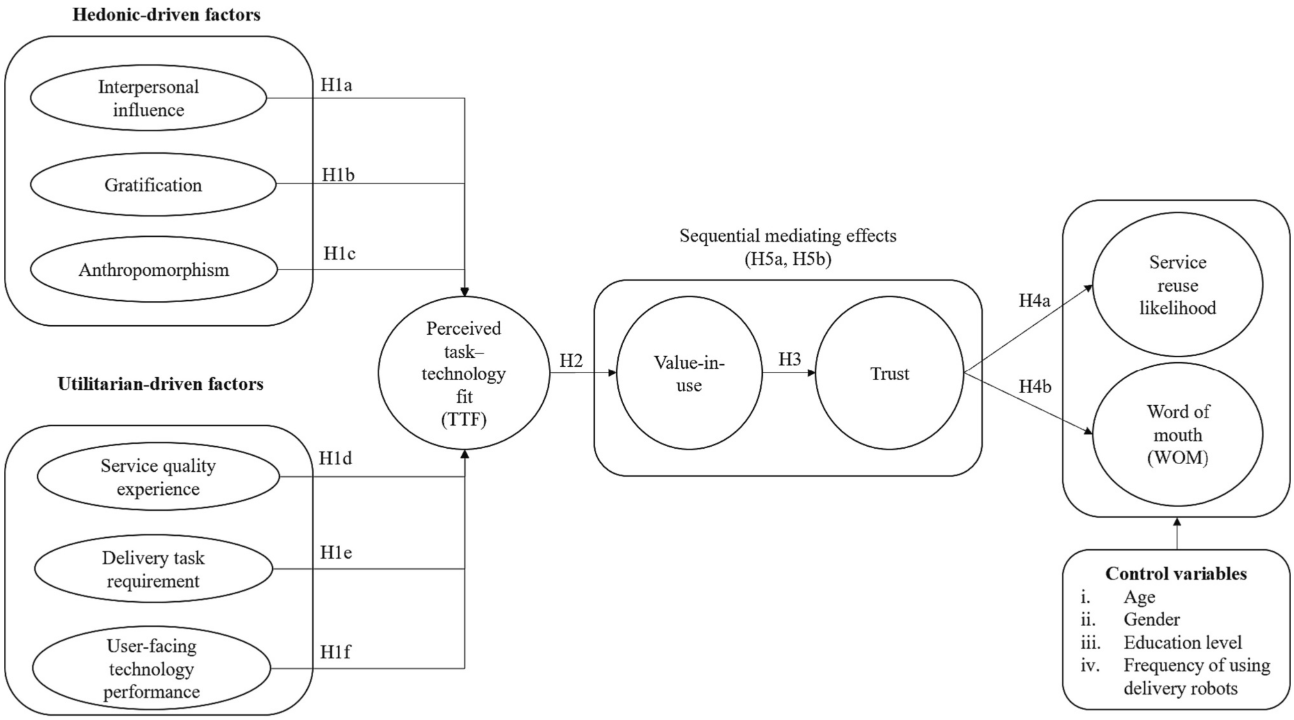

Fig. 1. The research model.

et al., 2023). Previous research has consistently shown that individuals are more inclined to align with group norms if the group holds significant value to them—a tendency that is particularly pronounced in scenarios where individuals lack sufficient knowledge for informed decision-making (Singh et al., 2020). Hwang and Kim (2021) empirical research on drone delivery services reinforces this notion, highlighting family and friends as pivotal in influencing decisions about technology-based services. Further studies corroborate this, revealing that interpersonal inputs, like peer or colleague recommendations and feedback, significantly shape technology perception (Cobelli et al., 2023; Kajikawa et al., 2022; Lim et al., 2023).

Our study aligns with these findings, suggesting that positive group experiences or endorsements of delivery robots amplify the perceived task-technology fit. We reason that observing others' successful use of delivery robots can act as a form of social proof, boosting the technology's credibility and trustworthiness in executing tasks effectively—a reasoning we extrapolate from prior research on digital and social landscapes (Sanak-Kosmowska, 2021). As individuals increasingly adopt and utilize the technology, its perceived suitability for the task strengthens, buoyed by successful social integration. This is supported by prior research showing that social support becomes pivotal, especially for those with limited knowledge about new innovations (Wu et al., 2023). In this regard, we argue that by sharing positive experiences, individuals can surmount perceived barriers, gaining confidence in their ability to use the technology effectively for their delivery needs, and as comfort and confidence in the technology grow, influenced by peer engagement, the perceived fit for the task is further reinforced. Therefore, based on this rationale, we propose the following hypothesis:

H1a. . Interpersonal influence is positively related to the perceived TTF of delivery robots.

Gratification in the context of delivery robots refers to the enjoyment or fun that individuals anticipate experiencing when using these robots (Hlee et al., 2023). Research consistently shows that people are more likely to adopt and use technology when it meets their intrinsic motivations, such as enjoyment and satisfaction (Faqih and Jaradat, 2021). Consequently, it is crucial for users to find enjoyment in and form an emotional bond with these robots. Positive interactions with them can foster a favourable disposition and encourage continued use (Baudier et al., 2023; Borghi and Mariani, 2022; Gursoy et al., 2019). Ribeiro et al. (2022) found that gratification enhances users' performance expectations when using autonomous vehicles. Similarly, de Jong et al. (2019) observed that users engage with social robots for longer periods when they derive gratification benefits, thereby facilitating acceptance of this technology. In the TTF model, task features are seen as useful characteristics that satisfy users' needs (Li et al., 2019). When the gratifications from technology use align with specific task requirements, individuals tend to perceive a stronger fit (Mai et al., 2021). If the features of delivery robots, such as optimized route planning, increased efficiency and accuracy, reduced delivery times, and improved logistics management (Hwang et al., 2021; Montobbio et al., 2022), offer a high degree of gratification, users are more likely to view these robots as suitable for their specific delivery tasks. This underscores the importance of gratification as a predictor of perceived TTF, particularly when employing delivery robots. Users who experience joy in using delivery robots are likely to view the technology as appropriate for their delivery needs, enhancing their perception of its functionality. This leads to the following hypothesis:

H1b. . Gratification is positively related to the perceived TTF of delivery robots.

Anthropomorphism involves endowing a robot with human-like characteristics, emotions, motivations, and intentions (Kim and McGill, 2018; Lim et al., 2022b). This technique can cater to humans' fundamental needs for social connection, control, and understanding of their surroundings (Epley et al., 2008). Smart technologies, including AI and robots, are relatively straightforward to anthropomorphise, making it a practical strategy to heighten user preferences. Research indicates that perceived human-likeness enhances user preference for and engagement with robots. It also aids in human-robot interaction, providing users with a sense that the robot is controllable and predictable (Blut et al., 2021; Jia et al., 2021). In this context, a pronounced sense of perceived anthropomorphism could elevate user confidence in the robot's ability to execute tasks efficiently and offer consistent, accurate services (Cheng et al., 2022). Consistent with the TTF model, we predict that an anthropomorphised delivery robot, adorned with human-like features, will foster a heightened sense of familiarity among users. Such increased familiarity is likely to make users view the robot as more proficient, thus bolstering the efficacy of last-mile delivery services. Accordingly, our hypothesis is:

H1c. . Anthropomorphism is positively related to the perceived TTF of delivery robots.

3.2. Utilitarian-driven factors and perceived TTF

Service quality experience in the context of service delivery robots refers to users' evaluation of the overall service provided by delivery robots (Prentice and Nguyen, 2021). The potential of service robots to seamlessly replace human employees remains under debate. Wirtz et al. (2018) posited that highly efficient service robots could replace humans for repetitive tasks and support them in handling complex duties. Users' decisions to interact with robots are influenced by the robot's responsiveness, immediacy of action, and task relevance (de Kervenoael et al., 2020). Drawing upon the scale proposed by Prentice and Nguyen (2021), this study conceptualises and operationalises robotics service quality experience through four dimensions:

- *Automation*, which entails the robot's level of automation and performance capabilities, such as constant availability and large data storage capacity;
- *Personalisation*, which pertains to the robot's ability to adapt its service according to individual needs, thus providing a bespoke experience;
- *Precision*, which refers to the robot's accuracy in relaying information, assisting users in making informed decisions; and
- *Efficacy*, which relates to the robot's timely and responsive service delivery, responding to users' requests reliably.

The influence of service quality on user satisfaction with robots is evident. Multiple studies indicate that user satisfaction and perceived value towards service robots correlate with the quality of services rendered (Chiang et al., 2022; Fan et al., 2022). From a demand perspective, robots can provide “smart services” that elevate the user experience (Belanche et al., 2020; Manthiou and Klaus, 2022). However, a robot lacking interpersonal and adaptive skills is often perceived as less adept than human employees, evoking a negative user response (Schwob et al., 2023). Aligning with this discussion and the TTF model's theoretical underpinning, this study suggests that the service quality experience could significantly influence users' perception of robots being more suited than humans for parcel delivery tasks. Thus, we hypothesise:

H1d. . Service quality experience is positively related to the perceived TTF of delivery robots.

The outbreak of lethal and highly contagious viruses like COVID-19 has significantly influenced user evaluations of delivery robots (AlKheder et al., 2023; Zeng et al., 2020). Since late 2019, the demand for robotic services has surged in various areas, including delivering, monitoring, disinfecting, preparing food, and serving individuals. Perceived fear of contagion and the prevalence of the virus outbreak are factors that influence user willingness to adopt and accept robotic services, as identified in studies by Chandra et al. (2022a) and Parvez et al. (2022). Besides that, Shin and Kang (2020) found that perceived health risks are also an important factor in staying at the robot hotel, in addition to technological factors. Similarly, Brengman et al. (2021) documented how COVID-19 influenced the choice of interacting with a humanoid robot in a retail store. During the virus outbreak, concerns about safety and social distancing have been significant reasons for users to prefer robotic-staffed hotels over human-staffed ones (Kim et al., 2021; Chang et al., 2022). Seyitoğlu and Ivanov (2020) also noted that hotel managers have made decisions to use service robots to enhance sanitation and physical distancing from the supply perspective. To validate the conclusion of Wang et al.'s (2021)a,b study, which suggests that improving robot services requires focusing on the extent to which the robot can offer new value propositions for long-term benefits, and extend it further, the current study argues that users' perception of the fit of a delivery robot is influenced by two utilitarian factors that are context-dependent: *delivery task requirement* and *user-facing technology performance*, which relates to the desire to stay at home and avoid human contacts, and the extent to which the robot can help users avoid social contacts during the parcel collection process, respectively. During virus outbreaks, smart technologies that possess these characteristics can be perceived to fit better, ultimately motivating users to adopt them. To achieve this, it is crucial to make users believe that the technology is designed with these characteristics and is capable of executing safe and gentle deliveries. Therefore, the following hypotheses are formulated:

H1e. . Delivery task requirement is positively related to the perceived TTF of delivery robots.

H1f. . User-facing technology performance is positively related to the perceived TTF of delivery robots.

3.3. Perceived TTF and value-in-use

The concept of *perceived TTF* is grounded in the idea that individuals benefit from systems and technologies that align well with their tasks (Goodhue and Thompson, 1995). On the other hand, *value-in-use* refers to the extent to which users believe they are better off or worse off through consumption experiences (Grönroos and Voima, 2013). The creation of value-in-use is inherently phenomenological (Vargo and Lusch, 2008), meaning users' experiences, logic, and ability to extract value from a resource are crucial factors (Grönroos and Voima, 2013). In prior IS studies, TTF has been associated with various outcome variables, such as technology adoption, perceptions, intentions, and performance (Jeyaraj, 2022). Efficient task completion is expected when technology is well-suited to facilitate the task (Franque et al., 2023). When the gap between the task and the technology is small, perceived TTF is higher, and users can perceive more benefits from the technology (Shin and Jeong, 2022). In this context, we propose that when the robot delivery effectively supports users in distributing and receiving parcels, they are more likely to perceive the robot as valuable for accomplishing their specific needs and requirements. Hence, we propose the following hypothesis:

H2. . Perceived TTF is positively related to value-in-use of delivery robots.

3.4. Value-in-use and trust

In the IS discipline, *trust* refers to an individual's belief in the technology's ability to perform tasks, which determines their willingness to rely on and be vulnerable to the technology (Chien et al., 2023). The extent to which individuals are willing to rely on delivery robots for collecting and receiving parcels heavily depends on trust (Yuen et al., 2022). As Shi et al. (2021) noted, the adoption of AI-based technologies often involves both cognitive and affective judgments, and thus requires a theoretical framework that considers both dimensions. In this study, we measure trust by integrating these two dimensions, cognitive trust and emotional trust. Cognitive trust refers to an individual's rational reasoning and evaluation of potential risks of adopting these innovations (Lewis and Weigert, 1985), while emotional trust reflects an individual's irrational judgment towards a technology (Gursoy et al., 2019).

Studies have shown that users' perception of value-in-use is a critical factor in determining their willingness to continue using automated or technological services, and is also a key factor in building high levels of trust (Hwang et al., 2022). This phenomenon occurs because users naturally develop more confidence in innovation when they perceive that certain services offer higher value than others (Picón-Berjoyo et al., 2016). Such superior value, derived from positive experiences, drives users to eliminate other available solutions and generates a positive response to the capabilities of service robots (Liu et al., 2022a,Liu et al., 2022b). Therefore, we posit that:

H3. . Value-in-use is positively related to trust in delivery robots.

3.5. Trust, word-of-mouth, and service reuse likelihood

WOM is a highly influential factor that affects post-adoption behavior; it refers to communication between individuals about a company, product, or service, where sources are independent of commercial influence (Chopra et al., 2024; Lim et al., 2022a; Litvin et al., 2008). Studies have shown that WOM is crucial in encouraging others to use service robots (Chen and Girish, 2022; Pozharliev et al., 2021). On the other hand, service reuse likelihood refers to the likelihood of individuals using the service repeatedly, which is a crucial concept in understanding the development of delivery robot innovation, wherein frequency of use is a key driver to sustain the relevance and grow the prominence of innovation (Bhattacherjee, 2001). In this study, we position WOM and service reuse likelihood as the key constructs in understanding users' post-adoption behavior for last-mile delivery robots.

Many service studies have shown that trust plays a crucial role in encouraging users to adopt and recommend service robots (Chi et al., 2021; Fuentes-Moraleda et al., 2020). Establishing a deep level of trust with service robots is especially important for promoting continuous use (Lei et al., 2021). This study argues that users who trust delivery robots to pick up and receive their parcels are more likely to evaluate the services positively, intend to reuse them, and share positive WOM about them. Thus, we postulate that:

H4a. . Trust is positively related to WOM of delivery robots.

H4b. . Trust is positively related to service reuse likelihood of delivery robots.

3.6. Sequential mediations of value-in-use and trust

In this study, we contend that the psychological states of value-in-use and trust can act as the missing links between perceived TTF and post-adoption behaviors (i.e., WOM and service reuse likelihood) of delivery robots, which are used for both hedonic and utilitarian purposes. This is because psychological barriers can make end-users reluctant to adopt an innovation (Roberts et al., 2021). To address the challenge of innovation adoption within the last-mile delivery robot, we propose that value-in-use and trust are two psychological constructs that can influence desired behavior.

As mentioned, value-in-use reflects the relative value that users acquire through the use of innovation (Payne et al., 2008). In technology usage, higher value-in-use occurs when the experience provides users with more benefits than sacrifice (Roy et al., 2018), which leads to greater satisfaction and continued use (Dwivedi and Merrilees, 2016). The mean-end-laddering theory suggests that users develop a mental evaluation of the value of the experience they have gained, which is influenced by their beliefs, subjective benefits, and personal values (Gutman, 1984; Kelly and Kelly, 1963; Petter et al., 2012). As evidenced by Japutra et al. (2021), value-in-use is a missing link in establishing the relationship between user experiences and loyalty when using smart retail technologies.

Similarly, trust plays a crucial role in countering negative attitudes and motivations towards new technologies. For instance, previous research has shown that trust has a positive influence on attitudes and willingness to adopt self-service hotel technology (Kaushik et al., 2015). In addition, Tussyadiah et al. (2020) found that individual propensity to trust technology positively influenced their intention to adopt service robots, with higher trust leading to higher usage intention. Therefore, to effectively adopt delivery robots, users must undergo a mental evaluation process to feel comfortable and secure when interacting with the technology, and perceive the robots as capable of offering useful, safe, and reliable services before reusing them and providing positive reviews. Based on this reasoning, we propose that:

H5a. . Value-in-use and trust sequentially mediate the relationship between perceived TTF and WOM of delivery robots.

H5b. . Value-in-use and trust sequentially mediate the association between perceived TTF and service reuse likelihood of delivery robots.

The research model, as shown in Fig. 1, maps all the proposed hypotheses (H1a to H5b). Sociodemographic characteristics, including age, gender, level of education, and frequency of usage, have been shown to influence technology reuse and positive WOM (Blut and Wang, 2020; Brandtzæg et al., 2011; Büchi et al., 2016; Lim et al., 2022c). Considering that this study examines both service reuse likelihood and WOM of last-mile delivery robots, it is worth noting that highly educated, tech-savvy women of a young age are often willing to reuse such innovations (Lim et al., 2022c). Furthermore, frequent users are likely to have a greater propensity to reuse the service and spread positive WOM (Blut and Wang, 2020). Therefore, control variables such as age, gender, education level, and frequency of using delivery robots were included in the model to avoid confounding results from the proposed hypotheses.

4. Methodology

4.1. Instrumentation and pre-survey validation

The questionnaire used in this study was divided into two sections. The first section contained items measuring the 11 constructs that were being studied. These items were modified from previous studies and were measured using seven-point Likert scales, with the highest value indicating strong agreement. The second section consisted of demographic questions, such as gender, marital status, age, occupation, education, annual income, and experience and frequency in using delivery robots (Table 1). Since the questionnaire was translated into Chinese for the convenience of the respondents, two preliminary tests were conducted to ensure the accuracy of the translations by back-translating the Chinese version into English (Brislin, 1970). The questionnaire was reviewed by four professors specialising in information systems and quantitative research (and thus establishing content validity), and then piloted on a group of 60 respondents after minor modifications were made (and thus establishing face validity).

4.2. Sampling method and data collection procedure

Data for this study was collected from China via the Qualtrics platform (www.qualtrics.com). This online platform was chosen due to its potential to provide representative samples of the target population and produce high-quality data, which is comparable to, or better than, traditional internet-based survey approaches (Ahmad et al., 2021). Furthermore, the Qualtrics platform has been used in previous robotics studies to reduce self-selection bias, as surveys are randomly distributed to qualifying participants (Chang and Busser, 2019; Prentice and Nguyen, 2021; Tojib et al., 2022).

To ensure that respondents had an adequate understanding of the scenario, a brief introduction on the last-mile delivery robot was included on the cover page. The main functions of the delivery robot were then explained through a video, and images were used to demonstrate the process of using the robot to collect a parcel.

In the first section of the survey, a screening question—i.e., do you have experience using a delivery robot?—was included to ensure that

Table 1
Profile of respondents.

Sociodemographic	Category	n (550)	% (100)
Gender	Male	235	42.7
	Female	315	57.3
Marital status	Single	451	82.0
	Married	99	18.0
Age	21 to 30 years old	387	70.4
	31 to 40 years old	130	23.3
	41 to 50 years old	33	6.0
Occupation	Self-employed	152	27.6
	Employee in public sector	159	28.9
	Employee in private sector	239	43.5
Education	Undergraduate degree (BSc, BA, etc.)	123	22.4
	Master's degree (MSc, MBA, etc.)	344	62.5
	Doctoral degree (PhD, DBA, etc.)	83	15.1
Annual income	80,000¥ to 100,000¥	35	6.36
	100,001¥ to 120,000¥	136	24.7
	120,001¥ to 140,000¥	133	24.2
	140,001¥ to 160,000¥	122	22.2
	160,001¥ and above	124	22.5
Experience in using a delivery robot	Yes	550	100.0
	No	0	0.0
Frequency of using delivery robots	Rarely	15	2.73
	Occasionally	85	15.5
	Sometimes	144	26.2
	Frequently	166	30.2
	Usually	118	21.5
	Every time	22	4.0

Notes: USD1 = RMB 7.24 as of August 13, 2023.

selected respondents had experience using a delivery robot. Respondents were then requested to only proceed with the survey, voluntarily, if they felt comfortable continuing to use the robot. The survey took around 15 to 20 min to complete, and respondents who completed the survey were given a token of appreciation. To control for potential confounding variables, such as age, gender, education level, and frequency of using delivery robots, these factors were included in the research model.

During the period of September to November 2022, the study collected 600 responses from users in China via the Qualtrics platform. After eliminating 50 incomplete questionnaires, 550 completed responses were deemed usable, corresponding to a usable response rate of 91.67 %. The majority of respondents were women (57.3 %), single (82.0 %), aged between 21 and 30 (70.4 %), employed in the private sector (43.5 %), held a master's degree (62.5 %), and earned between 100,001¥ to 120,000¥ per year (24.70 %). All the respondents had experience using a delivery robot (100 %), and the majority of them frequently used delivery robot services (30.2 %) (Table 1).

4.3. Data analysis technique and procedure

The data was analysed using SPSS v.29 to examine the demographic profiles and common method bias (CMB). The research model was tested using partial least squares structural equation modelling (PLS-SEM) with SmartPLS4. PLS-SEM is a quasi-technique that is useful in evaluating complex relationships among different latent variables such as higher-order constructs, mediation, and moderation while simultaneously maximising explained variance (Becker et al., 2023; Hair et al., 2022; Wang et al., 2023a,Wang et al., 2023b). PLS-SEM is well suited for prediction-oriented research goals and exploratory studies (Cheah et al., 2023; Shmueli et al., 2019), which is in line with the direction and scope of the present study.

5. Findings

5.1. Common method bias (CMB)

Since the survey used in this study is self-reported and cross-sectional, two tests were performed to check for CMB (MacKenzie and Podsakoff, 2012). The full collinearity test found that all variance inflation factors (VIFs) were below the threshold value of 3.3 (Kock and Lynn, 2012) (Table 2). Additionally, Harman's single-factor testing procedure suggested by MacKenzie and Podsakoff (2012) was used and showed that the variance explained by the first factor was 38.98 %, below the maximum threshold of 50 %. Therefore, both results suggest that CMB is not a concern for this study.

5.2. Measurement model evaluation

Using Hair et al. (2022) guideline, the construct measures were evaluated for reliability and validity (Table 2).

All variables with Cronbach's alpha, rho_A, and composite reliability values exceeding 0.70 were found to be reliable. All items with loadings above 0.70 demonstrated convergent validity, except for two items (SR1 and TA3) which were removed. The average variance extracted (AVE) values above 0.50 confirmed the constructs' convergent validity. Discriminant validity was tested using the heterotrait-monotrait (HTMT) ratio method, and all variables showed a ratio lower than the 0.90 threshold, indicating discriminant validity (Table 3).

The higher-order constructs (HOC) for service quality experience and trust were assessed using the reflective-formative (Type 2) approach and through the procedures outlined by Becker et al. (2023) and Sarstedt et al. (2019). In the initial step, two global items were initially developed and evaluated for each HOC, specifically: "Overall, the service quality of the robotic delivery system is superior" and "Overall, I trust the use of the robotic delivery system." The redundancy analysis showed that both HOCs achieved path coefficient values above the minimum threshold of 0.70, specifically 0.704 for service quality experience and 0.732 for trust, confirming the presence of convergent validity. The VIF results confirmed that the dimensions were distinct and below the maximum threshold of 3.3. In the final step, only the automation dimension of service quality experience did not show statistical significance, while both dimensions of trust were statistically significant at $p < 0.01$ (Table 4).

5.3. Structural model evaluation

As part of the structural model evaluation, the VIF values were initially assessed and found to be lower than the maximum threshold of 3.3 (Hair et al., 2022), indicating that collinearity was unlikely to be an issue in the structural model (Table 5).

Following that, the hypotheses were evaluated using the bootstrap (10,000 re-sampling) technique (Becker et al., 2023; Hair et al., 2022), and the results demonstrated that the four control variables (age, gender, level of education, and frequency of using service robots) had no significant effects on the model (Table 5). Since potential endogeneity problems could arise in the study, the Gaussian copula approach was employed to address them (Hult et al., 2018). As shown in Table 5, the endogeneity relationships generated via Gaussian copula were not significant ($p > 0.05$), indicating that there were no endogeneity problems and confirming the robustness of the model (Sarstedt et al., 2020).

The direct relationship results revealed that gratification (H1b: $\beta = 0.189$, $t = 3.985$, $p < 0.01$), anthropomorphism (H1c: $\beta = 0.060$, $t = 1.696$, $p < 0.05$), service quality experience (H1d: $\beta = 0.411$, $t = 7.399$, $p < 0.01$), delivery task requirement (H1e: $\beta = 0.143$, $t = 3.136$, $p < 0.01$), and user-facing technology performance (H1f: $\beta = 0.122$, $t = 2.181$, $p < 0.05$) were found to have significant influences on perceived TTF, except for interpersonal influence (H1a: $\beta = 0.007$, $t = 0.177$, $p = 0.430$). Thus, H1b to H1f were supported, in which service quality

Table 2
Statistics for measurement model evaluation.

Construct	Operationalisation	Loading	CA	rho_A	CR	AVE	FC	Source
Interpersonal influence	II1: People who are important to me think that I should use robotic delivery system.	0.910	0.887	0.889	0.93	0.815	1.523	Venkatesh, Thong and Xu (2012)
	II2: People who influence my behavior think that I should use robotic delivery system.	0.902						
	II3: People whose opinions I value prefer that I use robotic delivery system.	0.897						
Gratification	GF1: Using robotic delivery system is fun.	0.880	0.872	0.879	0.921	0.796	1.843	Venkatesh and Brown (2001)
	GF2: Using robotic delivery system is enjoyable.	0.913						
	GF3: Using robotic delivery system is entertaining.	0.882						
Anthropomorphism	AT1: The robotic delivery system has a mind of its own.	0.904	0.888	0.995	0.916	0.733	1.199	Lu et al. (2020)
	AT2: The robotic delivery system has consciousness.	0.904						
	AT3: The robotic delivery system has its own free will.	0.830						
	AT4: The robotic delivery system will experience emotions.	0.781						
Service quality experience								
• Automation	AUTO1: Robotic delivery system operates reliably.	0.855	0.770	0.777	0.867	0.685	2.323	Prentice and Nguyen (2021)
	AUTO2: Robotic delivery system performs effectively.	0.850						
	AUTO3: Robotic delivery system functions dependably.	0.776						
• Efficiency	EE1: Robotic delivery system is responsive to my requests.	0.793	0.755	0.763	0.859	0.670	2.312	Prentice and Nguyen (2021)
	EE2: Robotic delivery system provides service in a timely manner.	0.824						
	EE3: Robotic delivery system solves my problems effectively.	0.838						
• Precision	PRE1: Information from robotic delivery system is accurate.	0.831	0.814	0.816	0.890	0.729	2.421	Prentice and Nguyen (2021)
	PRE2: Information from robotic delivery system is reliable.	0.882						
	PRE3: Information from robotic delivery system is up to date.	0.849						
• Personalisation	PZ1: Robotic delivery system is adaptive to meet my needs.	0.849	0.814	0.814	0.890	0.729	2.991	Prentice and Nguyen (2021)
	PZ2: Robotic delivery system is flexibly adjusted to meet my demands.	0.871						
	PZ3: Robotic delivery system is versatile in addressing my needs.	0.841						
Delivery task requirement	TAS1: I need to receive my parcels without direct contact with delivery person.	0.921	0.814	0.815	0.915	0.843	1.951	Wang et al., 2021a, Wang et al., 2021b
	TAS2: I need to avoid unnecessary social contact for my daily activities including receiving the parcel.	0.915						
	TAS3: I need to stay at home as much as possible.	D						
User-facing technology performance	TEC1: Robotic delivery system helps me to avoid unnecessary social contact.	0.874	0.845	0.847	0.906	0.764	2.404	Wang et al., 2021a, Wang et al., 2021b
	TEC2: Robotic delivery system helps me to comply with social distancing practices	0.896						
	TEC3: Robotic delivery system enables me to stay at home as much as possible.	0.851						
Perceived task-technology fit	TTF1: The technologies' functions of robotic delivery system are sufficient in helping me to receive the parcel.	0.874	0.827	0.828	0.897	0.743	2.912	Zhou et al. (2010)
	TTF2: The technologies' functions of robotic delivery system are appropriate in helping me to receive the parcel.	0.887						
	TTF3: In general, the functions of robotic delivery system meet my needs.	0.823						
Value-in-use	VU1: I get significant value from using robotic delivery system.	0.882	0.830	0.832	0.898	0.746	2.571	Roy et al. (2018)
	VU2: The use of robotic delivery system creates superior value for me.	0.872						
	VU3: The benefits I gain from using robotic delivery system far outweigh the costs.	0.836						
Trust								
• Cognitive trust	CT1: Robotic delivery system is accurate.	0.876	0.820	0.821	0.893	0.736	2.946	Shi et al. (2021)
	CT2: Robotic delivery system is reliable.	0.888						
	CT3: Robotic delivery system is safe.	0.808						
• Emotional trust	ET1: I feel secure when collecting my parcel through robotic delivery system.	0.874	0.864	0.866	0.917	0.786	2.607	Shi et al. (2021)
	ET2: I feel comfortable when collecting my parcel through robotic delivery system.	0.894						
	ET3: I feel content when collecting my parcel through robotic delivery system.	0.891						
Service reuse likelihood	SR1: There is a high likelihood for me to re-use robotic delivery system.	D	0.864	0.864	0.917	0.786	3.452	Lee et al. (2019)
	SR2: I am very willing to re-use robotic delivery system.	0.878						
	SR3: It is highly probable that I will consider using robotic delivery system.	0.887						
	SR4: I am in favour of using robotic delivery system again when I order something.	0.894						

(continued on next page)

Table 2 (*continued*)

Construct	Operationalisation	Loading	CA	rho_A	CR	AVE	FC	Source
Word of mouth	WOM1: I will share positive word of mouth about robotic delivery system.	0.889	0.872	0.872	0.921	0.796	3.137	Mishra et al. (2022)
	WOM2: I will recommend robotic delivery system to my friends.	0.904						
	WOM3: I will encourage my friends to use robotic delivery system.	0.884						

Notes: D = Item deleted due to low loading (<0.50). CA = Cronbach's alpha. CR = Composite reliability. AVE = Average variance extracted. FC = Full collinearity.

Table 3
HTMT results for discriminant validity evaluation.

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Anthropomorphism															
2. Automation	0.353														
3. Cognitive trust	0.325	0.771													
4. Efficiency	0.351	0.893	0.824												
5. Emotional trust	0.230	0.631	0.833	0.732											
6. Gratification	0.139	0.525	0.619	0.652	0.606										
7. Personalisation	0.288	0.883	0.759	0.881	0.665	0.600									
8. Precision	0.293	0.816	0.870	0.874	0.771	0.676	0.863								
9. Service reuse likelihood	0.249	0.677	0.792	0.752	0.802	0.690	0.755	0.747							
10. Interpersonal influence	0.422	0.558	0.549	0.597	0.507	0.432	0.575	0.589	0.544						
11. Delivery task requirement	0.107	0.479	0.575	0.513	0.617	0.590	0.560	0.540	0.638	0.395					
12. User-facing technology performance	0.066	0.513	0.695	0.601	0.642	0.644	0.583	0.638	0.703	0.398	0.814				
13. Perceived task-technology fit	0.265	0.670	0.853	0.744	0.826	0.684	0.720	0.800	0.862	0.493	0.636	0.669			
14. Value-in-use	0.361	0.753	0.817	0.767	0.789	0.592	0.756	0.757	0.819	0.590	0.558	0.626	0.837		
15. Word of mouth	0.230	0.600	0.771	0.707	0.777	0.705	0.656	0.729	0.886	0.530	0.633	0.717	0.814	0.789	

Notes: HTMT <0.90.

Table 4
Statistics for higher-order construct evaluation.

Higher-order construct	Dimension	Outer weight	Outer VIF	*t*-value	Confidence interval	Convergent validity
Service quality experience	• Automation	0.083	2.293	0.944	[−0.085; 0.258]	0.704
	• Efficiency	0.164	2.693	2.106*	[0.002; 0.310]	
	• Personalisation	0.252	2.681	2.681**	[0.066; 0.434]	
	• Precision	0.615	2.487	7.546**	[0.455; 0.775]	
Trust	• Cognitive trust	0.557	1.877	9.170**	[0.437; 0.670]	0.732
	• Emotional trust	0.533	1.877	8.688**	[0.414; 0.650]	

experience resulted in a medium effect size (f2 = 0.183, $p < 0.01$), both gratification (f2 = 0.045, $p < 0.05$) and delivery task requirement (f2 = 0.023, $p < 0.01$) resulted in small effect sizes, and the rest of the relationships (i.e., interpersonal influence, anthropomorphism, and user-facing technology performance) resulted in a trivial effect on perceived TTF. Overall, these relationships explained 52.6 % of the variance in perceived TTF.

The results also showed that perceived TTF had a significant positive effect on value-in-use (H2: $\beta = 0.672$, $t = 17.189$, $p < 0.01$) while value-in-use had a significant positive effect on trust (H3: $\beta = 0.709$, $t = 24.517$, $p < 0.01$). Furthermore, trust had a significant positive effect on service reuse likelihood (H4a: $\beta = 0.719$, $t = 25.652$, $p < 0.01$) and WOM (H4b: $\beta = 0.698$, $t = 24.508$, $p < 0.01$). Therefore, H2, H3, H4a, and H4b were supported. These relationships explained >45 % of the variance in service reuse likelihood and WOM, which is considered satisfactory.

Next, the study used the guidelines of Hair et al. (2022) to estimate the proposed sequential mediation relationship. The results in Table 5 showed that both value-in-use and trust mediated the relationship between perceived TTF and service reuse likelihood ($\beta = 0.343$, t-value = 9.167, $p < 0.01$) as well as perceived TTF and WOM ($\beta = 0.333$, t-value = 9.121, $p < 0.01$). Thus, both H5a and H5b were supported. The effect size of the specific sequential mediation paths was measured using the recommended guidelines of Lachowicz et al. (2018) and interpreted using benchmarks of 0.01 (small), 0.09 (medium), and 0.25 (large). The results showed that both sequential mediation paths had a medium effect (0118 and 0.111). This suggests that value-in-use and trust play an important role in promoting service reuse likelihood and WOM, particularly in the context of last-mile delivery robots.

Finally, the study used PLSpredict to assess the predictive relevance of the structural model (Shmueli et al., 2019). The Q^2 predict values for perceived TTF (0.502), value-in-use (0.423), trust (0.417), service reuse likelihood (0.303), and WOM (0.286) were all greater than zero (Table 5), demonstrating the predictive relevance of the model.

The study also examined more precise prediction findings to focus on the key target endogenous items (Chin et al., 2020; Shmueli et al., 2019). Table 6 indicates that all endogenous items of the key target endogenous construct (i.e., service reuse likelihood and WOM) possessed strong predictive power. The Q^2 predict values for the indicators of the PLS model were higher than those generated for the linear model (LM) ($Q^2 > 0$), while all root mean squared error (RMSE) values for the PLS model were smaller than those of the LM model. To further scrutinise the predictive ability of the model, the study also used the cross-validated predictive ability test (CVPAT), which offers a comprehensive inferential test of the predictive model in predicting all endogenous constructs simultaneously (Sharma et al., 2023). The results showed that the proposed model had a strong predictive power compared to both indicator average and linear model benchmarks. Thus, it was concluded that the proposed model has a strong predictive ability to represent a new observation of the target population.

Table 5
Relationship statistical results for structural model evaluation.

Relationship	Standard beta	Standard error	t-value	p-value	BCa CI Lower bound	BCa CI Upper bound	VIF	f^2/v^2	R^2	Q^2 predict
Direct relationship										
H1a. Interpersonal influence → Perceived TTF	0.007	0.042	0.177	0.430	−0.061	0.078	1.460	0.000	0.526	0.502
H1b. Gratification → Perceived TTF	0.189	0.047	3.985	0.000	0.109	0.264	1.673	0.045		
H1c. Anthropomorphism → Perceived TTF	0.060	0.035	1.696	0.045	0.003	0.120	1.168	0.006		
H1d. Service quality experience → Perceived TTF	0.411	0.055	7.399	0.000	0.319	0.504	1.939	0.183		
H1e. Delivery task requirement → Perceived TTF	0.143	0.046	3.136	0.001	0.063	0.215	1.896	0.023		
H1f. User-facing technology performance → Perceived TTF	0.122	0.056	2.181	0.015	0.031	0.215	2.205	0.014		
H2. Perceived TTF → Value-in-use	0.672	0.039	17.180	0.000	0.601	0.730	1.000	NA	0.451	0.423
H3. Value-in-use → Trust	0.709	0.029	24.517	0.000	0.656	0.752	1.000	NA	0.503	0.417
H4a. Trust → Service reuse likelihood	0.719	0.028	25.652	0.000	0.669	0.761	1.000	NA	0.488	0.303
H4b. Trust → WOM	0.698	0.028	24.508	0.000	0.647	0.742	1.000	NA	0.518	0.286
Control variable										
Age → Service reuse likelihood	0.062	0.053	1.167	0.123	−0.033	0.096				
Gender → Service reuse likelihood	0.051	0.040	1.266	0.205	−0.013	0.085				
Level of education → Service reuse likelihood	0.025	0.060	0.407	0.389	0.068	−0.127				
Frequency of using delivery robots → Service reuse likelihood	0.042	0.051	0.828	0.292	−0.033	0.137				
Age → WOM	0.052	0.063	0.826	0.398	−0.067	0.141				
Gender → WOM	0.018	0.051	0.356	0.887	−0.060	0.097				
Level of education → WOM	0.027	0.054	0.506	0.787	−0.038	0.086				
Frequency of using delivery robots → WOM	0.040	0.054	0.745	0.859	−0.004	0.152				
Endogeneity										
GC (Anthropomorphism) → Perceived TTF	−0.034	0.176	0.195	0.845	−0.425	0.270				
GC (Gratification) → Perceived TTF	0.055	0.067	0.819	0.413	−0.074	0.185				
GC (Interpersonal influence) → Perceived TTF	0.011	0.118	0.094	0.925	−0.227	0.234				
GC (Service quality experience) → Perceived TTF	0.024	0.083	0.290	0.386	−0.113	0.160				
GC (Delivery task requirement) → Perceived TTF	0.070	0.056	1.265	0.206	−0.030	0.188				
GC (User-facing technology performance) → Perceived TTF	−0.011	0.060	0.184	0.854	−0.130	0.103				
GC (Perceived TTF) → Value-in-use	0.093	0.146	0.633	0.527	−0.163	0.408				
GC (Trust) → Service reuse likelihood	0.188	0.129	1.460	0.144	−0.048	0.455				
GC (Trust) → WOM	0.014	0.048	0.292	0.383	0.067	0.091				
Sequential mediation relationship										
H5a: Perceived TTF → Value-in-use → Trust → Service reuse likelihood	0.343	0.037	9.167	0.000	0.268	0.414		0.118		
H5b: Perceived TTF → Value-in-use → Trust → WOM	0.333	0.036	9.121	0.000	0.260	0.402		0.111		

Notes: GC = Gaussian copula test for examining endogeneity. BCa CI = Bias-corrected and accelerated (BCa) confidence interval. VIF = Variance inflation factor.

Table 6
PLSpredict and CVPAT results for structural model evaluation.

PLSpredict Item	Q^2 predict	PLS RMSE	LM RMSE	PLS RMSE – LM RMSE	Predictive relevance	CVPAT Focus on overall model	Average loss difference	t-value	Predictive power
SR1 (Item deleted)	NA	NA	NA	NA	Strong	PLS-SEM vs Indicator average (IA)	−0.388	10.816**	Strong
SR2	0.228	0.822	0.915	−0.093		PLS-SEM vs Linear model (LM)	0.073	5.500**	
SR3	0.255	0.783	0.902	−0.119					
SR4	0.255	0.757	0.866	−0.109					
WOM1	0.244	0.795	0.917	−0.122	Strong				
WOM2	0.227	0.826	0.915	−0.089					
WOM3	0.229	0.825	0.917	−0.092					

Notes: SR1 item deleted due to low loading. Q^2 = Predictive relevance. PLS = Partial least squares. LM = Linear model. RMSE = Root mean squared error. CVPAT = Cross-validated predictive ability test. SEM = Structural equation modelling.

6. Discussion and conclusion

6.1. Theoretical implications

Drawing on the TTF model, our study contributes several noteworthy theoretical insights in relation to the post-adoption of delivery robots in last-mile delivery.

Firstly, it establishes that users' evaluation of the perceived TTF of using delivery robots hinges on both hedonic- and utilitarian-driven factors. From the hedonic perspective, gratification was found to have a positive influence on perceived TTF (supporting H1b). Existing literature corroborates this, suggesting that the pleasure derived from engaging with novel technologies, such as robot services, fosters continued use and exploration of the benefits of such innovations (Lee et al., 2021a,Lee et al., 2021b; Merhi et al., 2019). Nonetheless, our study presents an inconclusive result for the effect of interpersonal influence on perceived TTF (H1a is not supported). This suggests that an individual's social networks, like family or friends' endorsements, do not significantly affect the perception of the delivery robots' functional efficacy in optimising parcel drop-off tasks. This can be attributed, in part, to the surge in robot utilisation across industries, particularly in burgeoning economies such as China, where robots have evolved into indispensable tools for offering value-added services, and touch-less, autonomous services are being more widely accepted as the way forward (Lu et al., 2020). Additionally, anthropomorphism emerges as another pivotal hedonic-driven element influencing perceived TTF (supporting H1c). As Blut et al. (2021) highlight, anthropomorphic designs influence service robots' perceived competence. Users often regard humanoid robots as more adept and dependable because they evoke a sensation of interacting with a sentient being. From a utilitarian standpoint, this study endorses the service quality experience scale developed by Prentice and Nguyen (2021), identifying it as the primary factor influencing perceived TTF (supporting H1d). Subsequent research should consider elements such as automation, personalisation, precision, and efficiency to obtain an encompassing understanding of robotic service quality and its effect on user perceptions, especially given the vast IT-enabled services that robots offer. Moreover, this study confirms that both the specificity of the delivery task and the efficiency of the user-facing technology bolster perceived TTF (supporting both H1e and H1f). This mirrors Wang et al.'s (2021)a,b discovery that a global perception has hastened the embrace of advanced robotic technologies. The incorporation of robots in parcel delivery introduces a technological barrier between consumers and couriers, nullifying physical proximity whilst enhancing health safety during interactions.

Secondly, our study elucidates the consequences of perceived TTF in the realm of delivery robots. Importantly, it bolsters earlier work by Shi et al. (2021), underscoring the necessity to consider both cognitive and emotional facets to fully grasp the influence of perceived trust on technological adoption. Our findings are congruent with the prevailing literature on technology adoption (Franque et al., 2023; Hwang et al., 2022). We verified the positive relationship between perceived TTF and value-in-use (supporting H2), as well as between value-in-use and trust (supporting H3) within the domain of delivery robots. Our investigation further delves into trust's role in service reuse likelihood and WOM, particularly in the context of last-mile delivery. Although prior research has acknowledged trust's impact on the propensity to embrace new innovations and diminish switching intention (Chi et al., 2021), a holistic view was absent. Our study bridges this gap, concluding that when users possess profound trust in an innovation, they exhibit an increased inclination to reemploy the service and convey affirmative feedback regarding delivery robots (supporting both H4a and H4b).

Lastly, our study transcends the direct effects of perceived TTF and post-adoption behavior by probing the intrinsic mechanisms at play. In alignment with prior research, which posits that individuals engage in a cognitive assessment during goal-driven behaviors (Lim et al., 2022a; Petter et al., 2012), our findings offer insights into the mechanisms by which perceived TTF sways service reuse likelihood and WOM. The results demonstrate that value-in-use and trust serve as conduits in the nexus between perceived TTF and post-adoption behavior, bridging existing voids to foster a more profound sense of trust and perceived value during interactions with delivery robots. Consequently, our findings substantiate H5a and H5b, suggesting that a heightened perceived fit sequentially results in a positive assessment of value-in-use and trust, resulting in the formation of service reuse likelihood and WOM.

6.2. Managerial implications

Based on the findings, our study offers several pivotal implications for managers considering the use of delivery robots for last-mile deliveries.

The findings of our study highlight the significance of hedonic values, specifically gratification and anthropomorphism, in enhancing perceived fit and promoting the use of delivery robots. Service providers can leverage these insights to emphasise the sensory benefits users can experience when utilising delivery robots. By focusing on the fun, pleasure, and playfulness of interacting with robots, service providers can assure users that delivery robots fully meet their needs. Additionally, our results align with previous research, supporting the idea that anthropomorphism features contribute to the perceived competence of robots (Blut et al., 2021; Rosenthal-von der Pütten et al., 2018). Incorporating human-like characteristics, such as flashing lights to simulate thinking, can enhance the human-like qualities of delivery robots. Service providers can further build users' confidence in robots' ability to perform tasks by employing human-like delivery robots that imitate human structure, characteristics, or behavior. For instance, the Ford Inc. delivery robot “The Digit”, designed in collaboration with Agility Robotics, features a two-legged design. This robot unfolds its legs from the back of an autonomous car and delivers packages directly to users' doors. The robot's capabilities include carrying up to 40 pounds, navigating stairs, climbing steps, walking on uneven terrain, and maintaining balance even when hit. As a result, this strategic approach enhances the delivery robot's professional appearance, instilling greater user trust and confidence in its performance.

Enhancing utilitarian values is undoubtedly crucial for logistics service providers seeking to optimise the perceived TTF and drive the update of delivery robots. To achieve this, service improvement strategies should concentrate on four key aspects: automation, personalisation, efficiency, and precision. Firstly, service providers should ensure that delivery robots are capable of performing the delivery task independently, reducing the need for human intervention and maximising efficiency. Secondly, offering personalised services tailored to individual needs can further enhance the perceived fit, making users feel the delivery process resonates more with their specific requirements. Thirdly, efficiency in completing the delivery task promptly is essential to meet users' expectations for swift and timely service. Lastly, precise, error-free parcel delivery can solidify user trust and confidence in the delivery robot's capabilities.

Moreover, it is crucial for service providers to consider the impact of health-related crises, such as COVID-19, on the perceived TTF of using delivery robots. During such crises, highlighting the benefits and positive impacts of adopting delivery robots becomes even more important. Emphasising the ability of delivery robots to maintain social distancing and prevent the spread of infectious diseases through contactless services can further bolster the perceived fit and encourage users to opt for robot-assisted deliveries during health emergencies. By positioning delivery robots as a safer and more hygienic alternative, service providers can tap into the growing demand for contactless services and strengthen the value proposition of delivery robots in the context of health-related crises.

Promoting long-term usage of delivery robots hinge on enhancing users' perception of value-in-use and trust. To build human-robot trust, service providers should prioritise the delivery system's reliability, accuracy, and responsiveness in all situations. By consistently providing up-to-date and reliable service, users will develop a sense of trust in the delivery robot's capabilities. Moreover, service providers can facilitate early adopters' learning process by offering clear information and solutions to maximise the value and benefits of using delivery robots when collecting their parcels. Offering guidance and support to users in understanding the robot's functionalities and features can contribute to a positive and enriching user experience.

Creating a sense of security and comfort is also crucial in building trust. Service providers can enable users to test the delivery robot before adopting it, allowing them to familiarise themselves with the technology and gain confidence in its performance. Transparent communication about the robot's programming and emphasising encryption procedures to safeguard users' data can further enhance trust and alleviate privacy concerns. However, it is important to recognise that building trust and experiential value towards a novel service and customer experience is an ongoing process. Service providers should continuously work on strengthening users' positive beliefs and experiences with delivery robots. By soliciting feedback and addressing user concerns proactively, service providers can foster a culture of trust and satisfaction, ensuring sustained adoption and usage of delivery robots in the long run.

6.3. Limitations and future research directions

As every research, also ours of course holds several limitations. Firstly, the sample is confined to China, making it problematic to extrapolate the results to different cultural or geographical settings. As such, subsequent research might explore other leading economies like the United States, the United Kingdom, or Germany to validate the proposed model. Secondly, this research, akin to numerous prior studies, was cross-sectional. Given that factors influencing trust and technology acceptance can evolve, longitudinal studies are advocated to elucidate how these predictors transform over time. Moreover, future research ought to delve into different facets of social cognition, such as warmth versus competence, or varied anthropomorphic traits like 'cute' versus 'cool' in delivery robots. This would offer deeper insights into their impact on the overarching results. For instance, Kim et al. (2019) discerned that robots perceived as 'competent' are more likely to positively affect actual or continued usage compared to those perceived as 'warm.' Conversely, Zhang et al. (2021) noted that 'cute' anthropomorphised robots evoke positive emotions, whilst 'cool' ones heighten effort expectancy. These pivotal concepts could elucidate the link between a user's choice and a last-mile delivery robot. Lastly, this study, by predominantly centring on the younger demographic as per Liu et al. (2019), might neglect essential insights into the potential advantages or obstacles delivery robots pose for older adults. With a discernible shift towards an ageing populace in numerous nations (Chua et al., 2023; Karakaş et al., 2023), incorporating older participants in upcoming studies would render a more holistic comprehension of the last-mile delivery experience. Such insights would illuminate how this technology might be tailored to address the distinct needs and challenges of older adults. This strategy would foster more inclusive and user-centric delivery robot systems, ensuring equitable access to its benefits for all age brackets.

CRediT authorship contribution statement

Xin-Jean Lim: Conceptualization, Writing – original draft, Writing – review & editing, Investigation, Data curation, Methodology, Software, Validation, Formal analysis. **Yee-Shan Chang:** Conceptualization, Methodology, Writing – original draft, Software, Validation, Formal analysis, Data curation. **Jun-Hwa Cheah:** Writing – original draft, Software, Validation, Formal analysis. **Weng Marc Lim:** Writing – original draft, Writing – review & editing. **Sascha Kraus:** Writing – original draft, Writing – review & editing, Visualization, Methodology, Supervision. **Marina Dabić:** Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

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