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Integrating technological, individual, and social perspectives: Formation mechanisms and group heterogeneity in willingness to adopt unmanned delivery service

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Abstract

As a pivotal innovation in smart logistics, unmanned delivery has become technically feasible but still lags expected market penetration. Its large-scale diffusion critically depends on improving consumer acceptance and usage intentions. This research investigates the psychological and behavioral determinants of consumer adoption of unmanned delivery services, specifically elucidating the underlying operative mechanisms and the demographic variation in their effects. Integrating the diffusion of innovations theory and social influence theory within the technology acceptance model framework, we develop and validate a comprehensive technology–individual–society analytical model using structural equation modeling. The findings show that perceived usefulness and perceived ease of use are the primary antecedents of consumers' intention to use unmanned delivery services, and that technological, individual, and social factors each exert significant influence on adoption behavior. Furthermore, the determinants of usage intention exhibit greater heterogeneity across age and education cohorts than across gender groups. By applying this analytical framework to the distinctive context of unmanned delivery, this study addresses a critical gap in the prior literature, which has traditionally overemphasized technical optimization while neglecting consumer perspectives.

Introduction

The rapid advancement of technologies such as the Internet of Things (IoT), big data, and artificial intelligence (AI) is fundamentally driving the logistics industry toward intelligent transformation. Within smart logistics systems, unmanned aerial vehicles (UAVs) and unmanned ground vehicles have emerged as key innovation directions and pivotal trends for the future of delivery. UAV delivery overcomes limitations of traditional ground transportation, offering significant advantages for the rapid dispatch of emergency medical supplies and in proving services to geographically remote areas. Research by H. Zhang et al. (2023) indicates that advanced scheduling schemes can substantially lower delivery costs and optimize routes, ensuring safe and efficient transport even in complex urban low-altitude airspace. Similarly, unmanned ground vehicle delivery achieves precise localization and autonomous navigation through multisource perception fusion and Simultaneous Localization and Mapping (SLAM) algorithms. These capabilities enable the reliable execution of contactless delivery tasks in remote areas and enclosed environments, while significantly mitigating risks associated with interpersonal contact (Zuo & Shen, 2023). Collectively, recent technological breakthroughs confirm the technical feasibility of unmanned delivery for improving operational efficiency and reducing costs. However, despite the technological merits, commercial rollout and large-scale market adoption of unmanned delivery remain far below expectations. This disparity underscores the imperative to redirect research attention from pure technological optimization to the psychological and behavioral factors that determine consumer needs and acceptance.

Rapid technological advancement does not automatically lead to commensurate market adoption. Successful large-scale deployment of unmanned delivery systems hinges not only on technological maturity but, more fundamentally, on consumer acceptance and willingness to use the service (Marangunić & Granić, 2015; Osakwe et al., 2022; Taherdoost, 2018). Consumer perceptions are crucial in determining the industry’s long-term viability, as persistent concerns—such as privacy risks inherent in drone operations and the potential for cargo damage due to equipment malfunction—can substantially erode user trust (Sun & Moon, 2025). Furthermore, contemporary consumer expectations for delivery services extend beyond basic performance metrics (e.g., speed and accuracy) to emphasize personalized and convenient user experiences (Ermağan et al., 2024). Therefore, it is important to analyze in depth consumers' needs and expectations for unmanned delivery services to better support the sustainable development of the industry.

Current logistics delivery research remains markedly technology-centric, with the literature concentrating heavily on process optimization, delivery-model innovation, and increasingly sophisticated routing algorithms (Guo, 2024; Hur & Won, 2024; Rinaldi et al., 2024). This body of work has produced a relatively mature theoretical base concerning intelligent scheduling, cost efficiency, and environmental benefits. Nevertheless, two interrelated shortcomings persist. First, the predominant emphasis on technical improvement has led to an insufficient examination of consumer acceptance of novel delivery paradigms, creating a meaningful gap between technological feasibility and market viability. Second, empirical investigation of user behavior regarding unmanned logistics is underdeveloped: extant studies prioritize engineering problems, such as drone path planning and scheduling optimization, while largely neglecting core issues of public perception, the determinants of those perceptions, and enduring concerns about privacy, security, and trust in unmanned services. This imbalance between supply-side (technological) and demand-side (behavioral) research therefore severely constrains the commercial diffusion of unmanned delivery technologies. Furthermore, studies on usage intention continue to rely heavily on classical frameworks—most notably the Technology Acceptance Model (TAM) and its extensions—which, despite strong validation in contexts such as e-government and self-directed learning, show limited explanatory power in the unmanned delivery domain (Y. Wang et al., 2025; Nguyen et al., 2024). TAM's core constructs insufficiently capture domain-specific attributes (e.g., perceived privacy risk and perceived safety) and often fail to account for heterogeneous individual needs and relevant psychological dispositions (Sun & Moon, 2025). Finally, much existing research adopts an individual decision-making perspective on technology adoption and lacks an integrated analysis that combines social, cultural, environmental, and technological innovation characteristics, which impedes the construction of a more comprehensive model of usage intention.

This study examines consumer behavior in unmanned delivery logistics. Anchored in the TAM, it develops a unified analytical framework to systematically explicate the mechanisms underlying consumers' intention to use unmanned delivery services. This framework integrates three critical dimensions—technological, individual, and social—and seeks to bridge the persistent gap between technology-oriented research and demand-side inquiry. Specifically, the research addresses the following key questions:

(1) What are the principal determinants of consumers' intention to use unmanned delivery services, and how large are their effects?

(2) When consumers are differentiated by gender, age, and educational attainment, do they exhibit significant heterogeneity in the formation of usage intention, and if so, which factors explain these differences?

To answer these questions, we extend TAM by constructing a usage-intention model that incorporates individual, technological, and social factors. We employ Structural Equation Modeling (SEM) to test the hypothesized relationships and assess consumers' willingness to adopt unmanned delivery services, and we conduct multigroup SEM to examine structural heterogeneity across demographic cohorts (e.g., gender, age, and educational attainment).

The remainder of this paper is organized as follows: Section 2 reviews relevant literature and systematically presents the research hypotheses derived from the integrated framework. Section 3 details the research methodology and data-collection procedures. Section 4 provides a comprehensive analysis of the results, including model-fit statistics, hypothesis-testing outcomes, and multigroup analysis findings. Section 5 discusses the theoretical and practical implications, offers recommendations for unmanned delivery companies, and outlines avenues for future research. Section 6 concludes with the key findings.

Theoretical background

Technology acceptance model, diffusion of innovation theory, and social influence theory

The TAM is a theoretical framework developed to explain and predict users' acceptance of, and subsequent behavioral engagement with, emerging technologies. Originally proposed by Davis (1989) to analyze adoption and utilization of computer technologies, the model centers on two core constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Its foundational premise is that PU and PEU jointly shape users' attitudes toward using technology, which in turn influence behavioral intention and ultimately actual usage. Moreover, PEU exerts a direct effect on PU: when a technology is perceived as intuitive and requires minimal effort, users are more inclined to evaluate it as functionally beneficial. Both PU and PEU affect usage attitude, which subsequently influences behavioral intention and mediates adoption outcomes. They are shaped by external variables, including system characteristics, individual differences, organizational factors, and environmental conditions. Subsequent refinement of TAM by Davis and Venkatesh (1996) indicated that the attitude only partially mediated the relationship between perceived usefulness and intention; for reasons of parsimony, later applications frequently omitted the attitude variable. TAM has exhibited broad generalizability across domains such as information systems, e-commerce, and mobile services. As scholarly inquiry deepened, the model was extended and theoretically enriched, yielding successor frameworks such as TAM2 and the unified theory of acceptance and use of technology. These models systematically incorporated additional variables, e.g., social influence, performance expectancy, and facilitating conditions, to enhance predictive precision and explanatory robustness across heterogeneous technological contexts. In the specific context of unmanned delivery services, PU can be reflected in their potential to enhance distribution efficiency and reduce operational costs, whereas PEU pertains to users' intuitive experience of the technological operation and interaction processes. Employing the TAM enables a more in-depth examination of the latent barriers and driving factors underlying consumer acceptance of unmanned delivery services.

The Diffusion of Innovations Theory (DIT), originally articulated by Everett M. Rogers, remains a foundational framework for explaining the complex process by which novel technologies or innovations disseminate and are adopted within social systems. Rogers defines an innovation as any idea, practice, or object perceived as new by an individual or other unit of adoption (Rogers et al.,2014). Diffusion is the time-ordered process through which innovation is communicated via various channels among members of a social system, encompassing how it is perceived, evaluated, adopted, and subsequently propagated throughout the broader social structure. Moreover, the aggregate spread of an innovation critically depends on communication channels—mechanisms through which information and influence flow from sources to potential adopters—commonly classified as mass-mediated and interpersonal channels. While mass media enables rapid, wide dissemination to large audiences, interpersonal channels facilitate bidirectional, face-to-face or peer-to-peer exchange and exert a stronger influence on attitude formation and adoption decisions. As an emerging technological innovation, unmanned delivery is subject to DIT factors that shape consumer acceptance. The DIT framework thus provides a robust lens for analyzing the key variables influencing consumer uptake. Consumers typically evaluate the relative advantage of unmanned delivery compared with conventional logistics modes, the perceived complexity of its interfaces and operational procedures, and its degree of trialability. Moreover, social influence and promotion through interpersonal communication channels can accelerate potential users' awareness and understanding of unmanned delivery's features and benefits, thereby substantially affecting their intention to adopt.

Social Influence Theory (SIT) examines the mechanisms through which individuals' attitudes, beliefs, and behaviors are shaped by their social environments and interactions with others (Kelman, 1958). It posits that behavior is influenced not only by internal motivations but also by relevant social groups, prevailing norms, and interpersonal

exchanges. Two foundational mechanisms—normative influence and informational influence—were distinguished by Deutsch and Gerard (1955). Normative influence involves shifts in attitudes or behavior driven by the desire for social approval or the avoidance of rejection, reflecting conformity motives. Informational influence arises in contexts of uncertainty or information asymmetry, where individuals rely on the judgments, actions, or verified knowledge of credible or expert others to adjust their own evaluations. Accordingly, SIT offers a critical lens for interpreting the determinants of technology-use behavior. Consumers' intention to use unmanned delivery services is likely shaped by factors such as peer recommendations, endorsements or evaluative coverage in authoritative media, and collective expectations about technology's novelty, reliability, and perceived safety. Together, these social influence mechanisms shape market acceptance and can alter the effectiveness of promotional and communication of unmanned delivery services.

Basic hypothesis of the model

The TAM is a well-validated and widely used theoretical framework for explaining individuals' adoption and use of information technologies. TAM identifies two central psychological constructs: PU and PEU (Fel et al., 2025). PU is a primary predictor of users' acceptance of unmanned delivery services; consumers are more willing to adopt such services when they perceive they substantially improve delivery efficiency, increase convenience, or offer other tangible benefits. PEU denotes users' subjective assessment of how easy and effort-free the system is to operate. Specifically, consumers are more likely to adopt an unmanned delivery system if they find it intuitive and simple to interact with. Crucially, PEU is theorized to positively influence both behavioral intention and PU. Huang et al. (2021), in a TAM-based study of designers' adoption of autonomous vehicles, confirmed that PU and PEU are critical predictors of technology acceptance: PEU positively influences PU, and both positively affect willingness to use. Similarly, Li et al. (2024) found that improving both PU and PEU increases acceptance of translation technology among college students. Therefore, this study proposes the following hypotheses:

H1: Consumers' perceived ease of use of unmanned delivery services positively influences their perceived usefulness.

H2: Consumers' perceived usefulness of unmanned delivery services positively influences their usage intention.

H3: Consumers' perceived ease of use of unmanned delivery services positively influences their usage intention.

Hypothesis considering technical factors

Service quality is defined as the gap between a user's prior expectations of a service and their subsequent perception of its performance (Parasuraman et al., 1988). High service quality improves users' overall experience and strengthens perceived usefulness. In the unmanned-delivery context, consistent high-quality performance—e.g., reliable timeliness, secure handling (low damage rates), and accurate fulfillment—leads consumers to perceive the service as more effective in meeting logistical needs. When users obtain tangible benefits—including greater convenience, operational efficiency, and cost reductions—their adoption intention increases (Sharma et al., 2024); such perceived benefits depend on the level of service quality delivered. High-quality support and timely problem resolution in information systems enhance perceived system helpfulness, indicating a positive association between service quality and perceived usefulness/system acceptance (X. Huang & Zhi, 2023). Accordingly, the following hypothesis is proposed:

H4: The service quality of unmanned delivery positively influences consumers' perceived usefulness of unmanned delivery services.

Perceived privacy risk refers to users' concerns about unauthorized access, use, or disclosure of personally identifiable information within a technological system (Lee, 2009). When consumers perceive elevated privacy risks, they tend to reassess the technology's practical utility. Specifically, if users believe unmanned delivery could facilitate data breaches or misuse of sensitive information, this negative perception reduces their evaluation of the technology's usefulness. Under high privacy risk, users may adopt unfavorable attitudes and perform a cognitive trade-off between perceived benefits and perceived threats (H. Wang et al., 2022). Prior research identifies perceived privacy risk as a robust negative predictor of service adoption and shows that it can undermine perceived usefulness. For example, in location-based services (LBS), privacy risk negatively affects both perceived usefulness and adoption intention; without adequate privacy safeguards, users cannot realize expected benefits, resulting in lower perceived usefulness (Oh et al., 2019; Zhou, 2013b). Unmanned delivery typically requires collecting and transmitting consumers' location and personal data (e.g., contact details, delivery addresses); the risk of interception or misuse by unauthorized third parties during transmission constitutes a credible threat. Consequently, privacy concerns can substantially discount consumers' evaluations of service value. Accordingly, the following hypothesis is proposed:

H5: Privacy risk negatively influences consumers' perceived usefulness of unmanned delivery services.

Hypothesis considering individual factors

Perceived technology anxiety is defined as a subjective state of unease, apprehension, or concern experienced when users interact with novel technological tools, systems, or environments (Meuter et al., 2003). It commonly arises from unfamiliarity with the technology, worries about potential operational errors or malfunctions, and doubts regarding one's self-efficacy. Elevated technology anxiety can substantially impair user engagement and interaction quality. When anxiety is pronounced, users show reduced confidence in their operational abilities, are less willing to experiment, and consequently form less favorable evaluations of perceived ease of use. Anxious users tend to construe technology as more difficult, cumbersome, and effort-intensive. Empirical research consistently demonstrates a negative association between technology anxiety and PEU. Individuals experiencing high technology anxiety are more likely to regard systems as challenging and of limited utility; as anxiety intensifies, subjective judgments of ease of use—and in some cases perceived usefulness—are adversely affected because cognitive concerns overshadow functional advantages (Baccarella et al., 2021; Yap et al., 2023). For example, a study on smartphone adoption among older adults conceptualized technology anxiety as an emotional fear response during device interaction and found that heightened anxiety reduces perceived ease of use and subsequent adoption propensity (T. Huang, 2023). Accordingly, this study advances the following hypothesis:

H6: Consumers' technological anxiety regarding unmanned delivery services negatively influences their perceived ease of use.

Individual innovation denotes a person's inherent propensity for openness to, and proactive engagement with, novel technologies and innovations. As a core construct in DIT, it functions as a critical predictor of technology acceptance behavior. Highly innovative individuals actively seek diverse information inputs and exhibit an enhanced capacity for reasoned decision-making even under uncertainty (Agarwal & Prasad, 1998kçearslan et al., 2025). From a consumer behavior perspective, such individuals display a pronounced preference for novelty; their cognitive systems are more adaptable to technological change, increasing their willingness to incur learning costs to master emerging systems and improving their ability to attenuate perceived application risks. This intrinsic motivational orientation fosters sustained intention and stable usage patterns. A study of pre-service teachers' adoption of IoT technologies demonstrated that individual innovativeness significantly influences the speed of innovation uptake, perceived ease of use, and recognition of enabling conditions (Gökçearslan et al., 2024). Likewise, research extending TAM into the

agricultural technology domain found a positive association between personal innovativeness and perceived ease of use (Mishra et al., 2024). Accordingly, this study advances the following hypothesis:

H7: Individual innovativeness positively influences consumers' perceived ease of use of unmanned delivery services.

Perceived pleasure is defined as the degree of intrinsic satisfaction or enjoyment an individual derives from interacting with a technological system (Davis et al., 1992). It captures the hedonic and affective quality of technology use and is a significant predictor of usage intention. In the unmanned delivery context, when consumers experience intrinsic enjoyment—stemming, for instance, from the service's novelty, seamless interaction, or futuristic attributes—this positive effect is hypothesized to elevate their cognitive appraisal of the system, particularly their judgment of its ease of use. A pleasant usage experience can induce cognitive ease, leading users to perceive operational processes as more intuitive and manageable. The facilitating effect of perceived pleasure on perceived ease of use has been empirically validated across diverse technological domains. Li et al. (2024) found that among Chinese university students, perceived pleasure significantly enhances perceived ease of use in the context of translation technologies; enjoyment reduces cognitive load and promotes effortless engagement. Similarly, Zhang et al. (2023) reported that pre-service teachers' perceived pleasure positively influences perceived ease of use of AI-enabled educational technologies, thereby reinforcing confidence and motivational readiness for adoption. Accordingly, this study proposes the following hypothesis:

H8: Consumers' perceived pleasure regarding unmanned delivery services positively influences their perceived ease of use.

Hypothesis considering social influence

Social influence denotes the extent to which an individual's decision process is shaped by actors in their social environment (Venkatesh et al., 2003). Individuals or groups can shape attitudes, behaviors, and technology-adoption choices through positive or negative social pressures manifested as social norms, peer influence, opinion leadership, and observational learning. As SIT articulates, adoption is conditioned by two mechanisms—normative and informational influence. In the unmanned-delivery context, consumers' exposure to others' usage behaviors and to explicit or implicit feedback can recalibrate their adoption assessment. Positive social feedback and endorsements are expected to strengthen adoption intention. Demonstrated social support and recognition function as reinforcing mechanisms that encourage engagement with novel technologies. SIT posits that users are more likely to adopt a technology when it is recommended by people with whom they have regular interpersonal contact. For example, social influence has been shown to significantly and positively predict intention to use online freight-forwarding platforms; higher perceived social influence correlates with stronger adoption willingness (Pinyanitikorn et al., 2024). Similarly, studies of electric vehicle adoption show that family members' and friends' perceptions and behaviors play a central role in shaping attitudes toward use (Boubker et al., 2024). Accordingly, this study advances the following hypothesis:

H9: Social influence positively influences consumers' usage intention for unmanned delivery services.

Construction of the overall model framework

This study uses the TAM as its foundational framework, given its proven ability to explain and predict users' technology acceptance and usage behavior. Within the emerging field of unmanned delivery, technical reliability and operational maturity are critical because they directly determine system performance and the user experience. Accordingly, service quality emerges as a primary technological antecedent of adoption. Consumers' evaluations of

operational stability, delivery accuracy, and performance efficiency substantially shape their adoption intention for such novel services. When unmanned delivery demonstrably meets expectations for time savings and logistical efficiency, PU is reinforced, increasing the likelihood of adoption. Conversely, users perceived privacy risk can significantly reduce acceptance, since concerns about the security of personal information diminish perceived benefits. In the broader context of digitalization and automation, privacy risk therefore assumes heightened salience. Consequently, this study treats service quality and perceived privacy risk as key technological determinants of intention to use unmanned delivery services.

Beyond technological and service attributes, consumer psychology and behavioral characteristics warrant systematic consideration. Individual cognition, attitudes, and needs influence how users interpret and evaluate unmanned delivery technologies. Incorporating individual-level variables clarifies motivational drivers and barriers to adoption. Because unmanned delivery frequently incorporates AI components, perceived complexity or opacity may depress PEU, potentially leading to avoidance or discontinuation. Drawing on DIT, individuals with higher personal innovation tend to be more open to novel technologies and more willing to try and adopt unmanned delivery services. Moreover, intrinsic enjoyment of the usage experience can amplify willingness to accept and use the service. Accordingly, this study includes technological anxiety, individual innovativeness, and perceived pleasure as individual-level constructs.

In socially embedded consumption contexts, individual decision-making is strongly influenced by the attitudes, expressed opinions, and observed behaviors of relevant social groups. Concurrently, discourse and information exchange in online and offline communities shape and recalibrate consumer perceptions of emerging technologies. Exposure to favorable evaluations and endorsements of unmanned delivery can raise awareness and, through normative and informational mechanisms, increase adoption intention. Hence, social influence is incorporated as a social-environmental factor affecting consumers' consideration and adoption decisions.

In sum, this study extends TAM by integrating technological, individual, and social dimensions to provide a comprehensive, multi-level explanatory framework for consumers' intention to use unmanned delivery services. Technological factors (service quality, perceived privacy risk) clarify how system attributes and vulnerabilities affect judgments of usefulness. Individual factors (technology anxiety, individual innovativeness, perceived pleasure) capture psychological dispositions and intrinsic evaluative tendencies that shape perceptions of ease of use and usefulness. Social factors (social influence) reflect exogenous normative pressures and informational cues from the broader social milieu. The overall conceptual model of consumers' intention to adopt unmanned delivery services is illustrated in Fig. 1.

Methods

This study uses SEM as the principal analytical technique because of its ability to estimate complex multivariate relationships, evaluate mediating pathways, and while simultaneously accounting for measurement errors. Additionally, SEM's multigroup analysis is essential for testing whether hypothesized relationships differ across demographic subgroups that influence intention to use unmanned delivery services. The questionnaire consisted of three sections designed to comprehensively assess respondents' intention to use unmanned delivery services. The first section provided a brief introduction to the survey's objectives and clarified the focal research phenomenon to promote informed participation. The second section collected demographic information—such as gender, age, and educational attainment—along with other characteristics required for subsequent heterogeneity analyses. The third section contained the measurement items for the nine core theoretical constructs (e.g., perceived usefulness, perceived ease of use, usage intention) comprising the integrated conceptual model, as summarized in Table 1. All items were adapted from established, validated scales; wording was carefully refined to ensure semantic equivalence

and contextual relevance to logistics service scenarios while preserving the constructs' theoretical integrity. To ensure measurement precision and robust statistical inference, all constructs were operationalized using a widely accepted five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). This scale captures both the direction and intensity of respondents' evaluative judgments, thereby improving sensitivity to differences among responses and supporting construct validity within the SEM framework.

Table 1
The scale items and literature sources.

Variables	Scale Items	Literature Sources
Perceived usefulness	PU1: I believe using unmanned delivery makes my package pickup and drop-off more efficient.	(Davis, 1989)
	PU2: I believe unmanned delivery improves my quality of life.	
	PU3: I believe unmanned delivery meets my need to pick up and drop off packages anytime.	
	PU4: I believe unmanned delivery reduces the chances of misplaced or lost packages.	
Perceived ease of use	PEU1: I can easily use unmanned delivery for picking up and dropping off packages.	(Davis, 1989)
	PEU2: I find the steps and rules for using unmanned delivery clear and easy to understand.	
	PEU3: I find using unmanned delivery for picking up and dropping off packages quite troublesome.	
Usage intention	UI1: I am willing to try using unmanned delivery.	(Davis, 1989)
	UI2: I would recommend unmanned delivery to others when it becomes available.	
	UI3: When I need to send or receive packages, I will prioritize using unmanned delivery.	
	UI4: I am willing to learn about and use additional features of unmanned delivery.	
Technology anxiety	TA1: I'm concerned that using driverless delivery will be more expensive.	(Meuter et al., 2003)(Xie et al., 2022)
	TA2: I feel that using driverless delivery carries a higher risk of accidents.	
	TA3: I'm worried that the systems or equipment of driverless delivery vehicles might malfunction during operation.	
Individual innovation	II1: I'm fascinated by emerging technologies like AI and actively explore how to use them.	(Rogers)(Agarwal & Prasad, 1998)
	II2: I closely follow the latest developments in autonomous delivery.	
	II3: I have some fresh ideas about autonomous delivery.	
Social influence	SI1: When my family uses unmanned delivery, I'll give it a try too.	(Venkatesh et al., 2003)
	SI2: After seeing the brand's promotional ads, I'll try using unmanned delivery.	
	SI3: When friends recommend unmanned delivery to me, I'll give it a try.	
Service quality	SQ1: I have greater confidence in the service quality of unmanned delivery.	(Parasuraman et al.)(Zhou, 2013a)
	SQ2: I believe the punctuality rate of unmanned delivery will influence my choice.	

Variables	Scale Items	Literature Sources
	SQ3: I believe the damage rate of goods during pickup and delivery by unmanned delivery will influence my choice.	
Perceived pleasure	PP1: I find the process of using unmanned delivery quite interesting.	(Davis et al., 1992)
	PP2: I believe using unmanned delivery for picking up and dropping off packages will be a pleasant experience.	
	PP3: Compared to traditional methods of picking up and dropping off packages, I consider unmanned delivery a superior option.	
Privacy risks	PR1: I'm concerned that when using unmanned delivery, hackers might attack my phone, leading to the leakage and illegal use of my personal privacy information.	(Dinev & Hart, 2006)(Niu & Meng, 2019)
	PR2: I'm concerned that when using unmanned delivery, merchants lack adequate safeguards for user privacy, resulting in receiving a flood of sales calls afterward.	
	PR3: I'm concerned that when using unmanned delivery, merchants require users to follow official accounts or download apps solely to divert traffic to other apps or collect user personal information.	

This study uses a sampling strategy to enhance generalizability and the robustness of the findings by covering a diverse cross-section of potential user segments, including habitual online shoppers, frequent parcel recipients, older adults, and other relevant groups. Data were collected via paper-based, offline questionnaires during 2025 in Changsha City, Hunan Province, China, targeting individual end-users. Surveys were administered in strategically selected zones with different logistical profiles: university campuses, industrial parks, residential communities, and commercial districts. University campuses and industrial parks present specific logistics demands and relatively enclosed environments conducive to unmanned delivery operation and management; residential communities generate high volumes of express deliveries (especially in high-rise or densely populated neighborhoods); commercial districts (e.g., office complexes and shopping centers) have distinct usage scenarios and attitudes. Throughout fieldwork, strict anonymity and confidentiality protocols were maintained; respondents were informed that their data would be used solely for non-commercial academic research. After removing questionnaires with missing data and outliers, 760 valid responses remained. Table 2 summarizes the sample characteristics.

In Table 2, gender distribution is nearly balanced: 387 males (50.9%) and 373 females (49.1%). Age composition is skewed toward younger cohorts: respondents aged 18–25 and 26–35 represented 44.3% and 21.7%, respectively; ages 36–45 account for 16.2%, while the 46–55 and 56 + groups comprise 8.2% and 6.2%, respectively. This pattern aligns with younger groups' higher transaction frequency and greater reliance on express delivery services. In terms of educational attainment, bachelor's degree holders constitute the largest segment (47.8%), whereas those with junior high education or below form the smallest group (9.3%), indicating a relatively concentrated educational profile given the age distribution. Occupationally, students account for 37.9% of the sample, underscoring the embedded role of parcel logistics in campus life. Employees of private enterprises and freelancers together account for 23.0%, indicating substantial demand among economically active and flexible labor segments. Regarding place of residence, respondents living in provincial capitals constitute the largest proportion (42.6%), while township residents represent only 7.1%, suggesting more developed service networks and higher utilization propensity in urban centers. Most respondents use express services multiple times per week or month, indicating these services are embedded in daily routines. Concerning awareness and use of unmanned delivery, 33.3% reported no prior exposure and 38.0% reported only partial knowledge; actual use remains comparatively low. This gap suggests limited diffusion of unmanned delivery services to date and shortcomings in current user experience relative to consumer expectations.

Table 2
Descriptive analysis of the sample.

Category		Frequency	Percentage (%)
Gender	Male	387	50.9
	Female	373	49.1
Age	< 18	26	3.4
	18–25	337	44.3
	26–35	165	21.7
	36–45	123	16.2
	46–55	62	8.2
	> 55	47	6.2
Education	Junior high school and below	71	9.3
	High school or technical Secondary school	140	18.4
	Junior college	105	13.8
	Undergraduate	363	47.8
	Master’s degree or higher	81	10.7
Average monthly income (CNY)	≤ 3000	317	41.7
	3001–5000	164	21.6
	5001–8000	160	21.1
	8001–10000	55	7.2
	> 10000	64	8.4
Occupation	Student	288	37.9
	Employees of state-owned enterprises or public institutions	99	13.0
	Private enterprise employees	175	23.0
	Freelance work	144	18.9
	Others	54	7.1
City	Beijing, Shanghai, Guangzhou, Shenzhen	109	14.3
	Provincial capital	324	42.6
	Prefecture-level city	177	23.3
	County town	96	12.6
	Township	54	7.1
Frequency of courier service usage	Every day	50	6.6

Category		Frequency	Percentage (%)
	A few times a week	286	37.6
	A few times in January	333	43.8
	Several times a year	60	7.9
	Rarely used	31	4.1
Awareness and Usage of Unmanned Delivery Services	Not familiar with it	253	33.3
	Familiar with it, but never used it	289	38.0
	Used it, but rarely	156	20.5
	Occasionally used it	43	5.7
	Frequently used it	19	2.5

Data analysis and results

Reliability testing of the model

Reliability refers to the dependability of measurement scores and reflects their consistency and stability (Carmines, n.d.). When random measurement error is effectively minimized, scales yield more consistent and stable outcomes. Scale reliability is commonly assessed using Cronbach's alpha (α), widely regarded as the primary index of internal consistency (Bonett & Wright, 2015). Alpha reflects the average interitem association relative to total score variance; higher values indicate stronger interitem correlation and, consequently, greater internal consistency. According to conventional benchmarks, $\alpha < 0.65$ indicates poor internal consistency; 0.66–0.70 suggests moderate reliability; and $\alpha > 0.70$ denotes strong internal consistency and high reliability (Devellis, n.d.). In this study, all nine constructs exhibited α values exceeding 0.70, indicating satisfactory to high internal consistency and supporting the suitability of these measures for subsequent validity analyses. Detailed reliability statistics are reported in Table 3.

Table 3
Model reliability tests.

Latent variable	Observed variable	CICT	Overall Cronbach's alpha
Perceived usefulness	PU1	0.681	0.828
	PU2	0.696	
	PU3	0.660	
	PU4	0.584	
Perceived ease of use	PEU1	0.692	0.792
	PEU2	0.680	
	PEU3	0.546	
Usage intention	UI1	0.690	0.837
	UI2	0.723	
	UI3	0.639	
	UI4	0.630	
Technology anxiety	TA1	0.552	0.768
	TA2	0.634	
	TA3	0.621	
Individual innovation	II1	0.560	0.772
	II2	0.646	
	II3	0.618	
Social influence	SI1	0.599	0.787
	SI2	0.621	
	SI3	0.663	
Service quality	SQ1	0.655	0.827
	SQ2	0.723	
	SQ3	0.683	
Perceived pleasure	PP1	0.674	0.817
	PP2	0.720	
	PP3	0.615	
Privacy risks	PR1	0.628	0.807
	PR2	0.673	
	PR3	0.667	

Validity testing

KMO and Bartlett's sphericity test

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy evaluates the suitability of data for factor analysis at both the overall sample and individual variable levels. Higher KMO values indicate that the sum of squared simple correlations substantially exceeds the sum of squared partial correlations—an ideal condition for factor extraction. Following Kaiser's guideline, datasets with KMO > 0.80 are considered highly suitable for factor analysis (Kaiser, 1974).

In this study, exploratory factor analysis (EFA) is conducted using IBM SPSS Statistics 24. As reported in Table 4, the overall KMO is 0.919, well above the 0.80 benchmark, indicating excellent sampling adequacy. Bartlett's test of sphericity is highly significant ($p < 0.001$), further confirming the factorability of the correlation matrix and providing a robust statistical foundation for subsequent analyses.

Table 4
KMO and Bartlett's test of sphericity.

Kaiser-Meyer-Olkin metrics		**0.919**
Bartlett's Sphericity Test	chi-square value	10382.322
	df	406
	significance	0.000

Model convergence validity test results

Convergent validity evaluates the extent to which multiple items intended to measure the same latent construct are strongly interrelated. It is commonly assessed via standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). Following Fornell and Larcker (1981), convergent validity is considered acceptable when AVE ≥ 0.50 and CR ≥ 0.60 (with ≥ 0.70 more typically recommended for mature scales). In this study, convergent validity is examined across nine constructs. As reported in Table 5, the CR values for the nine constructs are 0.827, 0.791, 0.835, 0.772, 0.764, 0.779, 0.828, 0.817, and 0.807, all exceeding the 0.60 criterion. Their AVE values surpass the 0.50 threshold. These results collectively indicate that all constructs exhibit satisfactory convergent validity, thereby supporting the reliability and validity of the measurement model.

Table 5
Model convergent validity test.

Latent variable	Observed variable	Standardized factor loading	P value	SMC	C.R.	AVE
Perceived usefulness	PU1	0.760	-	0.578	0.827	0.545
	PU2	0.784	***	0.614		
	PU3	0.740	***	0.548		
	PU4	0.663	***	0.440		
Perceived ease of use	PEU1	0.815	-	0.664	0.791	0.561
	PEU2	0.788	***	0.621		
	PEU3	0.630	***	0.397		
Usage intention	U1	0.788	-	0.622	0.835	0.560
	UI2	0.815	***	0.664		
	UI3	0.707	***	0.500		
	UI4	0.675	***	0.455		
Technology anxiety	TA1	0.647	-	0.419	0.772	0.531
	TA2	0.786	***	0.618		
	TA3	0.747	***	0.558		
Individual innovation	II1	0.761	-	0.579	0.764	0.519
	II2	0.714	***	0.509		
	II3	0.685	***	0.469		
Social influence	SI1	0.722	-	0.521	0.779	0.541
	SI2	0.749	***	0.561		
	SI3	0.735	***	0.540		
Service quality	SQ1	0.757	-	0.572	0.828	0.617
	SQ2	0.811	***	0.658		
	SQ3	0.787	***	0.619		
Perceived pleasure	PP1	0.769	-	0.591	0.817	0.598
	PP2	0.819	***	0.670		
	PP3	0.730	***	0.533		
Privacy risks	PR1	0.718	-	0.515	0.807	0.582
	PR2	0.783	***	0.612		
	PR3	0.786	***	0.618		

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

Model discrimination validity test results

Discriminant validity evaluates the degree to which latent constructs are empirically distinct from one another within a conceptual framework. It is commonly assessed by comparing the square root of each construct's average variance extracted (AVE) with its correlation coefficients. According to the Fornell–Larcker criterion, if the square root of a construct's AVE exceeds its correlations with all other constructs, adequate discriminant validity is established (Fornell & Larcker, 1981). In Table 6, the diagonal elements present the square roots of the AVEs for each latent construct, while the off-diagonal values denote the corresponding correlations. As shown, every diagonal value is greater than its associated correlations in the same row and column, indicating that each construct is empirically distinct from the others. These results substantiate strong discriminant validity for the measurement model.

Table 6
Model distinguishing validity tests.

SI	SI	PP	II	UA	PR	SQ	PEU	PU	UI
	0.736								
PP	0.722	0.773							
II	0.648	0.631	0.720						
AU	0.044	-0.125	-0.181	0.729					
PR	-0.251	-0.350	-0.292	0.062	0.763				
SQ	0.469	0.419	0.269	0.242	-0.081	0.785			
PEU	0.524	0.648	0.630	-0.200	-0.253	0.248	0.749		
PU	0.444	0.534	0.471	-0.070	-0.582	0.348	0.616	0.738	
UI	0.685	0.650	0.595	-0.068	-0.375	0.372	0.709	0.702	0.748

Common method bias test

This study employs Harman's single factor test to examine common method bias. The results indicate that the maximum factor variance explained is 31.88%, below the 40% critical threshold, suggesting that no significant common method bias is present in this research.

Structural equation model fit

This study employes AMOS 23.0 to estimate a covariance-based SEM, focusing on model evaluation via covariance structure analysis. In essence, the procedure compares the model-implied covariance matrix, derived from the hypothesized structure, with the observed covariance matrix from the sample data. When the discrepancy between these matrices falls within acceptable bounds, the model is considered to exhibit satisfactory fit to the empirical data, thereby supporting its adequacy.

As reported in Table 7, multiple global fit indices meet commonly accepted benchmarks. Specifically, the CMIN/DF ratio is 2.972 (< 3), RMSEA is 0.051 (< 0.08), and GFI, NFI, CFI, and AGFI each exceed 0.90 (Hu & Bentler, 1999). Collectively, these statistics indicate a high degree of congruence between the hypothesized model and the observed data, reinforcing the reasonableness and effectiveness of the SEM specified in this study.

Table 7
Model fitting results.

Fit index	Fitted value	Standard
CMIN	1048.996	-
DF	353	-
CMIN/DF	2.972	< 3
GFI	0.906	> 0.9
NFI	0.900	> 0.9
CFI	0.931	> 0.9
IFI	0.932	> 0.9
RMSEA	0.051	< 0.08

Path analysis of structural equation models

Path significance analysis (Table 8) indicates that both perceived ease of use and perceived usefulness exert significant positive effects on consumers' usage intention for unmanned delivery services ($\beta = 0.295$, $p < 0.001$; $\beta = 0.355$, $p < 0.001$), supporting Hypotheses H3 and H2, respectively. Service quality also has a significant positive effect on perceived usefulness ($\beta = 0.199$, $p = 0.015$), corroborating H4. Meanwhile, perceived usefulness is negatively affected by privacy risk ($\beta = -0.452$, $p < 0.001$) and positively affected by perceived ease of use ($\beta = 0.452$, $p < 0.001$), confirming H5 and H1. Individual innovativeness and perceived pleasure both exhibit significant positive effects on perceived ease of use ($\beta = 0.354$, $p < 0.001$; $\beta = 0.414$, $p < 0.001$), validating H7 and H8. By contrast, technology anxiety exerts a significant negative effect on perceived ease of use ($\beta = -0.084$, $p = 0.028$), supporting H6. Furthermore, social influence has a highly significant positive effect on usage intention ($\beta = 0.373$, $p < 0.001$), confirming H9. The final structural configuration of the model is depicted in Fig. 2.

Table 8
Significance analysis of model path coefficients.

Hypothesis	Path	Coefficient estimate	P value	Direction	Results
H1	PEU→PU	0.452	***	positive	Supported
H2	PU→UI	0.355	***	positive	Supported
H3	PEU→UI	0.295	***	positive	Supported
H4	SQ→PU	0.199	***	positive	Supported
H5	PR→PU	-0.452	***	negative	Supported
H6	TA→PEU	-0.084	0.028	negative	Supported
H7	II→PEU	0.354	***	positive	Supported
H8	PP→PEU	0.414	***	positive	Supported
H9	SI→UI	0.373	***	positive	Supported
Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.					

Multi-group analysis

This study conducts multi-group analysis (MGA) across three demographic dimensions—gender, age, and educational attainment—to probe structural heterogeneity and detect subtle cross-group differences in the hypothesized relationships influencing intention to use unmanned delivery services. Prior to MGA, cross-group model equivalence is evaluated via nested invariance testing in AMOS, which entails comparing a sequence of increasingly constrained models to determine whether key parameters exhibit equivalence across target groups. Specifically, we compare the baseline model, measurement-coefficient equality, path-coefficient equality, covariance equality, structural-residual equality, and measurement-residual equality models. Chi-square difference tests are used to assess model differences: a p-value > 0.05 indicates no statistical significance (i.e., invariance holds), whereas $p < 0.05$ signals significant differences. Because global model fit alone cannot reveal which parameters differ, we further examine critical ratios (CR) for cross-group parameter differences; $|CR| > 1.96$ indicates a statistically significant difference at the 0.05 level.

For segmentation, respondents are grouped as follows. Age: “young adults” (< 45 years) and “middle-aged and older adults” (≥ 45 years). Educational attainment: “lower-middle educational attainment” (junior high school or below; high school or technical secondary school) and “higher educational attainment” (junior college, bachelor’s, master’s or above).

Model fit for the multi-group analyses is excellent. Across the constrained models and the baseline model, the CFI and IFI range from 0.904 to 0.920, exceeding the conventional 0.90 benchmark, while the RMSEA ranges from 0.037 to 0.041, well below the 0.08 threshold. These results demonstrate strong congruence between the multi-group models and the observed data, supporting the reliability and validity of the findings.

Gender-based multi-group analysis

As shown in Table 9, the cross-tabulated cell entries report the critical ratios for differences in corresponding path coefficients between the male and female groups. All absolute CR values are below the 1.96 threshold, indicating no statistically significant gender differences in the mechanisms shaping consumers’ usage intention for unmanned delivery services. Accordingly, the hypothesized structural paths can be regarded as invariant across male and female cohorts.

Table 9
Critical ratios for path coefficient differences across gender groups.

A B	SQ→PU	PR→PU	TA→PEU	II→PEU	PP→PEU	PEU→PU	PU→UI	PEU→UI	SI→UI
SQ→PU	0.684	8.221	4.622	-0.322	-2.306	-4.122	-1.131	-1.671	-2.836
PR→PU	-8.057	-0.416	-4.785	-7.284	-9.495	-10.841	-9.501	-7.946	-9.802
TA→PEU	-3.635	4.484	0.276	-3.699	-5.838	-7.736	-5.196	-4.838	-6.338
II→PEU	1.476	7.752	4.671	0.522	-1.252	-2.777	-0.117	-0.774	-1.740
PP→PEU	1.037	7.608	4.359	0.087	-1.790	-3.235	-0.593	-1.176	-2.204
PEU→PU	4.341	9.506	7.270	3.041	1.522	0.087	2.746	1.850	1.092
PU→UI	2.563	9.338	6.054	1.401	-0.368	-2.020	0.907	0.021	-0.927
PEU→UI	1.536	6.287	3.987	0.756	-0.649	-2.037	0.288	-0.332	-1.100
SI→UI	2.164	8.339	5.385	1.100	-0.602	-2.223	0.570	-0.214	-1.174

Note: A indicates the influence path of unmanned delivery usage intention for the male group; B indicates the influence path for the female group.

The multi-group analysis by gender (Table 10) shows that when gender is treated as a moderating variable, no statistically significant differences emerge between male and female respondents in the structural paths shaping behavioral intention to use unmanned delivery services. This invariance may reflect relatively comparable educational attainment and informational access across genders within the sampled population, yielding similar levels of technological literacy and convergent initial attitudes toward unmanned logistics technologies. Such convergence, in turn, produces structurally consistent adoption pathways.

Moreover, as a consumer-oriented service, unmanned delivery furnishes identical core functional benefits—such as efficiency gains, time savings, and delivery punctuality—to both male and female users. When perceived usefulness and perceived ease of use derive primarily from these universal functional attributes, the underlying acceptance mechanisms are unlikely to manifest gender-contingent variation. Consequently, the absence of significant path differences is theoretically coherent with the functional neutrality and broadly shared evaluative criteria associated with unmanned delivery services.

Table 10
Multi-group structural path coefficients by gender.

Path	Male		Female	
	Standardized coefficient	**p**	**Standardized coefficient**	**p**
PEU→PU	0.470	***	0.436	***
PU→UI	0.315	***	0.394	***
PEU→UI	0.313	***	0.268	***
SQ→PU	0.179	***	0.223	***
PR→PU	-0.422	***	-0.483	***
TA→PEU	-0.104	0.047	-0.098	0.093
II→PEU	0.283	0.002	0.395	***
PP→PEU	0.525	***	0.322	***
SI→UI	0.423	***	0.320	***
Note: * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001.				

Age-based multi-group analysis

Table 11 reports the cross-group critical ratios for age-based comparisons; each cell presents the CR for the difference in the corresponding structural path between younger (< 45 years) and middle-aged/older (≥ 45 years) cohorts. The absolute CR values for the paths Privacy Risk→Perceived Usefulness, Perceived Ease of Use→Perceived Usefulness, and Perceived Ease of Use→Usage Intention all exceed 1.96, indicating statistically significant age-related moderation at the 0.05 level. Accordingly, these three relationships differ materially across age groups, revealing structural heterogeneity in the antecedents shaping intention to use unmanned delivery services.

Table 11
Critical ratios for path differences across age cohorts.

A B	SQ→PU	PR→PU	TA→PEU	II→PEU	PP→PEU	PEU→PU	PU→UI	PEU→UI	SI→UI
SQ→PU	0.063	4.892	2.290	-0.162	-1.514	-5.082	-1.901	0.004	-2.462
PR→PU	-7.713	-2.102	-5.335	-7.272	-8.929	-11.621	-9.428	-5.836	-9.867
TA→PEU	-4.320	1.997	-1.547	-4.032	-5.697	-9.727	-6.260	-3.163	-6.914
II→PEU	2.031	6.855	4.242	1.760	0.360	-3.185	-0.067	1.596	-0.612
PP→PEU	1.110	5.712	3.220	0.835	-0.464	-3.814	-0.844	0.866	-1.365
PEU→PU	0.122	4.044	1.932	-0.067	-1.179	-4.385	-1.535	0.064	-2.000
PU→UI	2.096	7.647	4.656	1.697	0.233	-3.662	-0.238	1.599	-0.852
PEU→UI	3.974	7.613	5.727	3.579	2.513	-0.566	2.323	3.478	1.882
SI→UI	0.597	3.915	2.118	0.419	-0.544	-3.260	-0.848	0.499	-1.263

Note: A indicates the influence path for the youth group; B indicates the influence path for the middle-aged and elderly group.

As shown in Table 12, age moderates several structural paths. First, the positive effect of perceived ease of use on perceived usefulness is stronger among younger respondents (β = 0.555) than among middle-aged and older adults (β = 0.171). By contrast, the positive effect of perceived ease of use on usage intention is stronger for the middle-aged/older cohort (β = 0.587) than for the younger cohort (β = 0.143), with both effects significant. Likewise, the negative effect of perceived privacy risk on perceived usefulness is more pronounced among middle-aged/older adults (β = −0.646) than among younger respondents (β = −0.379), with both effects significant.

Table 12
Multi-group structural path coefficients by age cohort.

Path	Young adults		Middle-aged and elderly adults	
	Standardized coefficient	p	Standardized coefficient	p
PEU→PU	0.555	***	0.171	0.083
PU→UI	0.422	***	0.375	***
PEU→UI	0.143	0.024	0.587	***
SQ→PU	0.187	***	0.190	0.055
PR→PU	-0.379	***	-0.646	***
TA→PEU	-0.049	0.253	-0.190	0.038
II→PEU	0.277	***	0.486	***
PP→PEU	0.460	***	0.348	0.003
SI→UI	0.429	***	0.181	0.076

Note: * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001.

Education-based multi-group analysis

Table 13 reports the critical ratios for cross-group comparisons by educational attainment; each cross-cell entry corresponds to the CR for the difference in each path coefficient. The absolute CRs for the paths Perceived Ease of Use→Usage Intention and Community Influence→Usage Intention exceed 1.96, indicating statistically significant differences at the 0.05 level. Therefore, the effects of perceived ease of use and community influence on usage intention differ significantly across education groups.

Table 13
Critical ratios for path differences across educational attainment groups.

A B	SQ→PU	PR→PU	TA→PEU	II→PEU	PP→PEU	PEU→PU	PU→UI	PEU→UI	SI→UI
SQ→PU	-0.213	8.678	4.710	-1.573	-2.481	-3.528	-1.370	-3.500	-0.413
PR→PU	-6.550	1.884	-2.300	-7.700	-8.235	-8.650	-8.146	-8.121	-5.561
TA→PEU	-2.985	6.316	1.954	-4.248	-5.004	-5.926	-4.332	-5.604	-2.634
II→PEU	-0.051	7.168	3.864	-1.267	-2.067	-2.910	-1.019	-3.014	-0.257
PP→PEU	1.452	9.203	5.637	0.190	-0.757	-1.692	0.478	-1.911	1.013
PEU→PU	4.604	11.127	8.710	3.268	2.317	1.446	3.703	0.906	3.810
PU→UI	2.153	10.417	6.669	0.861	-0.090	-1.166	1.250	-1.501	1.640
PEU→UI	0.037	6.168	3.450	-0.986	-1.717	-2.601	-0.806	-2.767	-0.160
SI→UI	2.916	10.879	7.401	1.589	0.605	-0.514	2.025	-0.884	2.334

Note: A indicates the influence path for the group with lower to medium educational attainment; B indicates the influence path for the higher education group.

As shown in Table 14, the positive effect of perceived ease of use on usage intention is stronger in the lower-middle education group (β = 0.512) than in the higher education group (β = 0.151), with both paths statistically significant. Conversely, the positive effect of social influence on usage intention is more pronounced in the higher education group (β = 0.445) than in the lower-middle education group (β = 0.181), and both effects are significant.

Table 14
Multi-group structural path coefficients by educational attainment.

Path	Lower-middle education		Higher education	
	Standardized coefficient	**p**	**Standardized coefficient**	**p**
PEU→PU	0.413	***	0.486	***
PU→UI	0.318	***	0.417	***
PEU→UI	0.512	***	0.151	0.021
SQ→PU	0.191	0.004	0.194	***
PR→PU	-0.517	***	-0.410	***
TA→PEU	-0.176	0.010	-0.031	0.512
II→PEU	0.400	***	0.240	0.008
PP→PEU	0.451	***	0.459	***
SI→UI	0.181	0.019	0.445	***
Note: * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001.				

Discussion

Further interpretation of the research results

This study examines the determinants of consumers' adoption intention toward unmanned delivery services and employs multigroup SEM analyses by demographic variables to assess structural heterogeneity across consumer cohorts. First, consistent with the core assumptions of TAM, perceived ease of use positively affects perceived usefulness (Hypothesis 1): when consumers regard unmanned delivery as simple and user-friendly, they are more likely to judge it useful and to recognize its practical value. Hypothesis 2 is confirmed: perceived usefulness positively influences usage intention, underscoring that recognition of a technology's practical value directly drives intention to use. When consumers perceive unmanned delivery as offering tangible benefits, they become more willing to use it and may adopt it on an ongoing basis. This finding suggests that, in the design and promotion of technologies or products, emphasizing concrete user benefits is essential; for unmanned delivery, clearly demonstrating efficiency and convenience may be particularly effective. Hypothesis 3—that perceived ease of use positively influences usage intention—is also supported, reaffirming the importance of operational simplicity in user decision-making and indicating that enabling consumers to learn and use unmanned delivery services quickly is crucial. This conclusion aligns with findings on usefulness from studies examining acceptance of self-directed learning within online education models based on the TAM framework(García et al., 2024).

From a technological standpoint, service quality exerts a significant positive effect on perceived usefulness (β = 0.199, p < 0.001), suggesting that high-quality service strengthens consumers' trust in unmanned delivery and, in turn, increases their intention to use it. For example, timely delivery and low damage rates directly shape consumers' assessments of the technology's value. This result aligns with Sharma et al. (2024), who identify service quality as a core driver of technology acceptance. High service quality alleviates concerns about delivery failures (e.g., delays, damaged goods) and bolsters confidence in the service's ability to complete tasks, thereby reinforcing perceptions that it can efficiently meet delivery needs. By contrast, the negative effect of perceived privacy risk on perceived

usefulness (β = -0.452, p < 0.001) underscores the critical importance of data security. Contemporary unmanned delivery systems rely heavily on users' personal information (e.g., location, payment data); absent transparent privacy safeguards, consumers may avoid these services out of concern about data leakage. This finding extends TAM to privacy-sensitive contexts, demonstrating how data-security concerns can distort evaluations of a technology's practical value. It also implies that unmanned delivery firms should strengthen privacy protections in system design to mitigate perceived risk.

Regarding individual factors, perceived technology anxiety significantly reduces perceived ease of use (β = −0.084, p < 0.05), indicating that anxiety experienced when interacting with technology directly degrades users' experiences and lowers their perceptions of the ease of using unmanned delivery services. This finding is consistent with T. Huang (2023) and Yap et al. (2023), which suggest that fear of technological complexity may hinder adoption. For example, middle-aged and older adults, who often exhibit lower technological readiness, are more prone to anxiety arising from operational difficulties, thereby diminishing their willingness to use such services. Conversely, the positive effects of individual innovativeness and perceived pleasure on PEU (β = 0.354, p < 0.001; β = 0.414, p < 0.001) indicate that more innovative consumers and those who derive enjoyment from the service are more likely to regard unmanned delivery as easy to use and thus more willing to adopt it. This aligns with the individual dimension of DIT, where individual innovativeness functions as a positive driver of adoption. Moreover, positive experiential enjoyment during use significantly enhances PEU, with favorable user experiences increasing consumers' readiness to adopt. Accordingly, design and promotion should balance functionality and user experience; for example, enhancing enjoyment through engaging interaction design can effectively improve usability evaluations.

In the social domain, the significant positive effect of community-level influence on adoption intention (β = 0.373, p < 0.001) indicates that recommendations and persuasion within social networks are critical drivers of consumer adoption, corroborating classical social influence theory (Kelman, 1958). According to this framework, community influence operates through two mechanisms: informational and normative influence. First, when community members frequently use unmanned deliveries and provide consistently positive feedback, those shared experiences reduce perceived uncertainty and offer indirect evidence of the service's reliability and convenience. This process is especially important in early adoption stages, when potential users lack direct trial experience and thus rely on vicarious evaluative cues. Second, prevailing group norms create implicit normative pressure, motivating individuals to conform to collective expectations; for instance, when unmanned delivery becomes a common choice in a community, non-users may adopt to avoid social incongruence. Consumers often base adoption decisions on word-of-mouth within social circles or endorsements from opinion leaders. Specifically, exposure to positive evaluations by existing users or favorable discourse on social media can encourage trial use. This finding implies that unmanned delivery providers can strategically leverage social media and community endorsements to amplify acceptance and accelerate diffusion.

Finally, no significant gender differences are observed in adoption intention, suggesting that gender does not materially moderate the acceptance pathways of unmanned delivery; the technology's core value proposition appears similarly to male and female users, and the widespread diffusion of mobile internet has likely narrowed gender-based gaps in technological exposure. By contrast, age differentiates effects. Specifically, the positive path from perceived ease of use to perceived usefulness (PEU→PU) is stronger among younger respondents (β = 0.555) than among middle-aged and older adults (β = 0.171). This pattern reflects younger users' greater receptivity and adaptability to novel technologies. Their frequent use of smart services (e.g., mobile payments, shared bicycles) fosters familiarity with smart devices, enabling them to translate operational simplicity into perceived utility, for example, interpreting streamlined delivery processes as efficiency gains and time savings. In contrast, middle-aged and older adults may rely more on prior experience and exhibit lower openness and adaptability due to the digital divide. Moreover,

perceived privacy risk exerts a more pronounced negative effect on PU among middle-aged and older adults (β = −0.646) than among younger users (β = −0.379). Significant age-based differences are also observed in the relationships between PEU→adoption intention and privacy risk→PU, with effects generally more pronounced among middle-aged and older cohorts. These patterns may stem from lower familiarity with new technologies and a more limited understanding of privacy-protection mechanisms among older users, who may more readily equate the collection of address information by unmanned delivery systems with privacy breaches. By contrast, younger generations socialized in a digital environment tend to better understand technological implementation and exhibit greater trust in privacy safeguards.

Regarding educational attainment, significant heterogeneity emerges along several pathways. Specifically, PEU exerts a stronger effect on adoption intention among individuals with lower-to-medium education (β = 0.512) than among those with higher education (β = 0.151). This pattern reflects that highly educated individuals typically possess broader knowledge, higher technical literacy, and a greater propensity to experiment with novel services, whereas individuals with lower educational attainment often lack technical backgrounds and thus rely more on intuitive judgments of usability when deciding whether to adopt. Furthermore, social influence is more pronounced among the higher-education cohort (β = 0.445) than among the lower-education cohort (β = 0.181), consistent with the informational-influence mechanism: highly educated individuals participate in more specialized social networks (e.g., academic and professional circles), are more attentive to peer evaluations, and place greater value on group identity—factors that increase the likelihood of conforming to prevailing views. Educational background may also shape preferences and innovation orientation; collectively, these factors contribute to systematic differences in adoption intention across educational strata.

Theoretical contributions

This study makes two theoretical contributions. First, by extending the technology acceptance model to the context of unmanned delivery services, it integrates multiple theoretical perspectives and key constructs to propose a "technology–individual–society" analytical framework. This extension strengthens TAM's theoretical foundations and applicability, providing a novel lens for examining unmanned delivery logistics. Second, responding to the literature's tendency to prioritize technical optimization (e.g., route planning) at the expense of consumer perspectives, this study adopts a consumer-centric approach. By investigating consumers' intention to adopt unmanned delivery, it develops a focused theoretical model that expands the analytical dimensions of last-mile logistics and helps close a gap in research on consumer behavioral intentions.

Practical implications

First, optimize the user experience to mitigate perceived technology anxiety. Given the inhibitory effect of perceived technology anxiety on perceived ease of use (β = −0.084), unmanned-delivery providers should design interfaces aligned with the cognitive habits of different user segments and adopt minimalist interaction flows. Specifically, develop one-click interfaces that integrate order placement, tracking, and delivery confirmation into a dedicated unmanned-delivery entry point within the app, thereby minimizing navigation overhead. For middle-aged and older adults, implement large-text modes and voice interfaces supporting voice-mediated ordering and guidance. For new users, provide first-use onboarding tutorials that combine animated walk-throughs and simulated operations to lower the learning curve. For segments with higher anxiety, equip delivery terminals and pickup points with prominent physical support buttons or QR codes that immediately launch live customer support or contextual help, thereby alleviating cognitive load during use.

Second, leverage community influences to drive word-of-mouth diffusion. The significant positive effect of community-level influence on adoption intention (β = 0.373) underscores the need for providers to activate social networks. Providers can run targeted campaigns on social media and in online communities to stimulate user-generated content and experience sharing. For example, recruit “experience officers” in innovation-dense settings (e.g., universities, technology parks) to invite early adopters and creators to trial services and publicize their experiences. Amplify reach through reviews, vlogs, and short-form videos that document end-to-end delivery processes and user experiences. Such social sharing not only raises awareness but also builds social trust in technology among potential users, thereby accelerating diffusion.

Third, implement differentiated promotion and trust-building strategies for distinct user segments. Because acceptance varies across cohorts, adopt targeted measures to increase relevance and reduce perceived risk. Embed robust data-protection measures across data collection, storage, and processing, and publish clear, transparent privacy policies and simple privacy notices to build trust. For younger cohorts, leverage platforms such as TikTok, Xiaohongshu, and Weibo to launch creative campaigns (e.g., “unmanned delivery challenge”) that incentivize user-generated pickup or retrieval videos. For middle-aged and older cohorts, deliver hands-on experiential training through community and senior learning centers, with live demonstrations and supervised trial sessions to reduce apprehension and improve self-efficacy.

Research limitations and prospects

Despite the findings, this study has several limitations.

First, the sample was drawn from a single geographic region, which limits the generalizability of the results to a broader consumer population. Acceptance of unmanned delivery services likely varies across countries and regions, and the current sample cannot capture such heterogeneity comprehensively. To improve external validity, future research should expand geographic coverage and adopt stratified or multi-site sampling designs.

Second, consumer awareness and acceptance of unmanned delivery technology are dynamic and may evolve as the technology matures and adoption deepens. This study is cross-sectional and therefore captures attitudes at a single point in time, focusing primarily on initial adoption intention. Longitudinal or panel studies would better examine attitude evolution, distinguish sustained from discontinued use, and model trajectories of long-term adoption.

Third, the multigroup analysis included only gender, age, and educational attainment, omitting other potentially important moderators such as income, occupation, product category (e.g., perishables, high-value items, pharmaceuticals), and urbanization level. Existing models also do not sufficiently differentiate among types of delivered goods, producing an incomplete account of factors that influence usage intention. Future studies should incorporate a broader set of demographic, socioeconomic, and contextual moderators — and consider methods such as multi-level modeling to capture cross-site and within-group heterogeneity.

Conclusions

This study uses the TAM to build an integrated framework that incorporates technological, individual, and social factors to explain consumers’ intention to use unmanned delivery services. It further performs multigroup analyses by gender, age, and educational attainment to evaluate how group differences moderate the adoption pathways of unmanned delivery services. The principal findings are as follows:

First, the proposed framework extends TAM’s applicability to the unmanned-delivery context. Addressing prior research’s emphasis on technical optimization at the expense of consumer behavior, the study integrates

technological factors (service quality, perceived privacy risk), individual factors (technology anxiety, individual innovativeness, perceived pleasure), and social factors (social influence) into a unified analytical model. Empirical tests of these effects on consumers' intention to use not only enrich theory on unmanned delivery but also generate actionable implications for service design and operations for service providers.

Second, the study validates the hypothesized relationships among determinants of intention to use unmanned delivery services. Perceived usefulness and perceived ease of use exert significant positive effects on adoption intention, and PEU positively influences PU. Specifically, when consumers perceive the service as easy to use, they are more likely to perceive it as useful—recognizing its convenience and benefits—and thus display stronger adoption intentions. The results confirm that service quality positively affects PU, whereas perceived privacy risk negatively affects PU. Individual innovation and perceived pleasure facilitate PEU, while technological anxiety inhibits it. Social influence directly and positively drives adoption intention, with community-level endorsement showing a clear effect.

Third, the study reveals that demographic heterogeneity moderates these pathways. Multigroup analyses indicate that heterogeneity is more pronounced across age and educational cohorts than across gender. The positive effect of PEU on PU is stronger among younger users than among middle-aged and older adults. Conversely, among middle-aged and older adults the positive effect of PEU on adoption intention and the negative effect of perceived privacy risk on PU are stronger than among younger users—consistent with differences in technological adaptability and privacy concerns. By educational attainment, the positive effect of PEU on adoption intention is stronger among individuals with lower education, whereas the positive effect of social influence on adoption intention is stronger among those with higher education.

Data availability

The dataset generated from the questionnaires during this study is available as an Excel file from the corresponding author on reasonable request. The discourse analysis corpus used in this study cannot be made publicly available due to confidentiality agreements with the participants.

Declarations

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The dataset generated from the questionnaires during this study is available as an Excel file from the corresponding author on reasonable request. The discourse analysis corpus used in this study cannot be made publicly available due to confidentiality agreements with the participants.

Competing interests

The author(s) declare no competing interests.

Ethical Approval

This study was reviewed and approved by the Academic Committee of [University Name; anonymized for double-blind peer review]. The committee, serving as the institution's highest academic review body, ensured that all aspects of the research protocol—including participant recruitment, the informed consent process, data collection instruments, and protocols for data handling, storage, and dissemination—adhered to rigorous ethical standards. The study was conducted in strict accordance with the principles outlined in the Declaration of Helsinki.

Informed consent

Implied informed consent was obtained from all participants prior to their involvement in the study. The consent procedure, which received full ethical approval from the Academic Committee of [University Name; anonymized for double-blind peer review] , was conducted as follows: Prior to the survey, a trained researcher presented the informed consent statement to each participant, provided sufficient time for reading, and offered a detailed oral explanation. This communication detailed the research objectives, data collection methods, and intention to publish aggregated results. It explicitly guaranteed anonymity, confidentiality, and the exclusive use of data for academic research purposes. Participants were advised of their voluntary participation and right to withdraw at any time before questionnaire submission without penalty. Given the non-interventional nature of this study, participants were informed that there were no foreseeable risks associated with their involvement. Clear contact details for the principal investigator were provided for any questions. The voluntary act of proceeding to complete and submit the questionnaire was taken as confirmation of their consent.

Author Contribution

R S: Writing – original draft, Methodology, Formal analysis, Funding acquisition, Conceptualization. W Q: Writing – original draft, Visualization, Methodology, Data curation. X X: Writing – review & editing, Validation, Funding acquisition, Conceptualization. All authors reviewed the manuscript.

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Figures

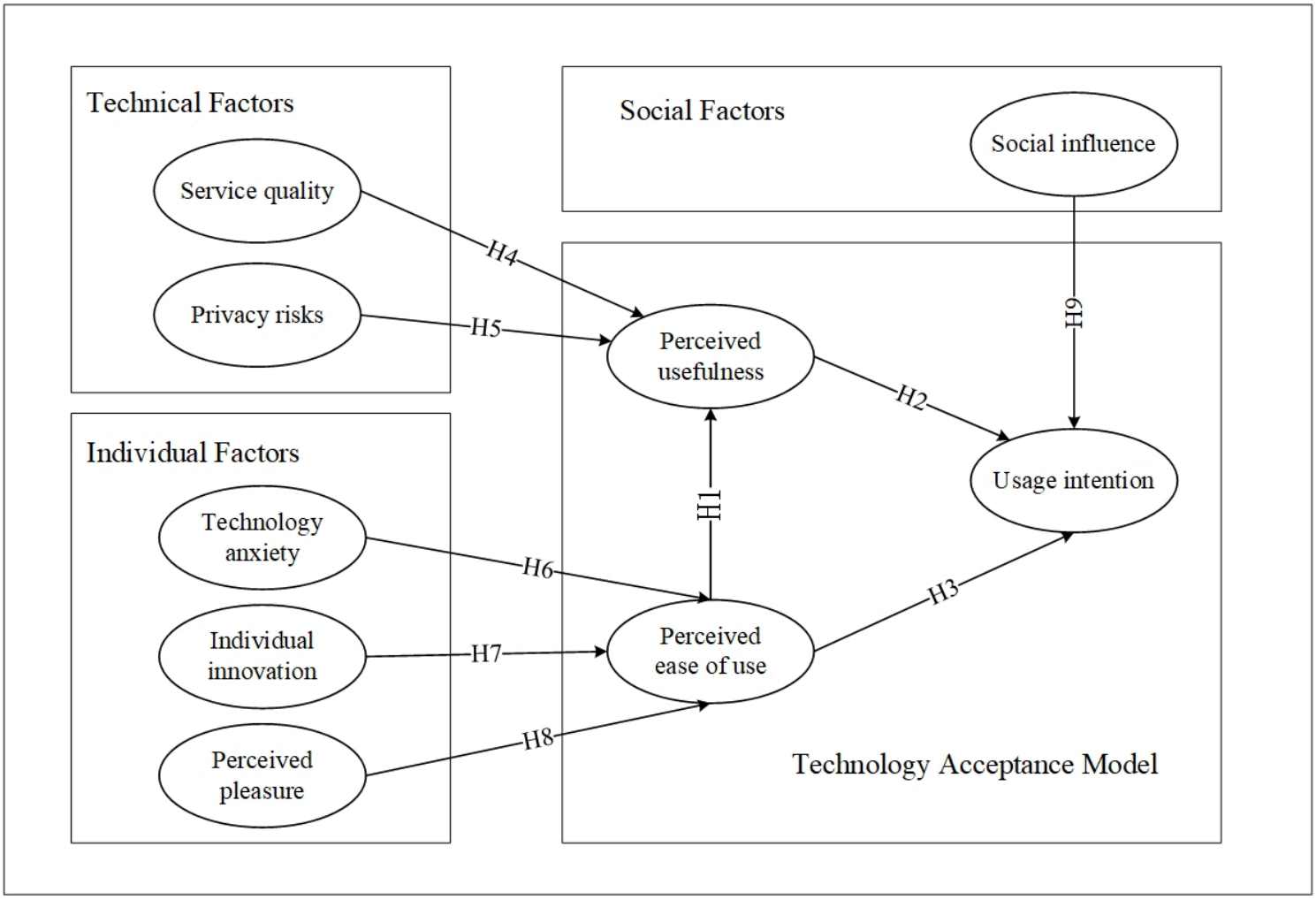


Figure 1

Conceptual framework for consumers' intention to use unmanned delivery services.

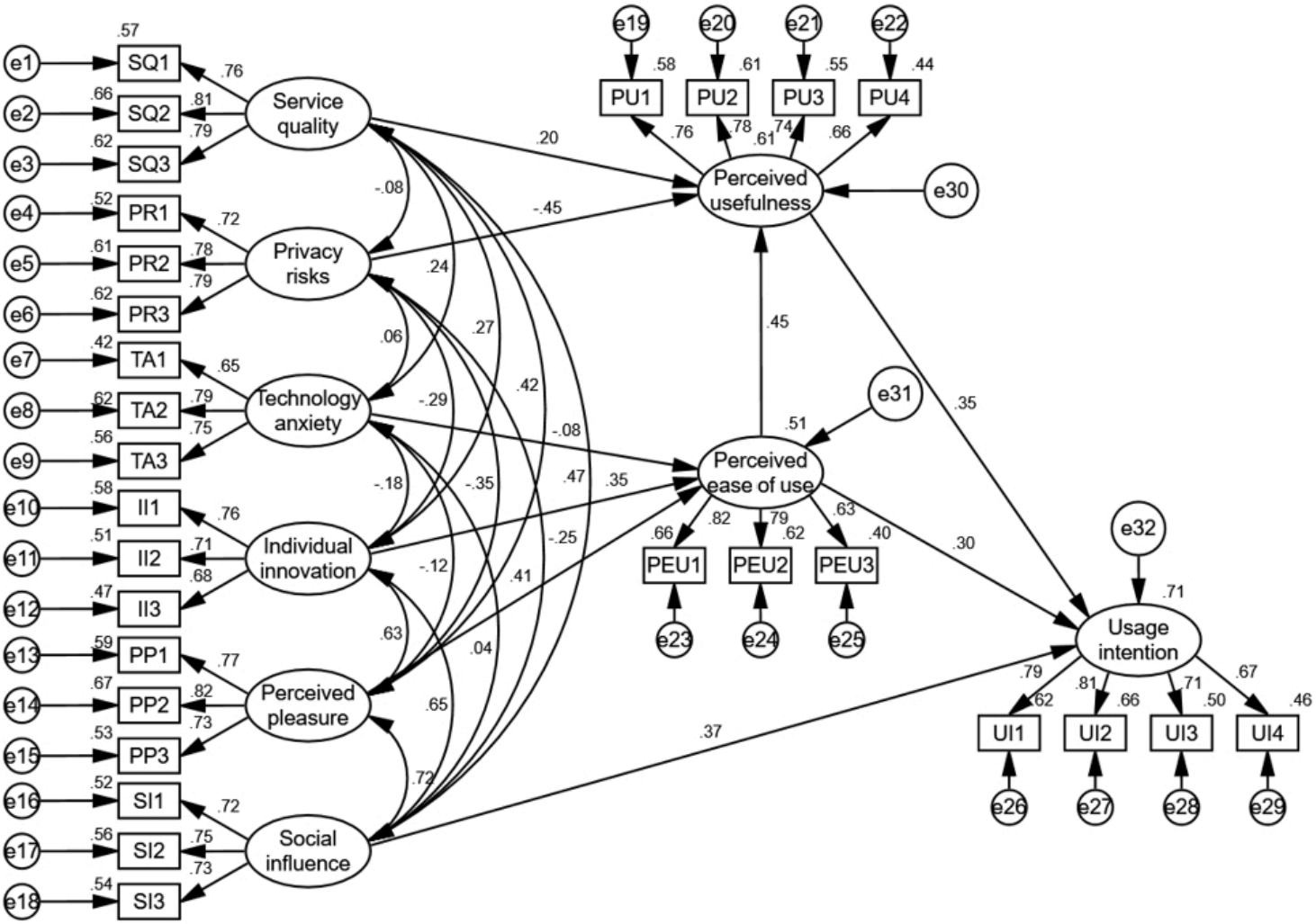


Figure 2

Normalized path coefficients of the structural equation model.