FROM ALGORITHM TO DOORSTEP: CONSUMER ACCEPTANCE OF CHATBOTS IN LAST-MILE LOGISTICS

DOI
https://doi.org/10.18690/um.fov.4.2026.21

ISBN
978-961-299-152-4

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Failed deliveries are a major source of inefficiency in last-mile logistics that could be addressed by AI-enabled chatbots that facilitate real-time interaction between parcel recipients and Logistics Service Providers. This study examines the factors driving parcel recipient intention to use AI-enabled chatbots in this context, drawing on an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model and a scenario-based experiment with 214 university students. Three chatbot conditions were compared: a well-functioning chatbot, an error-prone chatbot, and a privacy-invasive chatbot. Results show that chatbot errors indirectly reduce future usage intentions through lower user satisfaction. Furthermore, expected performance and social influence are the primary predictors of intention to use. These findings extend UTAUT to a utilitarian, post-purchase last-mile logistics context and offer practical guidance for Logistics Service Providers seeking to improve last-mile performance through AI-enabled chatbots.

Keywords:
artificial intelligence,
UTAUT,
last-mile logistics,
satisfaction,
consumer behavior

University of Maribor Press

1 Introduction

Convenience, variety, and competitive pricing have led to a sustained surge in Business-to-Consumer (B2C) e-commerce (Amaya et al., 2025; Nogueira et al., 2024). Consumers are ordering more frequently online and expecting swift delivery, preferably at home, and for free (Buldeo Rai et al., 2019). As these consumers increasingly settle in cities, this is compounding existing congestion problems, negatively impacting the social and ecological performance of supply chains. Given that the last-mile is also known for being the most expensive part of the supply chain, Logistics Service Providers (LSPs) are facing increasing pressure to improve the triple bottom line performance of their operations (Mangiaracina et al., 2015) while maintaining customer satisfaction (Kokkinou et al., 2026). A source of poor last-mile performance is the high rate of unsuccessful deliveries, which has estimates ranging from 1 to 60%, with 20% frequently mentioned as the upper limit (Niemeijer & Buijs, 2023). The primary reason for failed delivery is typically that the customer is not home (Norman, 2025). These failed deliveries lead to high costs for e-commerce players, negatively affect customer satisfaction, multiply emissions and congestion through repeated delivery attempts, and add pressure on drivers (Seghezzi & Mangiaracina, 2023).

Several solutions have been proposed to reduce failed deliveries and their negative consequences on last-mile performance. Unattended delivery options, such as parcel lockers, are effective but not accessible to all customers (Kokkinou & Quak, 2026). More recently, the use of Internet of Things (IoT) in combination with data analytics have been used to predict whether recipients will be home and (re)arrange routes accordingly (Seghezzi & Mangiaracina, 2023). Nevertheless, this only reduces the probability of failed delivery. Increasingly, customers and parcel recipients demand more control over when, where, and how their parcels are delivered (Norman, 2025). The development of Generative Artificial Intelligence (GenAI), and in particular AI-enabled chatbots, is a promising approach to aligning customer delivery preferences with the options offered by the LSP. AI-enabled chatbots (hereafter referred to as chatbots) are a class of intelligent software agents that facilitate interactive information sharing (Arce-Urriza et al., 2025). Driven by advances in GenAI, they are increasingly adopted across sales, marketing, and customer service for their capacity to deliver engaging, human-like conversations (Pillai & Sivathanu, 2020). Chatbots can facilitate real-time interaction between parcel recipients and LSPs, enabling them to (re)arrange delivery (time and place), thereby reducing missed deliveries and potentially increasing customer satisfaction (Richey et al., 2023). By offering conversational rescheduling options, chatbots can reduce friction and meet recipients' need for flexibility and autonomy (Alsarayreh et al., 2025; Seegers, 2025). Nevertheless, these outcomes can only be achieved if customers and parcel recipients are willing to use chatbots, a topic that has received limited attention (Richey et al., 2023).

The purpose of the present study is therefore to examine consumers' intention to use chatbots in the context of last-mile deliveries. Chatbot features have been examined across various contexts, including e-commerce, finance, hospitality, tourism, and retail (Alharbi et al., 2025; Arce-Urriza et al., 2025; Liu et al., 2024; Pillai & Sivathanu, 2020). Factors that have been examined include technology aspects, namely ease of use, usefulness, and trust, in combination with chatbot-specific features such as anthropomorphism and chatbot intelligence (Alharbi et al., 2025; Liu et al., 2024; Pillai & Sivathanu, 2020) Yet, last-mile logistics as a study context differs from the hospitality, tourism, and retail contexts due to the utilitarian nature of the interaction and the fact that it occurs post-purchase (Vakulenko et al., 2019). Our study thereby contributes to a better understanding of chatbot usage in a utilitarian, post-purchase context, where the primary goal is the efficient execution of a time-sensitive task, a context where empirical evidence on consumer acceptance remains limited (Alsarayreh et al., 2025; Richey et al., 2023), despite growing interest from the industry (King, 2024; Seegers, 2025).

2 Review of the Literature

In supply chains and logistics, the last mile is known as the most expensive (Gevaers et al., 2014) and polluting (Mangiaracina et al., 2019). This negative impact of last-mile logistics has been addressed through a mix of supply-side and demand-side innovations and interventions. Specifically, LSPs have made efforts to reduce the number and frequency of trips, drawing on efficient routing and the principle of consolidation (Savelsbergh & Van Woensel, 2016). Nevertheless, customers and parcel recipients play an important role therein, as a substantial number of trips are caused by recipients not being home to receive their parcels. LSPs have invested significant resources to improve communication with parcel recipients. For example, most large LSPs offer customers and parcel recipients the possibility to adjust delivery preferences through an online application (Norman, 2025). For example, in the Netherlands, DHL and PostNL offer parcel recipients the option to leave a package at their neighbours', in a safe location around the house, or have it rerouted to a nearby parcel locker (DHL, n.d.; PostNL, n.d.). Furthermore, LSPs increasingly partner with retailers to offer customers the option to select a delivery time and location at checkout. While these interventions are successful, they remain quite unilateral, leaving the initiative with the parcel recipient. Parcel recipients increasingly look for flexibility and convenience, with for example up to 35% of deliveries in the UK being re-directed while already in transit (King, 2024). There is thus much to be gained from offering real-time interaction between parcel recipients and LSPs that reduces friction in two-way communication (Alsarayreh et al., 2025; Seegers, 2025). Recent advances in GenAI have transformed chatbots from rule-based systems into flexible agents capable of natural, context-aware dialogue (Alharbi et al., 2025). Their use is widespread and expanding rapidly. This is unsurprising, as chatbots allow organizations to reduce operational costs while concurrently improving customer experience, user engagement, and satisfaction (Alsarayreh et al., 2025). Despite extensive research across numerous contexts (Alharbi et al., 2025), the adoption of chatbots in utilitarian, post-purchase settings such as last-mile logistics remains under-researched (Alsarayreh et al., 2025; Arce-Urriza et al., 2025).

Several research models have been used to explain users' intention to adopt a particular focal technology. The two broadest models are the Technology Acceptance Model (TAM) (Davis et al., 1989) and the Unified Theory of Acceptance and Usage of Technology (UTAUT) (Venkatesh et al., 2012). Both theories focus on the functional aspects of technology, such as its perceived usefulness and perceived ease of use (Kasilingam, 2020). UTAUT extends TAM by incorporating social factors, namely facilitating conditions and social influence (Arce-Urriza et al., 2025; Venkatesh et al., 2012). TAM and UTAUT are operationalized into consistent and concise tools of measurement (Kasilingam, 2020) that have demonstrated empirical soundness across a broad range of contexts (Alharbi et al., 2025; Arce-Urriza et al., 2025). Two other models are also relevant for the present study. The Expectation-Confirmation Model (ECM) similarly focuses on users' cognitive processes but also incorporates satisfaction with prior use of the focal technology to explain continued use (Bhattacherjee, 2001). Yet another model, the Technology Readiness Index (TRI) is a more general measure of individuals' technology readiness, captured by four components: optimism, innovativeness, discomfort, and insecurity (Parasuraman & Colby, 2015).

UTAUT and TAM were selected as more appropriate, as they are parsimonious yet comprehensive models, and have been applied in contexts relevant to this study (Alsarayreh et al., 2025), such as smartphone chatbots (Kasilingam, 2020), chatbots in retail communication (Rese et al., 2020), and chatbots in service settings (Liu et al., 2024; Pillai & Sivathanu, 2020). The TAM and UTAUT models have been extended to account for the specific characteristics of chatbots, and in particular relational elements. These can generally be grouped into two categories. The first category comprises variables describing how human-like the chatbot is, including anthropomorphism (Pillai & Sivathanu, 2020), perceived humanness (Arce-Urriza et al., 2025), and the authenticity of the conversation (Rese et al., 2020). The second category revolves around the concept of trust. Given that chatbots facilitate two-way communication, they may facilitate the exchange of sensitive data (Arce-Urriza et al., 2025). Several variables are linked to trust, namely, perceived risk (Kasilingam, 2020) and privacy concerns (Alharbi et al., 2025). While these models have been tested across diverse contexts, little research has examined their application to last-mile logistics. This context is characterized by utilitarianism and its post-purchase setting (Arce-Urriza et al., 2025). Therefore, the present study seeks to answer the following research question: *What factors drive consumer usage of chatbots in the context of last-mile logistics?*

3 Conceptual Framework

To understand parcel recipients' intentions to use chatbots, three models were tested. Consistent with previous research, the first model examined an augmented UTAUT model. The second model compared three different chatbots developed based on two salient aspects identified in the literature review, namely quality (translated to error proneness) and privacy. The third model examined whether the expanded UTAUT model could explain the effects of the different chatbots on future intention to use them.

The *first model, based on an augmented UTAUT model,* was used to identify the factors explaining parcel recipients' intention to use Chatbots for last-mile logistics. This model included the broadly accepted UTAUT variables (Alsarayreh et al., 2025;

Kasilingam, 2020; Venkatesh et al., 2012): expected performance (*HA1*), ease of use (*HA2*), social influence (*HA3*), and facilitating conditions (*HA4*). Additionally, perceived risk (*HA5*) was also included, given its importance in both chatbot and last-mile research (Zhou et al., 2020). Finally, given that satisfaction with past chatbot interactions has been shown to predict future intentions (Ashfaq et al., 2020), and consistent with ECM (Bhattacherjee, 2001), satisfaction was also included as a predictor (*HAS*).

The *second model was an experimental model based on two salient factors* identified in the literature review. These factors were found to play a role in consumers' satisfaction, attitude, and intention to use chatbots, namely the quality (Toader et al., 2019) and privacy aspects of the chatbot (Arce-Urriza et al., 2025). Errors by chatbots can frustrate users and lead them to perceive chatbots as less reliable and competent (Alharbi et al., 2025). In the related context of human-robot interaction, errors by agents similarly led to them being perceived as less reliable and competent, and having weaker reasoning abilities (Ragni et al., 2016). In an experiment comparing four chatbots in a hedonic pre-purchase context, De Sá Siqueira et al. (2024) found that attitude towards the chatbot was negatively impacted by errors, and this effect was not mitigated by human-like characteristics. We therefore hypothesize that errors by the chatbot decrease parcel recipients' intention to use chatbots for last-mile logistics (*HB1*). Interaction with chatbots typically involves two-way communication, with users sharing information so the chatbot can better understand their queries and provide more accurate answers. Nevertheless, this raises concerns about privacy and risk. Previous research showed that even as customers became more accustomed to AI technologies, their concerns about privacy remained unchanged (Arce-Urriza et al., 2025). Therefore, parcel recipients, confronted with an inquisitive chatbot that asks personal questions, may feel at risk, leading to the following hypothesis: private questions by the chatbot decrease parcel recipients' intention to use chatbots for last-mile logistics (*HB2*).

The *third model tested was a mediation model*, combining the previous two, and illustrated in Figure 1. Using TAM as a research model, De Sá Siqueira et al. (2024) found that errors by chatbots negatively affected perceived usefulness, the TAM counterpart of the UTAUT construct expected performance. We therefore hypothesize that: expected performance mediates the effect of errors by the chatbot on future intention to use (*HM1*). Similarly, chatbot errors are likely to decrease satisfaction, and we therefore hypothesize that satisfaction mediates the effect of chatbot errors on future intention to use (*HMS*). Finally, as an inquisitive chatbot that asks personal questions may trigger feelings of risk, we hypothesize that perceived risk mediates the effect of private questions by the chatbot on future intention to use (*HM2*).

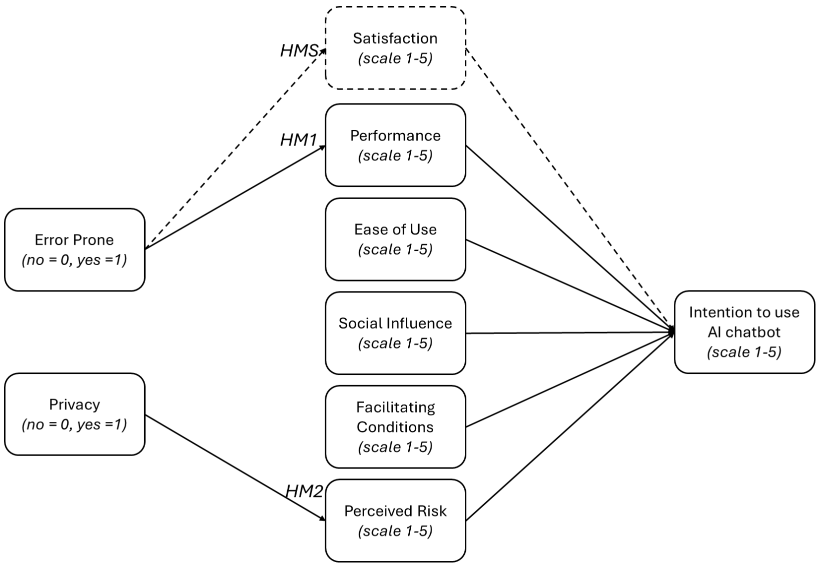

Figure 1: Mediation Model

Source: Own

4 Methods

An online scenario-based experiment was used to test the study hypotheses. Such experiments, also known as vignette-based experiments, are common in both the context of last-mile logistics consumer behavior research (Buldeo Rai et al., 2019, 2021; Kokkinou et al., 2024) and chatbot research (De Sá Siqueira et al., 2024) as they allow researchers to manipulate conditions without interfering with sensitive business processes (Kokkinou & Cranage, 2011).

An online survey was developed using the software Qualtrics. The survey consisted of four parts. After receiving information about the study procedures and providing informed consent, participants were asked to imagine themselves in the situation where they received the following message: "*Dear customer, you recently ordered a pair of shoes to be delivered to your door. However, we believe we may be able to deliver your order sooner* *and would like to ask you to work with our Chatbot, Miles, to arrange delivery at a mutually suitable time. Miles the Chatbot can explore various options with you to deliver your package at a time and place that suits you. Miles is enabled by AI technology and has been trained by our customer service,*" and asked if they were willing to interact with Miles the Chatbot. If participants refused, they were redirected to the third section of the survey. The second section of the survey consisted of an interaction with one of three versions of the chatbot (De Sá Siqueira et al., 2024). The chatbots were programmed to exhibit human-likeness, following the characteristics as developed by De Sá Siqueira et al. (2024).

Participants were randomly assigned to one of three conditions. Condition 1 consisted of a "Good" version of the chatbot that allowed the participant to reschedule and/or redirect delivery. Possible options included delivery at home, at work, or at a parcel locker located close to either. Condition 2 represented the Privacy concerns version. This version of the chatbot only differed from Condition 1 in that the Chatbot asked personal information from the participant (e.g., to confirm their identify, confirm delivery location, etc.). Condition 3 represented the Error Prone Chatbot. This version of the chatbot was programmed to make illogical mistakes. For example, if a respondent indicated not being at home for delivery, the chatbot would offer to arrange delivery by electric van. The three versions of the chatbot were pre-tested extensively by researchers, lecturers, and (Master) students to ensure that they exhibited the desired behavior. This section of the survey also included control measures. Participants were asked to indicate on a scale from 1 to 5 whether the chatbot that they interacted with (1) asked for personal information, (2) responded illogically, and (3) helped them achieve the objective to reschedule the delivery. Participants were also asked to rate their satisfaction with their interaction with the chatbot. Section 3 of the online survey consisted of measurement scales based on the UTAUT framework (Venkatesh et al., 2012) and adapted from previous studies (Kokkinou et al., 2025; Venkatesh et al., 2012; Zhou et al., 2020).

Participants were recruited from the student population of a Dutch mid-sized university using a census approach. Of the 4000 students approached by e-mail, 233 participated in the research, a response rate of 5.8%. 19 surveys were removed due to excessive incomplete data and/or straightlining. The final sample consisted of 214 students, of whom 37% indicated being male, 54% female, and 1% non-binary. On average, participants reported 2.047 (sd = 1.969) online monthly purchases.

5 Results

Prior to testing the study hypotheses, the reliability of the measurement scales was examined using Cronbach Alpha (Hair, 1998). For all measurement scales except Facilitating Conditions and Perceived Risk, the Cronbach Alpha exceeded 0.7. Given that Facilitating Conditions is a well-established scale in the literature, it was kept as is for further research. Perceived Risk is also a widely used scale, however for this scale only two items were retained for further research. For all measurement scales, the values of the items were averaged to compute a single score. One-way ANOVAs were used to test differences among the three chatbot conditions. Participants assigned to condition 1 reported fewer personal questions ($p<.000$) and illogical interactions ($p<.000$) than participants in the other conditions. Participants in condition 3 reported being less successful in accomplishing the objective of rescheduling delivery than participants in other conditions ($p<.045$).

Table 1: Reliability and Descriptive Statistics

	Source	Nr. Items	Alpha	Mean	St. Dev.
Intention to use Chatbot	Zhou et al. (2020)	5	0.914	2.858	1.034
Performance	Zhou et al. (2020)	3	0.840	3.382	1.051
Ease of Use	Zhou et al. (2020)	4	0.768	4.265	0.678
Social Influence	Zhou et al. (2020)	3	0.893	2.636	0.977
Facilitating Conditions	Zhou et al. (2020)	4	0.613	3.933	0.653
Perceived Risk	Zhou et al. (2020)	2 (from 4)	0.693	3.341	1.039

Source: Authors' Own Work

Table 2: Control Measures: One-Way ANOVAs

	Condition 1 (Good)	Condition 2 (Inquisitive)	Condition 3 (Error Prone)	p-value	No Chatbot
Personal	1.344	2.300	2.017	0.000	
Illogical	1.571	2.116	2.052	0.045	
Objective	4.138	4.200	3.333	0.000	
	n = 59	n = 60	n = 58		n = 36

Source: Authors' Own Work

Of the 214 participants, 36 chose not to interact with the chatbot. For these participants, there is no score for satisfaction with the chatbot. This explains the difference in sample size for models including vs. not including satisfaction as a dependent variable.

Linear regression was used to test the hypotheses of the *UTAUT model* in two steps. First, only the UTAUT variables were included. The overall regression model was statistically significant, $F(5, 208) = 22.95$, $p < .001$, and explained approximately 35.6% of the variance in the outcome variable (adjusted $R^2 = .340$). The examination of individual predictors showed that two variables made significant contributions, namely Performance ($\beta = 0.151$, $p <.000$) and Social Influence ($\beta = 0.229$, $p <.05$), supporting HA1 and HA3. Subsequently, a second model that also included satisfaction was examined. This second overall regression model was also statistically significant, $F(6, 170) = 12.07$, $p < .001$, and explained approximately 29.9% of the variance in the outcome variable (adjusted $R^2 = .274$). Satisfaction was also significant ($\beta = 0.229$, $p < .05$), providing support for HAS.

Table 3: Linear Regression Results

	Model 1		Model 2		Hyp.
	Estimate	p-value	Estimate	p-value	
Intercept	-0.110	0.825	-0.040	0.947	
Performance	0.294	**0.000**	0.200	**0.017**	HA1 Sup.
Ease of Use	0.151	0.133	0.071	0.506	
Social Influence	0.229	**0.002**	0.248	**0.002**	HA3 Sup.
Facilitating Conditions	0.207	0.084	0.199	0.109	
Perceived Risk	-0.026	0.664	-0.041	0.528	
Satisfaction			0.194	**0.004**	HAS Sup.

Notes: Model 1: R2 0.356, Adj. R2 0.340; Model 2: R2 0.299 Adj. R2 0.274

Source: Authors' Own Work

Linear regression was also used to test the *effect of the interventions* on intention to use the chatbot. The overall regression model was not statistically significant, $F(2, 174) = 2.231$, $p = .110$, only explaining 2.5% of the intention to use the chatbot.

A *mediation analysis* was conducted to examine whether satisfaction mediates the relationship between the Error Prone intervention and future intention to use Chatbots for last-mile delivery. The analysis was performed using Hayes' process function in R. A bootstrapping procedure with bias-corrected confidence intervals based on 5,000 bootstrap samples was employed. The total effect of the Error Prone intervention on satisfaction was statistically significant ($b = -0.41$, $SE = 0.15$, $t = -2.71$, $p < .01$, 95% CI [-0.70, -0.11]), indicating that this intervention negatively impacted satisfaction. This intervention accounted for 4.0% of the variance in satisfaction, $F(1, 175) = 7.34$, $p <.01$. In the model predicting future intention to use AI, both the Error Prone intervention and satisfaction were included as predictors. This model explained 7.5% of the variance in future intention to use AI, $F(2, 174) = 7.019$, $p < .001$. Within this model, satisfaction was a significant positive predictor of AI usage ($b = 0.220$, $SE = 0.072$, $t = 3.059$, $p < .005$, 95% CI [0.078, 0.362]). However, the direct effect of the intervention on AI usage was not statistically significant ($b = -0.219$, $SE = 0.146$, $t = -1.506$, $p = .134$, 95% CI [-0.507, 0.068]).

The indirect effect of the intervention on intention to use the chatbot through satisfaction was statistically significant ($b = -0.089$, $SE = 0.049$, 95% CI [-0.200, -0.011]), indicating that satisfaction mediated the relationship between this intervention and future intention to use a chatbot. This means that when the chatbot made more mistakes, users were less satisfied, which in turn was associated with lower intentions to use chatbots in the future. These findings support a mediation model in which satisfaction serves as a mechanism through which an Error Prone chatbot negatively influences future intention to use AI, supporting H_{MS}.

6 Discussion

The purpose of this study was to examine the factors that drive consumer use of Chatbots in the context of last-mile logistics. The results of the extended UTAUT model showed that expected performance and social influence were positively associated with parcel recipients' future intention to use chatbots for rescheduling deliveries. Satisfaction with a past chatbot interaction was also a significant predictor, supporting previous research that found that positive experiences carry forward into future behavioral intentions (Ashfaq et al., 2020). The experimental manipulations did not produce a statistically significant direct effect on future intention to use. However, the mediation analysis revealed that the error-prone chatbot negatively affected satisfaction, which in turn reduced future intention. This suggests that, rather than directly impacting intention, chatbot errors influence intention through satisfaction (Bhattacherjee, 2001), providing nuance to our understanding of how chatbot quality influences long-term usage.

In terms of *implications for theory*, the findings confirm the partial applicability of the UTAUT framework to this novel context (Alsarayreh et al., 2025). Consistent with prior research in retail and service settings (Arce-Urriza et al., 2025; Liu et al., 2024), expected performance emerged as a robust predictor of intention to use chatbots to reschedule deliveries. This implies that parcel recipients are principally motivated by whether the chatbot can help them arrange delivery more conveniently and reliably. This was inconsistent with Alsarayreh et al. (2025)'s results, although this could have been due to their inclusion of the effect of habit, which may have been confounding. Conversely, and similar to Alsarayreh et al. (2025), our findings showed that perceived ease of use was not a statistically significant predictor. This suggests that, in a task-oriented, logistical interaction, usability concerns may be subordinate to outcome expectations. This is consistent with the utilitarian framing of this context (Arce-Urriza et al., 2025) and diverges from findings in hospitality and retail (Liu et al., 2024; Pillai & Sivathanu, 2020). Consistent with ECM (Bhattacherjee, 2001), satisfaction significantly predicted future intention to use chatbots for rescheduling delivery. It also served as the pathway through which chatbot errors indirectly reduced future intention, despite the direct effect of the error-prone condition being non-significant. This reinforces the need to integrate affective and evaluative constructs into predominantly cognitive models such as UTAUT when studying interactive AI technologies (Arce-Urriza et al., 2025; Chih et al., 2025). The absence of a direct effect of chatbot condition on intention is interesting and merits further research. It could imply that a single interaction with a flawed or intrusive chatbot may not be sufficient to influence behavioral intentions, especially in a utilitarian context and/or users may attribute errors to novelty or technical limitations. (De Sá Siqueira et al., 2024).

In terms of *implications for practitioners*, the significant effect of expected performance suggests that LSPs and chatbot developers should prioritize functionality. A chatbot that reliably helps recipients reschedule or redirect their parcel delivery will drive adoption more effectively than one that is kept too simple. This implies that chatbot development should focus on providing a comprehensive set of options, including delivery times, location, and alternative delivery options such as parcel lockers. Furthermore, the significance of social influence suggests that LSPs can benefit from social comparison mechanisms, for example, by communicating usage rates or customer ratings, which may encourage hesitant recipients to try the chatbot. The mediation findings highlight the importance of satisfaction. Even if chatbot errors do not directly affect parcel recipients' future usage intentions, they do erode satisfaction. This can potentially erode recipients' usage intentions over time if these errors are not addressed. LSPs and chatbot developers should therefore invest in extensive testing, iterative improvement, and swift referral to human agents when needed. Even though privacy-invasive chatbot behavior was not shown to directly reduce intention in this study, it remains a reputational risk and should be minimized through transparent data practices and minimal data collection.

Several limitations need to be acknowledged. First, data were collected from a student sample at a single university, in a single country, limiting generalizability. Students tend to be younger and more digitally literate than the general population (Kokkinou et al., 2025; Zhou et al., 2020). The non-significance of facilitating conditions and perceived risk may also reflect students' digital fluency. Future research should therefore use more diverse, representative samples. Second, although using live chatbots in experimental chatbot interactions increased ecological validity, these systems remain dynamic and unpredictable (De Sá Siqueira et al., 2024). As such, it is not entirely possible for the researchers to maintain tight control over experimental conditions, as would be desirable in a scenario-based experiment (Kokkinou & Cranage, 2011). The control measures demonstrated that, in general, the manipulations were successful. However, the study could be replicated either by having participants read a simulated interaction or by interacting with the chatbot in the presence of researchers as part of a think-aloud qualitative research design. Additionally, the privacy manipulation, while successfully verified by the control measures, did not produce the expected effects on intention to use. Future research might explore more salient privacy violations.

Acknowledgments

This study is part of the project From Click to Clean: Consumer-Driven Sustainable Last-mile Logistics (LOG.KIEM.02.009) funded by Regieorgaan SiA and supported by the SiA SPRONGgroep LILS (Low Impact Lastmile logisticS SPR.ALG.03.006).

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