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HUMAN - AI COLLABORATION AND CUSTOMER INTENTION TO USE AUTONOMOUS DELIVERY ROBOTS IN LAST-MILE LOGISTICS: THE ROLE OF CUSTOMER TRUST

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ABSTRACT

The growing adoption of artificial intelligence and robotic systems in logistics has brought autonomous delivery robots (ADRs) to the forefront of last-mile distribution innovation. This paper investigates the extent to which three consumer-level perceptions, human–AI collaboration (HAC), AI transparency (AIT), and perceived safety (PS) shape customer trust (CT) and subsequent behavioral intention (BI) toward ADR services. Using Trust Theory and the Technology Acceptance Model as theoretical anchors, ten research hypotheses were constructed and validated through Partial Least Squares Structural Equation Modeling (PLS-SEM) on survey responses from 750 Vietnamese consumers with exposure to autonomous delivery robots (ADRs)-related services. The findings revealed that all proposed relationships received statistical support that human–AI collaboration (HAC) emerged as a dominant predictor of both customer trust (CT) and behavioral intention (BI) toward autonomous delivery robots (ADRs) services, with perceived safety (PS) and AI transparency (AIT) also yielding significant coefficients; moreover, customer trust (CT) predicted BI (β = 0.197) and served as a partial mediator linking each antecedent to adoption intention, as confirmed by bootstrapped 95% BCa intervals that did not include zero. The reliance on self-reported, single-country data constrains causal interpretation and geographic generalizability, pointing to the need for longitudinal and multi-cultural research designs that incorporate real behavioral outcomes. By simultaneously examining human–AI collaboration (HAC), AI transparency (AIT), and perceived safety (PS) within one coherent framework, this study offers a novel theoretical contribution to autonomous delivery robots (ADRs) adoption scholarship and delivers concrete recommendations for logistics practitioners, technology designers, and regulatory bodies aiming to foster trustworthy autonomous delivery ecosystems.

Keywords: Autonomous delivery robots, human–AI collaboration, AI transparency, perceived safety, customer trust, behavioral intention, PLS-SEM.

1. INTRODUCTION

The rapid convergence of artificial intelligence and robotics is transforming last-mile logistics. Autonomous delivery robots (ADRs), including both ground-based and aerial systems, are increasingly being explored and deployed to enhance delivery speed, efficiency, and service reliability [1], [2]. Despite technological advances and growing commercial adoption, the large-scale implementation of ADRs ultimately depends on consumer acceptance. Prior research suggests that adoption is influenced not only by technical performance but also by users' psychological perceptions, particularly trust [3], [4]. This challenge becomes even more salient in autonomous service environments, where reduced human involvement may increase uncertainty and perceived risk.

Recent studies have identified several factors that shape trust in AI-enabled services. Human–artificial intelligence collaboration reflects the extent to which users perceive meaningful human oversight and intervention in automated processes [5]. Artificial intelligence transparency refers to the degree to which system operations, decision-making processes, and data practices are communicated clearly to users [6], [7]. Perceived safety captures users' evaluations of the potential physical, operational, and data-related risks associated with autonomous systems [8]. Although these factors have received increasing scholarly attention, existing studies have largely examined them independently, providing limited understanding of their combined influence on trust formation in consumer-facing autonomous delivery contexts.

Furthermore, the mediating role of trust remains insufficiently explored. While trust is widely recognized as a critical determinant of technology acceptance, its role as an underlying mechanism linking perceptions of human–AI collaboration, AI transparency, and perceived safety to behavioral intention remains unclear in autonomous delivery settings. This limitation is particularly relevant in emerging markets, where technological readiness, digital literacy, and contextual conditions may significantly influence adoption behavior.

To address these gaps, this study proposes and empirically tests an integrated framework in which human–AI collaboration, AI transparency, and perceived safety jointly influence customer trust, which subsequently drives behavioral intention to use ADR services. The proposed model is primarily grounded in the Technology Acceptance Model (TAM) and Trust Theory, complemented by contemporary research on human–AI interaction [3]–[7]. The hypotheses are examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) based on survey data collected from Vietnamese consumers.

This study contributes to the literature in three ways. First, it develops a unified framework that integrates key perceptual antecedents of trust in autonomous delivery contexts. Second, it extends the concept of human–artificial intelligence collaboration to the consumer level by emphasizing the role of perceived human oversight in trust formation. Third, it provides empirical evidence regarding the mediating role of customer trust, thereby offering deeper insights into how consumer perceptions are translated into adoption intentions toward ADR services.

2. THEORETICAL BACKGROUND

The conceptual framework of this study is grounded in two foundational theories: the Technology Acceptance Model (TAM) and Trust Theory. First introduced by Davis [1] and later refined by Venkatesh et al. [2], TAM holds that an individual's willingness to adopt a new technology is shaped predominantly by how useful and easy to use that technology is perceived to be. Despite its widespread application across varied technological settings, researchers have progressively called for extending this model to account for psychological and relational dimensions, most notably trust, especially in contexts marked by uncertainty, risk delegation, and limited human control, all of which are defining features of artificial intelligence-powered autonomous systems [9], [11].

Trust Theory provides a complementary perspective by conceptualizing trust as a multidimensional cognitive construct grounded in beliefs about a system's competence, integrity, benevolence, and predictability [3], [4]. In digitally mediated service environments, customer trust reflects users' confidence that a system will perform reliably, act in accordance with their interests, and deliver outcomes in a dependable and consistent manner [3]–[5]. For autonomous delivery robots, trust becomes particularly important because consumers must rely on the system's decisions and actions despite having limited direct control over its operations.

When integrated, TAM and Trust Theory provide a comprehensive foundation for understanding technology adoption in AI-enabled service environments. While TAM explains how users form intentions to adopt new technologies, Trust Theory offers insight into the psychological mechanisms through which uncertainty and perceived risk are reduced. Building on these perspectives, the present study proposes that human–AI collaboration, artificial intelligence transparency, and perceived safety represent key antecedents of customer trust toward autonomous delivery robots (ADRs), which subsequently influences consumers' behavioral intention to use such services.

To establish conceptual clarity, the principal constructs are defined as follows. Autonomous delivery robots (ADRs) refer to ground-based or aerial robotic systems designed to autonomously perform last-mile delivery tasks with minimal human intervention [20], [21]. Customer trust reflects consumers' confidence that an ADR system is reliable, dependable, and capable of acting in their best interests [3]–[5]. Behavioral intention refers to an individual's willingness and likelihood of using ADR services in the future [1], [2]. Human–AI collaboration describes the extent to which consumers perceive meaningful human involvement in supervising, monitoring, and managing AI-driven operations [6], [7]. AI transparency refers to the perceived openness and understandability of system processes, including decision-making procedures and data-handling practices [12]–[15]. Perceived safety captures consumers' assessments of the potential physical, operational, and data-security risks associated with ADR usage [16]–[18].

Within the fields of human–computer interaction and organizational behavior, human–AI collaboration has emerged as an increasingly important construct for understanding trust formation in artificial intelligence-enabled systems. Seeber et al. [6] conceptualize human–AI collaboration as a cooperative arrangement in which human and artificial intelligence agents contribute complementary capabilities while humans retain responsibility for consequential decisions. In consumer-oriented autonomous service environments, perceptions of meaningful human oversight are expected to play a particularly important role in fostering trust. When consumers believe that human operators actively monitor system performance, evaluate outcomes, and can intervene when necessary, perceived uncertainty and concerns regarding autonomous system failures are significantly reduced [7], [8]. From a Trust Theory perspective, the presence of human oversight enhances perceptions of accountability, reliability, and controllability, thereby strengthening consumers' confidence in the system's ability to operate in a safe and dependable manner [9]–[11].

Empirical support for this proposition is well established. Yang et al. [7] conducted a large-scale experimental investigation in which participants were exposed to varying levels of human involvement in artificial intelligence decision-making environments. Their findings revealed that individuals who perceived greater human presence consistently reported higher levels of trust than those interacting with fully autonomous systems lacking visible human oversight. Similar evidence was reported by Heerink et al. [8], whose longitudinal study of socially assistive robots demonstrated that perceived human supervisory involvement significantly contributed to trust development over time, even after controlling for prior technological familiarity and individual differences in attitudes toward automation. More broadly, Glikson and Woolley [9] identified human oversight, accountability, and opportunities for human intervention as critical antecedents of trust in artificial intelligence systems across diverse application domains. These findings suggest that users are more willing to trust AI-enabled services when they believe that human operators remain capable of monitoring system performance and correcting potential errors. Complementing this perspective, Floridi et al. [10] argue that meaningful human oversight represents a fundamental prerequisite for responsible and trustworthy artificial intelligence, while Lee and See [11] contend that appropriate trust in automation develops only when users are confident that effective human corrective mechanisms remain available. Taken together, this body of evidence indicates that perceptions of human–AI collaboration are likely to strengthen customer trust in autonomous delivery robots. Therefore, the following hypothesis is proposed:

H1a: Human–AI collaboration positively affects customer trust in autonomous delivery robots.

Transparency has been widely recognized as a fundamental principle in the responsible design and governance of artificial intelligence systems [12], [13]. As a multidimensional construct, AI transparency encompasses the explainability of algorithmic outputs, the interpretability of system processes, and the openness of data handling and operational practices [14], [15]. From a Trust Theory perspective, transparency reduces information asymmetry between users and service providers, thereby lowering uncertainty and facilitating trust formation [3]–[5].

A growing body of empirical research supports this theoretical rationale. Shin [13] found that perceived algorithmic transparency was a significant predictor of trust across multiple artificial intelligence application domains, including recommendation systems, healthcare technologies, and navigation services. The study further demonstrated that transparency perceptions partially mediated the relationship between prior experience and trust, suggesting that transparency serves both as a direct antecedent of trust and as a mechanism through which familiarity is translated into user confidence. Similarly, Liao and Varshney [14] argue that explainability and user-centered transparency enhance individuals' understanding of artificial intelligence systems, thereby increasing trust and acceptance. Supporting this view, Larsson and Heintz [15] emphasize that transparent and accountable algorithmic practices are essential for fostering public confidence in artificial intelligence-enabled systems. Collectively, these studies suggest that greater transparency can reduce uncertainty, strengthen trust, and improve user acceptance of AI technologies. Therefore, the following hypothesis is proposed:

H1b: Artificial intelligence transparency positively affects customer trust in autonomous delivery robots.

Among the determinants of trust in autonomous systems, perceived safety consistently emerges as one of the most influential factors, encompassing consumers' evaluations of physical safety, operational reliability, and data security [16]–[18]. From a Trust Theory perspective, safety perceptions reduce uncertainty and perceived vulnerability, thereby strengthening confidence in a system's ability to operate reliably and in users' best interests [3]–[5]. Consequently, perceived safety is expected to play a central role in trust formation within autonomous delivery contexts.

A growing body of empirical research supports this proposition. Fridman [17] found that perceptions of operational safety significantly influence users' confidence in autonomous technologies and their willingness to engage with such systems. Similarly, Chen et al. [16] reported that perceived reliability and security were important predictors of customer trust in autonomous delivery technologies, highlighting the importance of both physical and information-related safety dimensions. These findings are consistent with Featherman and Pavlou [18], who argue that perceived risk and safety considerations represent fundamental determinants of technology acceptance, particularly in environments characterized by uncertainty and limited user control. Collectively, this evidence suggests that consumers are more likely to trust autonomous delivery robots when they perceive them as safe, reliable, and capable of minimizing potential risks. Therefore, the following hypothesis is proposed:

H1c: Perceived safety positively affects customer trust in autonomous delivery robots.

Beyond their role in fostering customer trust, human–AI collaboration, AI transparency, and perceived safety may also exert direct influences on consumers' behavioral intentions toward autonomous delivery robots. This proposition is consistent with the Technology Acceptance Model (TAM), which suggests that users form adoption intentions not only through evaluative beliefs but also through perceptions that reduce uncertainty and enhance perceived control over technology use [1], [2].

In the context of autonomous delivery services, perceptions of meaningful human involvement may directly increase behavioral intention by enhancing users' sense of control, accountability, and reassurance regarding system operations [17], [11]. Similarly, AI transparency may encourage adoption by improving users' understanding of how the system functions, thereby reducing ambiguity and increasing confidence in interacting with autonomous technologies [13], [15]. Perceived safety may also directly influence behavioral intention, as consumers are generally reluctant to engage with technologies that they perceive as physically unsafe, operationally unreliable, or vulnerable to data-security risks [18]. Prior research has consistently shown that safety-related perceptions play a central role in shaping users' willingness to adopt emerging technologies, particularly in environments characterized by uncertainty and limited human control [16], [18].

Taken together, these arguments suggest that human–AI collaboration, AI transparency, and perceived safety may influence behavioral intention not only indirectly through trust but also through direct psychological mechanisms related to perceived control, understanding, and risk evaluation. Accordingly, the following hypotheses are proposed:

H2a: Human–AI collaboration positively affects behavioral intention to use autonomous delivery robots.

H2b: AI transparency positively affects behavioral intention to use autonomous delivery robots.

H2c: Perceived safety positively affects behavioral intention to use autonomous delivery robots.

The role of customer trust as a key determinant of behavioral intention is among the most consistently supported propositions in the technology adoption literature [3]–[5]. By reducing perceived uncertainty, vulnerability, and psychological discomfort associated with novel technologies, trust creates the conditions necessary for individuals to develop favorable adoption intentions [1], [2]. This mechanism is particularly relevant in the context of autonomous delivery robots, where consumers must rely on the system's decisions and performance despite having limited direct control over its operations.

Substantial empirical evidence supports this relationship. Gefen et al. [5] demonstrated that customer trust significantly influenced both purchase intention and continued usage behavior in online environments, even after accounting for traditional technology acceptance factors. Similarly, Shin [13] found that trust was a significant predictor of behavioral intention across multiple AI application domains, highlighting its central role in shaping users' willingness to engage with AI-enabled services. More broadly, Glikson and Woolley [9] conclude that trust represents one of the most important mechanisms through which users evaluate and accept artificial intelligence systems. Consistent with these findings, Huang and Rust [19] argue that trust is essential for fostering positive user responses to AI-driven service technologies, particularly when service delivery involves a high degree of autonomy. Collectively, these studies suggest that stronger customer trust is likely to translate into greater willingness to adopt autonomous delivery robot services. Therefore, the following hypothesis is proposed:

H3: Customer trust positively affects behavioral intention to use autonomous delivery robots.

In addition to its direct influence on behavioral intention, customer trust functions as an important psychological mechanism through which perceptions of technology are translated into behavioral outcomes [3]–[5]. Within Trust Theory, trust reduces uncertainty and perceived vulnerability, thereby enabling favorable perceptions to evolve into adoption intentions. Consequently, trust is expected to serve as a key mediating mechanism linking human–AI collaboration, AI transparency, and perceived safety to consumers' behavioral intentions toward autonomous delivery robots.

With respect to human–AI collaboration, perceptions of meaningful human oversight enhance beliefs regarding accountability, reliability, and system controllability, which subsequently strengthen trust and increase willingness to adopt artificial intelligence-enabled services [17], [11]. Similarly, artificial intelligence transparency reduces informational asymmetry and improves users' understanding of system operations, thereby fostering trust that encourages behavioral engagement [13], [15]. In the case of perceived safety, favorable evaluations of physical, operational, and data-related safety reduce perceived risk and reinforce trust in the system's competence and dependability, ultimately increasing adoption intentions [16], [18].

Prior research provides substantial support for the mediating role of trust in technology adoption contexts. Gefen et al. [5] demonstrated that trust serves as a critical mechanism linking user perceptions to behavioral outcomes in online environments. Similarly, Shin [13] found that trust played a central role in explaining how perceptions of AI systems influenced users' intentions to engage with artificial intelligence-enabled services. Glikson and Woolley [9] further conclude that trust constitutes one of the primary pathways through which perceptions of AI characteristics are translated into acceptance and usage behaviors. Taken together, these findings suggest that customer trust is likely to mediate the effects of human–AI collaboration, artificial intelligence transparency, and perceived safety on behavioral intention. Therefore, the following hypotheses are proposed:

H4a: Customer trust mediates the relationship between human–AI collaboration and behavioral intention to use autonomous delivery robots.

H4b: Customer trust mediates the relationship between artificial intelligence transparency and behavioral intention to use autonomous delivery robots.

H4c: Customer trust mediates the relationship between perceived safety and behavioral intention to use autonomous delivery robots.

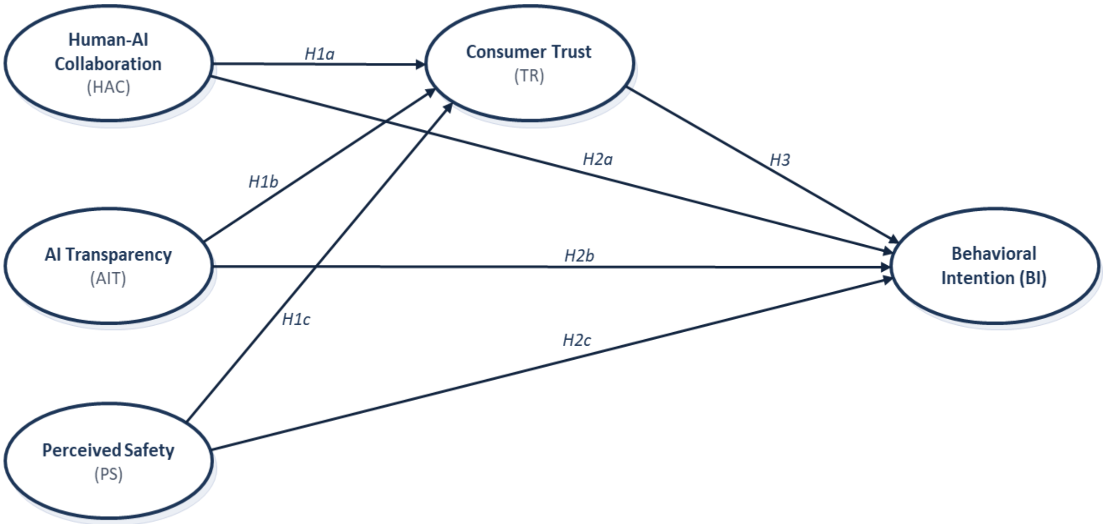

Figure 1. Proposed research model. (Source: Authors' own elaboration)

3. METHOD

3.1. Samples and data collection

This study employed a quantitative cross-sectional survey design to examine the relationships among Human–AI Collaboration (HAC), AI Transparency (AIT), Perceived Safety (PS), Customer Trust (CT), and Behavioral Intention to use autonomous delivery robots (BI). The target population consisted of urban consumers residing in Ho Chi Minh City, Vietnam, who had prior awareness of or exposure to automated and contactless delivery services. Ho Chi Minh City was selected as the research setting because of its large urban consumer base, high concentration of e-commerce activities, and relevance to emerging last-mile delivery services.

Data were collected through a structured online questionnaire distributed via social media platforms (Facebook and Zalo) and messaging applications between December 2025 and March 2026. A convenience sampling approach was employed due to the exploratory nature of autonomous delivery robot adoption in Vietnam, targeting respondents aged 18 years and above who resided, worked, or studied in urban districts of Ho Chi Minh City.

PLS-SEM was selected as the analytical approach because the study sought to predict behavioral intention and examine both direct and mediating relationships among multiple latent constructs. Consistent with established PLS-SEM guidelines, the ten-times rule was used as a preliminary minimum criterion, whereby the required sample should be at least ten times the maximum number of structural paths directed toward any endogenous construct [21]. Because Behavioral Intention received four direct structural paths, the preliminary minimum sample size was 40 observations. However, a substantially larger sample was targeted to improve statistical power and the stability of the PLS-SEM estimates. After data screening and the removal of incomplete or inconsistent responses, 750 valid questionnaires were retained for analysis.

The demographic profile of the sample was characterized by a predominance of Generation Z respondents, particularly individuals born between 2005 and 2007. This composition indicates that the sample was relatively concentrated among younger consumers who are familiar with digital and app-based services...

Table 1. Respondent Demographic Profile

Sample: N = 750 Vietnamese consumers | Study: Autonomous Delivery Robots (ADRs)			
Demographic Variable	Category	n	Percentage (%)
Gender	Male	377	50.3%
	Female	373	49.7%
Age Group	18–25	153	20.4%
	26–35	248	33.1%
	36–45	156	20.8%
	45+	179	23.9%
	Not specified	14	1.9%
Residential Area	Central District	204	27.2%
	Inner Suburban District	181	24.1%
	Outer Suburban District	187	24.9%
	Other	178	23.7%
Housing Type	Apartment	160	21.3%
	Private House	142	18.9%
	Urban Area (Housing Complex)	149	19.9%
	Rental Room	144	19.2%
	Other	155	20.7%
Occupation	Student	128	17.1%
	Office Worker	153	20.4%
	Business Owner/ Self-employed	157	20.9%
	Civil Servant / Public Official	157	20.9%
	Other	155	20.7%
Monthly Income	< 5,000,000 VND	159	21.2%
	5,000,000 - 10,000,000 VND	142	18.9%
	10,000,000 - 20,000,000 VND	162	21.6%
	20,000,000 - 30,000,000 VND	143	19.1%
	> 30,000,000 VND	144	19.2%
ADR Usage Frequency (Prior Experience)	Rarely / Never	213	28.4%
	1–3 times per month	182	24.3%
	1–2 times per week	163	21.7%
	More than 3 times per week	192	25.6%
Total		750	100.0%

Note: 'ADR Usage Frequency' serves as a proxy for prior experience with autonomous delivery robots (ADRs). Percentages are calculated as proportions of the total sample (N = 750).

3.2. Measures

All constructs were operationalized using reflective multi-item scales adapted from validated instruments in the existing literature. Each item was measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The research model consists of four independent variables: Human-AI Collaboration (HAC) was measured using four items (HAC1–HAC4), AI Transparency (AIT) was assessed with four items (AIT1–AIT4), Perceived Safety (PS) was operationalized through four items (PS1–PS4), Customer trust (CT) was measured using four items (CT1–CT4), Behavioral Intention to Use ADRs (BI) was measured with four items (BI1–BI4). Each concept is measured by 4 observed variables, a total of 20 items.

Table 2 provides a construct-level overview, mapping each latent variable to its conceptual definition and the primary validated sources from which the measurement approach was derived. This ensures conceptual traceability and alignment with established academic theory.

Table 2. Construct Overview: Conceptual Definitions and Theoretical Sources

Construct	Code	Conceptual Definition	Items	Theoretical Basis
Human–AI Collaboration	HAC	The degree to which consumers believe that human agents meaningfully oversee, monitor, and intervene in AI-driven delivery operations, thereby contributing to service quality and safety.	4	[5], [17], [19]
AI Transparency	AIT	The perceived degree to which autonomous delivery robot systems communicate clearly how they operate, make decisions, and handle user data.	4	[6], [7], [21]
Perceived Safety	PS	Consumers' subjective evaluations of physical hazards, operational dependability, and data-related risks associated with using autonomous delivery robots.	4	[8], [26]
customer trust	CT	Consumers' aggregate confidence in the dependability, safety, honesty, and ethical operation of autonomous delivery robot systems.	4	[10], [11], [9], [25]
Behavioral Intention	BI	An individual's stated readiness and anticipated likelihood of using, recommending, and engaging with autonomous delivery robot services in the near future.	4	[3], [4], [10], [7], [21], [25]

Note: HAC = Human–AI Collaboration; AIT = AI Transparency; PS = Perceived Safety; TR = Customer Trust (also referred to as CT); BI = Behavioral Intention to Use ADRs. All construct definitions were developed in accordance with the conceptual framework of the present study and grounded in the cited theoretical sources. Each construct is measured by four reflective indicators on a five-point Likert scale.

Table 3 provides a comprehensive item-level mapping, listing all 20 survey items, the specific conceptual dimension each item captures, and the validated academic sources from which each item was adapted. Items were modified to reflect the autonomous delivery robot context specific to this study.

Table 3. Measurement Constructs, Survey Items, Dimensions, and Sources

Construct	Code	Survey Item	Dimension	Source
Human-AI Collaboration (HAC)	HAC1	Delivery robots collaborate well with human staff.	Coordination	[5], [17]
	HAC2	The combination of humans and AI makes the delivery process more efficient.	Efficiency	[5], [17]
	HAC3	When issues arise, the coordination between humans and robots enables quick resolution.	Problem-solving	[17]
	HAC4	A hybrid human-AI model provides a better experience than using robots alone.	Hybrid preference	[5], [17]
AI Transparency (AIT)	AIT1	Delivery robots provide clear information about order status.	Information clarity	[7], [20]
	AIT2	I understand how the robot operates during the delivery process.	System understanding	[21], [7]
	AIT3	The AI system clearly explains its decisions (e.g., changes to delivery time).	Decision explainability	[6], [21]
	AIT4	The robot's processing is transparent and easy to understand.	Process transparency	[7], [20]
Perceived Safety (PS)	PS1	I feel that delivery robots operate safely in public areas.	Physical safety	[8], [26]
	PS2	I am not concerned about accident risks when using delivery robots.	Accident risk	[26]
	PS3	Delivery robots ensure the safety of goods.	Goods protection	[8], [26]
	PS4	The robot system is designed to minimize risks.	Risk minimization	[8]
Customer Trust (CT)	CT1	I trust the reliability of delivery robots.	Reliability trust	[10], [11]
	CT2	Delivery robots fulfill their commitments.	Commitment trust	[9], [10]
	CT3	Delivery robots operate honestly and dependably.	Integrity trust	[10], [9]
	CT4	I am willing to rely on delivery robots in the future.	Reliance intention	[23], [9]
Behavioral Intention (BI)	BI1	I intend to use delivery robots in the near future.	Usage intention	[3], [4]
	BI2	I will prioritize services that utilize delivery robots.	Service priority	[4]

	BI3	I am willing to recommend delivery robot services to others.	Word-of-mouth	[10]
	BI4	If given the opportunity, I would like to experience a delivery robot.	Trial intention	[3], [4]

Note: All items were measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Items were adapted from validated instruments and modified to reflect the autonomous delivery robot context. The 'Dimension' column identifies the specific conceptual sub-facet each item is designed to capture within its assigned construct.

3.3. Data analysis

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 software [27]. PLS-SEM was selected because of its suitability for prediction-oriented research, its ability to assess complex relationships among multiple latent constructs, and its robustness to violations of multivariate normality assumptions [13]. Consistent with established PLS-SEM procedures, the analysis was conducted in two stages: assessment of the measurement model followed by evaluation of the structural model [13].

In the first stage, the measurement model was evaluated to establish reliability and validity. Internal consistency reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR), with recommended thresholds exceeding 0.70 [15]. Convergent validity was examined through the Average Variance Extracted (AVE), with values above 0.50 indicating adequate convergence [13]. Discriminant validity was assessed using the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait Ratio (HTMT), with HTMT values below 0.85 considered acceptable [16].

In the second stage, the structural model was evaluated using a bootstrapping procedure with 5,000 resamples to estimate path coefficients, standard errors, and t-values for hypothesis testing [13]. In addition, collinearity diagnostics, coefficients of determination (R^2), and effect sizes were examined to assess the explanatory power and predictive capability of the proposed model.

4. RESULTS

4.1. Measurement model assessment

Prior to hypothesis testing, the measurement model was evaluated in terms of internal consistency reliability, convergent validity, and discriminant validity. As reported in Table 4, all indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.720 to 0.823 [22]. Cronbach's alpha values ranged from 0.720 to 0.798, while Composite Reliability (CR) values ranged from 0.826 to 0.868, exceeding the recommended threshold of 0.70 [22]. Convergent validity was supported by Average Variance Extracted (AVE) values ranging from 0.544 to 0.623, all above the recommended minimum value of 0.50 [22]. These results confirm satisfactory internal consistency reliability and convergent validity for all constructs.

Table 4. Construct Reliability and Validity

	Items	Loading	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Human-AI Collaboration (HAC)	HAC1	0.805	0.798	0.799	0.868	0.623
	HAC2	0.766				
	HAC3	0.79				
	HAC4	0.795				
AI Transparency (AIT)	AIT1	0.757	0.798	0.807	0.868	0.621
	AIT2	0.823				
	AIT3	0.772				
	AIT4	0.8				
Perceived Safety (PS)	PS1	0.788	0.793	0.793	0.866	0.617
	PS2	0.785				
	PS3	0.789				
	PS4	0.78				
Customer trust (CT)	CT1	0.733	0.72	0.72	0.826	0.544
	CT2	0.735				
	CT3	0.732				
	CT4	0.749				
Behavioral Intention to Use ADRs (BI)	BI1	0.721	0.72	0.722	0.826	0.544
	BI2	0.749				
	BI3	0.759				
	BI4	0.72				

Table 5. Fornell-Larcker Criterion

	HAC	AIT	PS	CT	BI
HAC	0.789				
AIT	0.033	0.788			
PS	0.02	-0.05	0.785		
CT	0.575	0.209	0.307	0.737	
BI	0.524	0.232	0.276	0.533	0.737
Note: HAC: Human-AI Collaboration, AIT: AI Transparency, PS: Perceived Safety, CT: Customer trust, BI: Behavioral Intention to Use ADRs					

Table 6. Heterotrait-Monotrait Ratio (HTMT)

	HAC	AIT	PS	CT	BI
HAC					
AIT	0.044				
PS	0.034	0.07			
CT	0.758	0.273	0.406		
BI	0.69	0.301	0.365	0.74	
Note: HAC: Human-AI Collaboration, AIT: AI Transparency, PS: Perceived Safety, CT: Customer trust, BI: Behavioral Intention to Use ADRs					

Table 7. Loadings and Cross Loadings

	HAC	AIT	PS	CT	BI
HAC1	0.805	0.021	0.022	0.445	0.43
HAC2	0.766	0.049	0.02	0.447	0.387
HAC3	0.79	0.021	0.019	0.443	0.429
HAC4	0.795	0.014	0.002	0.479	0.409
AIT1	0.028	0.757	-0.066	0.159	0.143
AIT2	0.034	0.823	-0.039	0.189	0.211
AIT3	0.034	0.772	-0.014	0.133	0.185
AIT4	0.008	0.8	-0.041	0.172	0.184
PS1	0.006	-0.067	0.788	0.258	0.208
PS2	0.041	-0.045	0.785	0.235	0.22
PS3	0.011	-0.036	0.789	0.242	0.221
PS4	0.005	-0.008	0.78	0.227	0.217
CT1	0.427	0.168	0.223	0.733	0.385
CT2	0.389	0.153	0.261	0.735	0.403
CT3	0.436	0.196	0.2	0.732	0.39
CT4	0.444	0.099	0.222	0.749	0.396
BI1	0.374	0.186	0.229	0.388	0.721
BI2	0.397	0.147	0.207	0.393	0.749
BI3	0.416	0.198	0.188	0.42	0.759
BI4	0.357	0.149	0.189	0.369	0.72

Discriminant validity was assessed using three complementary approaches. First, the Fornell–Larcker criterion was satisfied, as the square root of each construct's AVE exceeded its correlations with all other constructs (Table 5) [23]. Second, cross-loading analysis showed that each indicator loaded more strongly on its assigned construct than on any other construct (Table 7) [22]. Third, all HTMT values were below the recommended threshold of 0.85, with the highest value observed between Human–AI Collaboration and Customer Trust (HTMT = 0.758), indicating adequate discriminant validity (Table 6) [24].

Taken together, the results provide consistent evidence of discriminant validity across the three assessment criteria. Therefore, the measurement model demonstrates satisfactory internal consistency reliability, convergent validity, and discriminant validity, supporting its suitability for subsequent structural model assessment and hypothesis testing.

4.2. Structural model and hypothesis testing

Following the assessment of the measurement model, the structural model was evaluated using a bootstrapping procedure with 5,000 resamples. The results are presented in Table 8 and Figure 2.

The findings indicate that all proposed direct relationships were positive and statistically significant at the 0.001 level. Regarding the determinants of Customer Trust (CT), Human–AI Collaboration (HAC) exerted the strongest positive effect ($\beta = 0.562$, $t = 27.509$), followed by Perceived Safety (PS) ($\beta = 0.306$, $t = 12.037$) and AI Transparency (AIT) ($\beta = 0.206$, $t = 7.817$). These results provide support for H1a, H1b, and H1c. With respect to Behavioral Intention (BI), HAC remained the most influential predictor ($\beta = 0.400$, $t = 11.847$), while PS ($\beta = 0.217$, $t = 7.351$) and AIT ($\beta = 0.188$, $t = 6.661$) also demonstrated significant positive effects. In addition, Customer Trust positively influenced BI (β = 0.197, t = 5.119), supporting H2a, H2b, H2c, and H3.

The mediation hypotheses were examined through the indirect effects of HAC, AIT, and PS on BI via CT. The results revealed significant indirect effects for all three relationships. Specifically, HAC generated the strongest trust-mediated effect (β = 0.111, t = 5.032), followed by PS (β = 0.060, t = 4.544) and AIT (β = 0.041, t = 4.204). Because both the direct and indirect effects remained significant, Customer Trust was found to partially mediate the relationships between the three antecedent constructs and Behavioral Intention, thereby supporting H4a, H4b, and H4c.

Overall, all ten hypotheses were supported. The results confirm the explanatory power of the proposed model and highlight the important roles of Human–AI Collaboration, AI Transparency, Perceived Safety, and Customer Trust in shaping consumers' intentions to adopt autonomous delivery robot services.

Table 8. Structural parameter estimates

Hyp.	Path	Path coefficient	SE	t-value	Result
Direct Effects					
H1a	HAC → CT	0.562^{***}	0.020	27.509	Supported
H1b	AIT → CT	0.206^{***}	0.026	7.817	Supported
H1c	PS → CT	0.306^{***}	0.025	12.037	Supported
H2a	HAC → BI	0.400^{***}	0.034	11.847	Supported
H2b	AIT → BI	0.188^{***}	0.028	6.661	Supported
H2c	PS → BI	0.217^{***}	0.029	7.351	Supported
H3	CT → BI	0.197^{***}	0.039	5.119	Supported
Indirect Effects (Mediation)					
H4a	HAC → CT → BI	0.111^{***}	0.022	5.032	Supported
H4b	AIT → CT → BI	0.041^{***}	0.010	4.204	Supported
H4c	PS → CT → BI	0.060^{***}	0.013	4.544	Supported
*Notes: *** p < 0.001, ** p < 0.01, * p < 0.05. HAC: Human-AI Collaboration, AIT: AI Transparency, PS: Perceived Safety, CT: Customer trust, BI: Behavioral Intention to Use ADRs*					

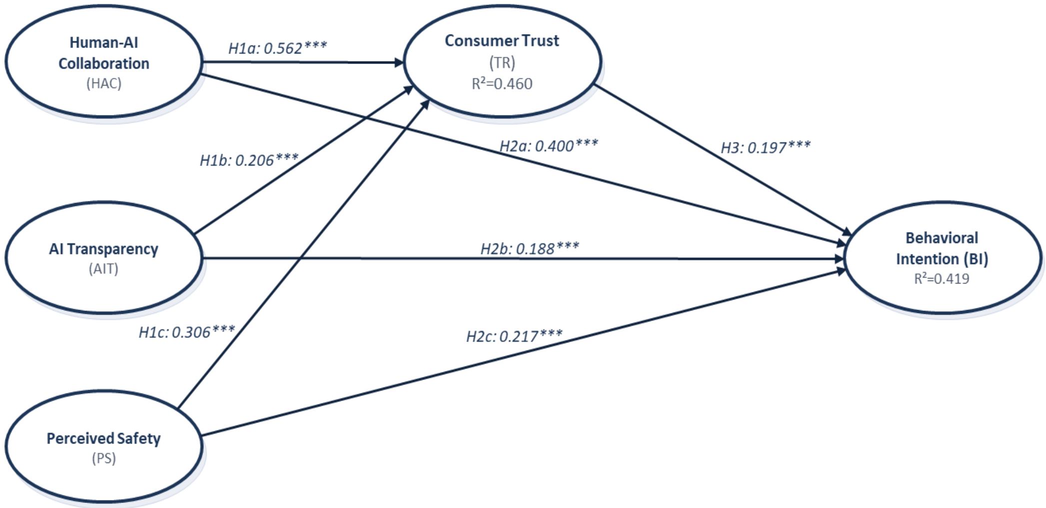

Figure 2. Structural model with standardized path coefficients.

Source: Authors' own elaboration

4.3. Discussion

The finding that Human–AI Collaboration (HAC) exerted the strongest positive effect on both Customer Trust (CT) and Behavioral Intention (BI) aligns with prior scholarship on trust in automation and human–AI interaction. Lee and See [16] emphasized that appropriate trust in automation depends on users' belief that human monitoring and corrective mechanisms remain available. Similarly, Raisch and Krakowski [25] argued that collaborative intelligence, in which human judgment complements AI autonomy, can enhance confidence in AI-enabled systems. Glikson and Woolley [14] further highlighted the importance of human oversight, accountability, and transparency in shaping trust in artificial intelligence. In the context of autonomous delivery robots, the strong effect of HAC suggests that consumers may place particular value on visible human involvement when autonomous systems operate in shared physical spaces. This finding indicates that perceived human oversight not only strengthens trust but also directly increases consumers' willingness to use ADR services.

The positive effect of AI Transparency (AIT) on Customer Trust (CT) is consistent with Shin [6], who showed that algorithmic transparency contributes to user trust in AI systems. It also aligns with Liao and Varshney [13], who argued that user-centered explainability can improve individuals' understanding of AI systems and thereby support trust and acceptance. The comparatively smaller effect of AIT relative to HAC suggests that, in embodied and service-oriented AI environments, consumers may prioritize human oversight, accountability, and perceived controllability over transparency alone when forming trust judgments [16], [18], [25]. Nevertheless, the significant direct effect of AIT on BI confirms that informational openness remains an important adoption cue. By reducing ambiguity and improving users' understanding of system operations, AI transparency can lower cognitive barriers and encourage consumers' willingness to engage with autonomous delivery technologies [6], [7].

The positive effect of Perceived Safety (PS) on Customer Trust (CT) is consistent with prior research identifying safety as a fundamental prerequisite for the acceptance of autonomous technologies. Fridman [19] found that perceptions of operational safety significantly influence users' confidence in autonomous systems, while Chen et al. [8] reported that reliability and security perceptions are important determinants of trust in autonomous delivery technologies. These findings suggest that consumers are more likely to trust autonomous delivery robots when they perceive the technology as reliable, secure, and capable of minimizing potential risks. From a Trust Theory perspective, favorable safety perceptions reduce perceived vulnerability and uncertainty, thereby strengthening confidence in the system's competence and dependability [3], [4].

The direct effect of PS on Behavioral Intention (BI) is also consistent with existing literature. Chen et al. [8] highlighted the importance of safety-related perceptions in shaping consumers' willingness to adopt autonomous delivery technologies, while Featherman and Pavlou [20] argued that risk and safety evaluations directly influence technology adoption decisions, particularly in contexts characterized by uncertainty and limited user control. These findings indicate that consumers may be reluctant to engage with autonomous delivery services if they perceive unacceptable physical, operational, or data-security risks, regardless of their overall trust in the technology.

The positive influence of Customer Trust (CT) on BI further corroborates extensive technology adoption research linking trust to behavioral outcomes [3], [4]. This finding is also consistent with Glikson and Woolley [14], who identified trust as one of the primary mechanisms through which perceptions of AI systems are translated into user acceptance and usage behavior. Together, these results reinforce the central role of trust in shaping consumers' intentions to adopt autonomous delivery robot services.

All ten hypotheses received empirical support, collectively confirming the coherence and explanatory power of the proposed model. Among the direct effects, Human–AI Collaboration (HAC) emerged as the strongest predictor of both Customer Trust (CT) and Behavioral Intention (BI). This finding suggests that, in the context of autonomous delivery robots operating in shared public environments, consumers place considerable importance on the perception that meaningful human oversight remains available. The comparatively smaller, yet still significant, effects of AI Transparency (AIT) and Perceived Safety (PS) indicate that these factors also contribute to consumer evaluations of autonomous delivery technologies, although their influence appears less pronounced than that of perceived human involvement.

The results further demonstrate that Customer Trust (CT) partially mediates the relationships between HAC, AIT, PS, and BI. This finding suggests that trust serves as an important, but not exclusive, mechanism through which consumer perceptions are translated into adoption intentions. The coexistence of significant direct and indirect effects indicates that consumers evaluate autonomous delivery robots through multiple psychological pathways. On the one hand, perceptions of collaboration, transparency, and safety enhance trust, which subsequently encourages adoption. On the other hand, these perceptions also exert direct influences on behavioral intention, reflecting more immediate evaluations of system controllability, understandability, and perceived risk.

The differing magnitudes of the indirect effects provide additional insight into the mediation mechanism. Human–AI Collaboration generated the largest trust-mediated effect, followed by Perceived Safety and AI Transparency, suggesting that perceptions of human oversight are more strongly associated with trust formation than safety or transparency evaluations. This finding may reflect the reassurance provided by visible human involvement, which enhances perceptions of accountability and intervention capability in autonomous service environments. Overall, the results support a partial mediation structure in which Customer Trust serves as an important, though not exclusive, mechanism linking Human–AI Collaboration, AI Transparency, and Perceived Safety to Behavioral Intention. While trust translates favorable perceptions into stronger adoption intentions, consumers also respond directly to cues related to human oversight, transparency, and safety when evaluating autonomous delivery robot services.

The prominent roles of Human–AI Collaboration (HAC) and Customer Trust (CT) may be particularly relevant in the context of emerging markets, where autonomous delivery technologies remain at an early stage of deployment and direct consumer experience is relatively limited. Under such conditions, consumers may rely more heavily on visible signals of human oversight and trustworthiness when forming judgments about unfamiliar technologies. This interpretation is consistent with the broader technology adoption literature, which suggests that trust becomes especially important when users face uncertainty and lack prior experience with technological innovation [3], [4], [14].

5. CONCLUSION

5.1. Theoretical implications

This study makes several important theoretical contributions to the literature on artificial intelligence adoption and autonomous logistics systems. First, it extends existing research by integrating three key perceptual antecedents Human–AI Collaboration (HAC), AI Transparency (AIT), and Perceived Safety (PS), within a unified trust-mediated framework. While prior studies have typically examined these constructs independently, the present study demonstrates their simultaneous and complementary influences on Customer Trust (CT) and Behavioral Intention (BI) in the context of autonomous delivery robots. By examining these factors within a single model, the study contributes to a more comprehensive understanding of consumer acceptance of embodied AI technologies.

Second, the findings contribute to Trust Theory by demonstrating that Customer Trust functions as a partial rather than a full mediator between the proposed antecedents and Behavioral Intention. This result suggests that trust operates as an important mechanism through which perceptions of collaboration, transparency, and safety influence adoption intentions, while also indicating that these factors exert direct effects on consumer decision-making. The findings therefore support a more nuanced view of technology adoption, in which both trust-based and direct cognitive evaluation processes jointly shape behavioral outcomes.

Third, the study contributes to the human–AI interaction literature by highlighting the prominent role of perceived Human–AI Collaboration. The results indicate that perceptions of meaningful human oversight exert the strongest influence on both Customer Trust and Behavioral Intention among the examined antecedents. This finding suggests that, in physically interactive autonomous service environments, consumers place particular importance on the availability of human supervision and intervention capabilities. Such evidence lends support to emerging hybrid intelligence perspectives, which emphasize the complementary integration of human judgment and AI autonomy in fostering user acceptance of embodied AI systems.

Finally, the study extends the application of technology adoption theories to the emerging context of autonomous delivery robots in an emerging market setting. By providing empirical evidence from Vietnam, the research broadens the geographical and contextual scope of existing AI adoption literature, which has predominantly focused on developed economies and digital service environments.

5.2. Practical implications

The findings of this study provide several practical implications for logistics firms, technology developers, and policymakers seeking to facilitate the adoption of autonomous delivery robots (ADRs).

First, organizations should prioritize the development and communication of visible human oversight mechanisms. Given that Human–AI Collaboration (HAC) emerged as the strongest predictor of both Customer Trust (CT) and Behavioral Intention (BI), ADR systems should be designed to make human supervision explicit to users. Features such as real-time remote monitoring, emergency intervention capabilities, customer service support channels, and human-assisted problem resolution can enhance perceptions of accountability and controllability, thereby strengthening trust and encouraging adoption.

Second, improving AI Transparency (AIT) remains essential for reducing uncertainty and increasing user confidence. Organizations should clearly communicate how ADR systems operate, how delivery decisions are made, and how customer data are collected, stored, and protected. User-friendly interfaces that provide understandable explanations of system behavior can improve consumers' understanding of autonomous technologies and reduce resistance to adoption.

Third, ensuring and communicating safety standards should be a strategic priority. Firms should invest in both operational safety measures, such as obstacle detection, collision avoidance, and emergency response protocols, and information security mechanisms designed to protect customer data. Equally important is the effective communication of these safeguards through certifications, safety guidelines, public demonstrations, and awareness campaigns that reinforce consumer confidence in ADR services.

Fourth, policymakers can support ADR adoption by establishing clear regulatory frameworks governing safety, accountability, and data protection. Transparent regulations and certification standards can reduce public uncertainty while providing organizations with guidelines for the responsible deployment of autonomous delivery technologies.

Finally, the identified mediating role of Customer Trust suggests that organizations should adopt a trust-centered design approach. Rather than focusing exclusively on operational efficiency and technological performance, firms should incorporate psychological acceptance factors into the development and implementation of ADR systems. Strategies that simultaneously enhance perceptions of human oversight, transparency, and safety are likely to be more effective in fostering long-term consumer acceptance and sustainable adoption.

5.3. Limitations and future directions

Despite its contributions, this study has several limitations that should be acknowledged. First, the use of a cross-sectional research design limits the ability to establish causal relationships among the examined constructs. Although the proposed relationships are theoretically grounded, future studies should employ longitudinal designs to investigate how customer trust and adoption intentions evolve as consumers accumulate direct experience with autonomous delivery robots (ADRs).

Second, the study relied on convenience sampling and self-reported data collected from consumers in Vietnam. While this approach is appropriate for exploratory research in an emerging technological context, it may limit the representativeness and generalizability of the findings. Future studies should consider probability-based sampling techniques and larger, more diverse populations to improve external validity.

Third, the research was conducted within a single-country context. Consumer perceptions of AI systems may vary across cultural, economic, and technological environments. Therefore, future research should undertake cross-cultural and cross-national comparisons to assess the stability and generalizability of the proposed model across different institutional settings.

Fourth, the study employed a scenario-based evaluation approach rather than observing actual usage behavior. Although this method is widely used for emerging technologies that have not yet achieved widespread adoption, stated behavioral intentions may differ from real-world behavior. Future research should incorporate field experiments, pilot implementations, or behavioral tracking data to enhance ecological validity and provide stronger evidence regarding actual ADR adoption.

Finally, future studies may extend the proposed framework by incorporating additional antecedents and boundary conditions. Variables such as perceived usefulness, social influence, perceived risk, regulatory trust, and service quality may provide further insight into ADR adoption. In addition, examining moderating effects associated with age, technology readiness, digital literacy, and prior experience with AI technologies may contribute to a more nuanced understanding of heterogeneous adoption patterns across consumer segments.

5.4. Concluding remarks

This study investigated the psychological mechanisms underlying consumer adoption of autonomous delivery robots (ADRs) in last-mile logistics by developing and empirically testing a trust-mediated framework. Drawing upon the Technology Acceptance Model (TAM) and Trust Theory, the research examined the effects of Human–AI Collaboration (HAC), AI Transparency (AIT), and Perceived Safety (PS) on Behavioral Intention (BI), as well as the mediating role of Customer Trust (CT).

Based on survey data collected from 750 consumers in Vietnam and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings provided support for all proposed hypotheses. Among the examined antecedents, Human–AI Collaboration emerged as the strongest predictor of both Customer Trust and Behavioral Intention, highlighting the importance of perceived human oversight in fostering acceptance of autonomous delivery technologies. AI Transparency and Perceived Safety also exerted significant positive effects, both directly and indirectly through Customer Trust. Furthermore, Customer Trust was found to partially mediate the relationships between the antecedent variables and Behavioral Intention, indicating that consumers rely on both trust-based and direct cognitive evaluations when forming adoption intentions.

These findings demonstrate that the successful deployment of ADRs depends not only on technological capabilities but also on the effective management of consumer perceptions and psychological acceptance. By integrating Human–AI Collaboration, AI Transparency, and Perceived Safety within a unified trust-mediated framework, this study contributes to a more comprehensive understanding of consumer adoption of embodied AI systems and extends existing knowledge on human–AI interaction in real-world service settings.

In practical terms, the results suggest that organizations seeking to accelerate ADR adoption should prioritize human-centered system design, transparent communication, and robust safety mechanisms that strengthen customer trust. As autonomous delivery technologies continue to evolve, fostering trust through accountable, transparent, and safe AI systems will be essential for their sustainable integration into modern logistics ecosystems.

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