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Digital Platform Adoption and User Behaviour in Urban Freight Services: Implications for Sustainable Logistics Management in Jakarta

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ABSTRACT

This study examines how digital platform adoption shapes user behaviour in urban freight services and considers its implications for more sustainable logistics systems. Focusing on Jakarta, where rapid growth in e-commerce has placed increasing pressure on urban delivery networks, the study explores how effort expectancy (EE), social media (SM) influence, and digital facilitating conditions (DFC) affect both behavioural intention and actual service use. A survey of 323 users of online freight services was conducted, and the data were analysed using structural equation modelling. The results show that behavioural intention plays a central role in translating user perceptions into actual usage. DFCs and social media influence are found to directly affect use behaviour, while EE mainly operates through behavioural intention. In addition, customer experience (CX) strengthens the link between intention and actual use, whereas age introduces noticeable differences in how users respond to digital services. Beyond individual-level behaviour, the findings highlight broader implications for urban logistics systems. Greater adoption of digital freight platforms can contribute to improved coordination, more efficient resource use, and reduced operational friction in last-mile delivery. However, these benefits depend on both technological readiness and user acceptance. The study suggests that sustainable urban logistics cannot be achieved through infrastructure improvements alone. Instead, attention must also be given to user behaviour, platform design, and inclusive digital strategies that account for demographic differences. These insights provide practical guidance for policymakers and service providers seeking to enhance the efficiency and sustainability of urban freight systems in rapidly digitalising cities.

1. INTRODUCTION

The rapid proliferation of digital technologies has transformed not only the global business landscape but also the foundational mechanisms of how goods and services are distributed. In recent years, e-commerce has emerged as one of the most disruptive forces in contemporary business models, driven by advances in internet connectivity, smartphone adoption, and the shifting preferences of digital-native consumers. This transformation has had significant implications for the logistics and courier service industry, particularly in emerging markets like Indonesia, where digital infrastructure development and consumer adoption are progressing at an unprecedented pace. Logistics services, including last-mile delivery platforms, have become essential enablers of online commerce, connecting buyers and sellers with increased speed and efficiency. Indonesia's strategic positioning as the largest digital economy in Southeast Asia is reflected in its increasing internet penetration, which reached 79.5% in 2024 [1], and the substantial rise in e-commerce users, projected to surpass 99 million by 2029 (Ministry of Trade, 2024). This digital growth is mirrored in the expanding contribution of transportation and warehousing services to the national GDP. The sector experienced a significant recovery post-COVID-19, growing by 19.87% in 2022 and 13.96% in 2023, according to the Central Bureau of Statistics (BPS, 2023). Courier, Express, and Parcel (CEP) services, particularly those integrated with digital platforms, have become key players in facilitating commerce, with dominant actors such as J&T Express commanding over 50% of the courier market share [2]. This dominance is underpinned not only by logistical capability but also by the ability to leverage digital platforms for user engagement and trust-building.

However, the rise of digital logistics has not been without challenges. Despite strong growth in volume and user base, courier service providers in Indonesia continue to face issues relating to service reliability, delivery timeliness, and consumer trust. According to the World Bank [3], Indonesia's Logistics Performance Index (LPI) score declined to 3.0, placing it 61st globally, significantly below regional peers such as the Philippines (43^{rd}) and Vietnam (43^{rd}). The LPI's timeliness sub-indicator dropped to 3.3, underscoring persistent delays and inefficiencies in the country's logistical systems. These performance issues are not merely operational in nature but deeply influence the behavior of end-users, who increasingly base their choices on digital reviews, platform usability, and prior delivery experiences. In the context of e-commerce-driven logistics, consumer behavior plays a pivotal role in determining the success of delivery platforms. The shift from traditional retail to online transactions has altered how users evaluate service quality. Modern consumers not only prioritize cost and speed but are also highly sensitive to application usability, privacy protection, and peer-based reputation systems. This behavioral evolution necessitates deeper inquiry into how various digital and social constructs, such as effort expectancy (EE), social media (SM) influence, digital infrastructure, and customer experience (CX), affect behavioral intention (BI) and actual use of courier services.

Prior research has established foundational frameworks to explain technology adoption in digital services, notably the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) [4, 5]. These models have been widely used to explain the relationship between perceived usefulness, ease of use, and BI. In the logistics and e-commerce domain, EE, defined as the degree to which a system is perceived as easy to use, has been consistently linked to user engagement [6, 7]. Furthermore, the presence of digital facilitating conditions (DFC) such as stable internet access and accessible platforms is crucial for user participation, particularly in a country with significant digital divide issues [8]. SM platforms, too, have reshaped the dynamics of service adoption. Consumers increasingly rely on e-word-of-mouth, reviews, and influencer recommendations to make purchasing decisions [9, 10]. In Indonesia, the role of SM is particularly salient, given its high penetration rate among urban youth. This phenomenon warrants an examination of how social influence via digital platforms shapes user attitudes and decisions in the courier service context.

Despite the wealth of studies examining technology adoption and e-commerce behaviors, several gaps remain unaddressed in the literature. First, there is limited empirical research integrating both technological and social variables in a unified behavioral model for courier service users. While models such as UTAUT have been applied in general e-commerce and mobile service contexts, their application in last-mile delivery services remains underexplored, especially in Southeast Asia. Furthermore, most studies emphasize intention to use, but few extend the analysis to actual usage behavior, thus omitting the critical link between perception, motivation, and action.

Second, Jakarta, as the commercial and digital capital of Indonesia, presents a unique context for examining behavioral usage of online delivery platforms. Its metropolitan characteristics, high digital literacy, dense population, diversified socio-economic demographics, and advanced internet infrastructure, make it an ideal setting for understanding how EE, SM influence, and digital conditions interact in shaping user behavior. Yet, surprisingly few studies have been conducted that focus specifically on Jakarta's digital consumers in the courier service domain. Third, while the role of CX is acknowledged in service quality literature, it has rarely been examined as a moderator between BI and actual usage in the courier context. Given the increasingly competitive landscape of logistics services, CX, especially in terms of transparency, delivery satisfaction, and application interaction, may critically determine whether users follow through on their intentions to use a service. Similarly, demographic factors such as age remain under-theorized in moderating key adoption relationships. Younger users may respond differently to DFC or SM cues compared to older demographics, indicating the need for more nuanced, age-based behavioral models.

This study seeks to address these gaps by proposing a comprehensive model that investigates the determinants of use behavior (UB) in the context of online courier services in Jakarta. It integrates three key exogenous variables, EE, SM engagement, and DFC, along with mediating effects of BI and moderating effects of CX and age. The inclusion of SM as a behavioral driver, combined with CX as a moderator, reflects a novel attempt to capture the interplay between user trust, usability, and engagement in a service environment shaped by digital interactivity. The empirical focus on Jakarta further enhances the relevance of this research. As Indonesia's economic and technological hub, Jakarta provides a high-density context where logistics services are both widely used and intensely scrutinized by users. The city's active participation in the digital economy, combined with its varied user experiences, presents a fertile ground for analyzing the behavior of courier service users across different age groups and digital competencies.

Moreover, this study adds to the discourse on digital transformation in logistics by moving beyond infrastructural or firm-level analyses. It centers on the behavioral microfoundations of digital service use, specifically, how users perceive and act upon the digital affordances and limitations provided by online expedition platforms. By focusing on constructs such as ease of use, digital readiness, and peer influence, this research offers strategic implications for logistics firms aiming to increase adoption, reduce churn, and build long-term customer loyalty in an increasingly competitive market. This study contributes to the field by offering a holistic behavioral model of online courier service usage in an urban Southeast Asian context. It challenges existing models that treat technological ease or social influence in isolation, and instead posits that usage behavior is the outcome of a constellation of interrelated psychological, technological, and demographic factors. The findings of this research are expected to inform not only academic debates on user behavior and digital transformation but also practical strategies for improving service delivery, platform design, and customer trust in the e-logistics sector.

2. LITERATURE REVIEW

2.1 Theoretical foundation

2.1.1 Logistics theory - general logistics concept

Logistics can be broadly defined as a set of activities ensuring that customers receive the right products, in the right quantity, at the right time. It serves as the bridge between production and consumption, establishing pathways across spatial and temporal gaps between manufacturers and markets. This includes managing not only the movement of physical goods but also of individuals and the related information [11]. Throughout a product's lifecycle, logistics contributes to added value through manufacturing (creating form utility), transportation (place utility), inventory and warehousing (time utility), and marketing (ownership utility). According to Kasilingam [11], the logistics supply chain comprises inbound logistics, intra-facility logistics, and outbound logistics.

Specific segments of a firm's logistics chain may include manufacturing, warehousing, and retail functions. Not all entities in the supply chain are universally present, some retailers, for example, may not maintain their own distribution centers or manufacturing facilities. Distribution centers may also follow a hierarchical structure (e.g., national, regional, and local levels) to optimize logistics operations.

Logistics management governs the flow of goods, money, and information [12]. It involves planning and coordinating material flows through thirty-four key transfer points between suppliers and customers. Strategic trade-offs are inherent in logistics planning. For instance, high-speed transport can reduce inventory costs, while slower modes may necessitate increased inventory levels [12]. Hence, logistics decisions are made using a total cost approach, which accounts for interdependencies among supply chain functions such as transportation, warehousing, and inventory [11]. Ballou [13] defined logistics as the effective and efficient management of the flow and storage of goods, services, and information from origin to consumption. Similarly, Bowersox [14] emphasized the strategic nature of moving raw materials and finished goods through a supply chain. Siahaya [15] and Klumpp and Heragu [16] added that logistics is an integral part of supply chain management, which includes procurement, production, distribution, and customer service. It not only involves physical flows but also the accompanying flow of information, enabling real-time decision-making. Klumpp and Heragu [16] also argued that logistics is pivotal in transforming raw materials into finished products through interrelated functions. This includes not just forward logistics (distribution and sales) but also reverse logistics (returns and recycling), highlighting the need for an integrated end-to-end supply chain network.

2.1.2 The role of logistics in business

Logistics has evolved from a support function to a strategic lever within business operations. According to Eunike [17], logistics encompasses supplier procurement, packaging, inventory management, fleet operations, and the supervision of deliveries across various stages of the supply chain. Logistics now contributes significantly to operational efficiency, customer satisfaction, and competitive advantage [18]. Modern logistics plays a pivotal role in creating value for businesses by enhancing operational effectiveness and supporting strategic goals across several dimensions. One of the most significant contributions of logistics is its ability to improve cost efficiency. Through effective inventory optimization, companies can avoid overstocking or stockouts, which helps in reducing unnecessary storage costs. Additionally, selecting the most suitable and cost-effective transportation modes and routes enables firms to minimize fuel consumption, lower distribution expenses, and ultimately reduce overall operational costs. These cost savings can then be reinvested into other business areas, such as innovation or market development.

Another critical dimension where logistics adds value is in enhancing customer satisfaction. In an increasingly competitive market, timely and accurate delivery of products is no longer a differentiator but a fundamental expectation. A well-functioning logistics system ensures that products are delivered in good condition and within promised timeframes, which boosts consumer trust and fosters long-term loyalty. Customers who receive reliable service are more likely to become repeat buyers and act as brand advocates through positive word-of-mouth, which is essential for maintaining a favorable brand reputation. Market expansion is also facilitated by strategic logistics capabilities. Companies that can efficiently manage their supply chains are better positioned to distribute their products across diverse geographic locations. This ability to reach customers in urban, suburban, and even remote regions opens up new revenue streams and allows businesses to compete in global markets. By leveraging advanced logistics networks, firms can ensure consistent product availability and responsiveness to regional demand fluctuations, which is especially vital in industries with seasonal or time-sensitive goods.

Moreover, logistics contributes significantly to risk management by providing the necessary structure to anticipate, prevent, and respond to potential disruptions. Well-designed logistics systems include contingency plans and diversified supply chain routes, enabling businesses to maintain continuity in operations even in the face of unexpected events such as natural disasters, labor strikes, or political unrest. Effective tracking and monitoring mechanisms also allow for real-time decision-making and immediate corrective actions, minimizing the impact of disruptions on service levels and customer relationships. Lastly, logistics enhances resource utilization, ensuring that materials, labor, and capital assets are used optimally. By synchronizing procurement, production, and distribution processes, logistics helps avoid redundancy and waste. For example, coordinated scheduling of transport and warehouse operations prevents idle time for workers and equipment, increasing throughput and lowering per-unit costs. Furthermore, digital tools such as warehouse management systems and transport optimization software enable precise allocation and deployment of resources, which not only improves efficiency but also contributes to sustainability by reducing energy usage and carbon emissions. Modern logistics is not merely a support function but a strategic enabler that integrates cost efficiency, customer service excellence, market outreach, risk mitigation, and optimal resource deployment into a cohesive value-creating system. Furthermore, logistics is a strategic tool to manage production, improve customer satisfaction, and lower costs. Companies that automate logistics functions can increase efficiency and reduce human error. Logistical optimization improves coordination, quality control, and resource allocation, allowing firms to focus on value-added activities [17].

2.1.3 Logistics activities

Logistics operations encompass a comprehensive range of interrelated functions that are crucial in managing the seamless flow of products from their point of origin to the final destination of consumption [19]. These functions begin with procurement, which involves more than simply purchasing goods, it includes establishing and maintaining strong relationships with suppliers, negotiating favorable terms, and ensuring the timely acquisition of materials and components essential for production. Effective procurement lays the groundwork for supply chain reliability and cost efficiency. Closely linked to procurement is supply management, which integrates procurement activities with production planning to ensure that inventory levels align with demand. This synchronization prevents both overstocking and stockouts, enabling firms to maintain lean operations while remaining responsive to customer needs. Efficient supply management supports operational agility and helps businesses quickly adapt to changes in market demand. Another critical element is order processing, which refers to the internal procedures for receiving, verifying, and fulfilling customer orders. Fast and accurate order processing minimizes delays and errors, contributing significantly to customer satisfaction. Complementing this is order management, which involves monitoring and coordinating the execution of customer orders to ensure products are delivered accurately and on time. These two functions together form the backbone of customer fulfillment strategies.

To anticipate market demand and plan accordingly, logistics operations rely heavily on demand forecasting. This involves using statistical tools and historical data to predict future sales patterns, which then inform inventory planning, staffing, and transportation needs. Accurate forecasting enables businesses to stay proactive rather than reactive, ensuring resources are allocated efficiently. Integral to all logistics functions is customer service, which serves as the touchpoint between the logistics system and the end-user. High-performing logistics services ensure that customers receive their products in the right condition and timeframe, thereby building trust and fostering brand loyalty. Logistics teams must not only resolve delivery issues but also engage in proactive communication to keep customers informed and satisfied. A core function of logistics is inventory management, which involves maintaining the right amount of stock to meet customer demand while minimizing holding costs. It includes decisions regarding reorder points, safety stock levels, and lot sizing, all aimed at balancing service levels and cost control. Proper inventory management prevents lost sales due to stockouts and excessive capital lock-up due to overstocking.

Warehousing plays a critical role by providing secure and efficient storage for raw materials, work-in-process items, and finished goods. Warehousing strategies focus on optimizing space, improving picking efficiency, and minimizing handling time. Within warehouses and across logistics networks, material handling systems facilitate the movement, packaging, and placement of goods using equipment such as conveyor belts, forklifts, and automated storage and retrieval systems. Proper material handling not only enhances productivity but also reduces the risk of damage and workplace injuries. At the center of outbound logistics is transportation, the function responsible for moving goods from one location to another, by road, rail, air, or sea. Transportation decisions involve route planning, carrier selection, and cost optimization. The effectiveness of transportation affects lead times, distribution costs, and service quality, making it one of the most strategic elements of logistics management. Equally important is packaging, which serves both a protective and communicative function. Good packaging ensures that goods are not damaged during handling and transit, and it also conveys brand identity and product information. Packaging decisions must balance durability, cost, sustainability, and customer convenience. Returns management addresses the reverse flow of goods from customers back to the company. This function is vital for handling defective, unwanted, or excess products in a manner that preserves customer goodwill and recaptures value through refurbishment, resale, or recycling. Effective returns management enhances sustainability and customer retention, especially in industries like e-commerce where returns are frequent. Together, these functions form the operational backbone of logistics, enabling firms to deliver value, maintain competitiveness, and ensure the smooth functioning of complex supply chains. Each activity is interdependent, and their integration is essential for achieving excellence in logistics performance.

2.1.4 Importance of distribution and management

From an economic perspective, logistics is a vital industry employing significant labor and capital resources. Armstrong and Associates [20] estimated logistics costs at 8–18% of GDP, depending on a country's development level. In industrialized economies such as the U.S. and EU, the figure ranges between 8% and 9.5%, while in countries like India and China, it rises to 13% and 18%, respectively. In North America, Europe, and Asia Pacific, logistics expenditure averaged 11% of sales revenue. The variance in costs across industries is influenced by the value-to-weight ratio of products. For example, cement has high logistics costs due to its bulk and low value, while high-value alcoholic beverages incur lower logistics expenses relative to their price. Distribution costs, particularly transportation, are often the largest component of logistics expenses. In the U.S., transportation accounted for 47% of logistics spending in 2014 [6]. Conversely, warehousing and inventory costs comprised 24% and 21%, respectively. High transportation costs in the U.S. are partly due to greater distances and fuel expenses compared to European contexts. The global logistics market is dominated by retail logistics (63.9%), followed by automotive (13.2%) and consumer goods (12.6%). This underscores the significant influence of e-commerce and consumer-facing industries on logistics development.

2.1.5 Freight transportation and expedition services

Freight transportation, an essential element of logistics, ensures the physical movement of goods via multimodal channels. Effective freight logistics depends on coordination among third-party service providers, suppliers, intermediaries, and customers [16]. The role of logistics in omnichannel supply chains, especially in online retail, has grown significantly [21]. Speed and delivery reliability (on-time delivery) are now fundamental metrics of logistics performance [22]. However, speed (elapsed time) and timeliness (adherence to promised delivery times) must be distinguished conceptually. Studies by Ata Jalili Marand [23] emphasized that while both contribute to customer satisfaction, only timeliness reflects the system's reliability.

2.1.6 E-commerce and its integration with logistics

E-commerce refers to buying and selling goods and services over digital platforms, often eliminating the need for face-to-face interaction [16]. With the advancement of internet technologies, firms must adapt their marketing strategies to remain competitive in digital marketplaces [24, 25]. Increased online shopping has raised expectations for faster, more accurate logistics. Cerasis [26] argued that logistics underpins e-commerce through tracking systems, electronic billing, and real-time order fulfillment. Still, challenges remain in inventory management, packaging, and last-mile delivery [27]. Global supply chains also face complexity due to cultural and regulatory differences [28]. The rise of business-to-consumer (B2C) platforms like Tokopedia and Amazon has transformed logistics requirements. Customer demands now include flexible payment systems, real-time tracking, and multi-option delivery services. Consequently, logistics providers must evolve from bulk freight transport to parcel-level last-mile solutions.

2.1.7 Theoretical models: Technology acceptance model and unified theory of acceptance and use of technology

Technology adoption within logistics and e-commerce is often explained using the TAM and the UTAUT. According to Davis [5], TAM posits that perceived usefulness and perceived ease of use determine an individual's intention to use a technology. TAM has been widely validated and expanded [29]. UTAUT, developed by Venkatesh et al. [4], integrates eight prior models, including TAM and the Theory of Planned Behavior. It identifies four main predictors of BI and UB: performance expectancy, EE, social influence, and facilitating conditions. These are moderated by factors such as gender, age, experience, and voluntariness of use. EE refers to the ease of system use [30], while DFC reflect the infrastructure and support for technology usage [31]. BI, as per Yueh et al. [32], measures the likelihood that a user will engage in a specific behavior, which directly impacts UB and system adoption success [33].

2.1.8 Role of social media and digital facilitation

SM has emerged as a critical enabler of logistics communication, both internally and externally [34]. Platforms like WeChat and Facebook enhance supplier-buyer coordination and allow for transparent tracking of logistics performance. Internally, enterprise social networks improve collaboration and innovation [35]. From the perspective of social capital theory, digital platforms enhance bonding and bridging capital, enabling efficient information exchange and stakeholder engagement [36]. This extends the strategic role of logistics in customer satisfaction and organizational learning.

2.1.9 Digital facilitating conditions

"Facilitating conditions" refer to the degree to which an individual believes that technical and organizational infrastructure exists to support the use of a technology [4]. In the context of logistics and e-commerce, these conditions include reliable internet access, integrated IT infrastructure, software tools, training, and organizational support systems that enable efficient use of digital services. Aksoy et al. [31] further emphasized that DFC include a user's belief that help will be available when using a system. In e-commerce environments, this encompasses platform usability, digital payment systems, real-time support, and responsive troubleshooting. For logistics providers, DFC involve robust tracking technologies, automation, and real-time inventory systems. Inadequate DFC often result in user dissatisfaction and hinder the adoption of new logistics technologies. Digital infrastructure, including ERP systems, cloud logistics, and AI-based forecasting tools, has become increasingly central to efficient logistics operations. As noted by Klumpp and Heragu [16], the integration of digital platforms with traditional logistics processes significantly enhances end-to-end visibility and responsiveness, reducing both cost and risk.

2.1.10 Behavioral intention

BI is a critical variable in TAM and UTAUT models, representing the willingness or likelihood of an individual to perform a specific behavior, in this context, adopting and using logistics or e-commerce technology. According to Ling Keong et al. [37], BI reflects a user's motivation to act. Yueh et al. [32] described it as the probability that an individual will engage in a specific technological behavior. In the context of logistics systems, a high BI indicates a user's readiness to utilize digital tracking, e-fulfillment, and self-service platforms. TAM posits that BI is primarily influenced by perceived usefulness and ease of use, while UTAUT expands this to include social influence and facilitating conditions. BI serves as a leading indicator for actual system usage and is often a precursor to sustained adoption. As Venkatesh et al. [4] argued, understanding what influences BI is essential for increasing technology adoption rates in logistics organizations, particularly in developing economies where resistance to digital transformation may persist.

2.1.11 Use behavior

UB refers to the actual utilization of technology by end users. It is a key construct in evaluating the success of system implementations and technology adoption efforts [33]. In logistics, UB includes using warehouse management systems, mobile inventory scanners, tracking dashboards, and cloud-based order fulfillment applications. UB can be assessed through system logs, usage statistics, and performance metrics such as transaction frequency, error rates, and processing time. Analysis of UB helps organizations tailor their digital platforms to user needs, identify training gaps, and measure return on investment in digital infrastructure. Data mining techniques and analytics tools are often employed to understand UB in depth. This includes tracking mouse clicks, user paths, session durations, and platform engagement [33]. These insights are crucial for logistics and e-commerce businesses seeking to optimize digital workflows and improve user experience.

2.1.12 Customer experience

CX is the internal and subjective response that customers have when interacting with a company [38]. In the context of logistics and e-commerce, CX encompasses all touchpoints, from searching for a product to order placement, delivery, and post-sale service. A positive CX is essential for customer retention, repeat purchases, and word-of-mouth marketing. Ahmed et al. [39] and Khan and Abideen [40] asserted that good CXs significantly enhance the relationship between BI and actual UB. In logistics, this includes accurate tracking, timely delivery, professional packaging, and responsive customer support. The role of CX as a moderating variable is also highlighted in empirical studies. For instance, even if customers perceive a platform as useful and easy to use, poor delivery experiences can negate the intention to repurchase. Therefore, optimizing CX requires a holistic approach that integrates logistics performance, digital service quality, and customer engagement.

2.1.13 Social media integration

SM plays a dual role in modern logistics and e-commerce. First, it enhances communication and coordination within the supply chain; second, it serves as a powerful marketing and engagement tool. Gilang Kharisma [41] highlighted how platforms like Facebook, LinkedIn, and Twitter are used by logistics companies to engage stakeholders, promote transparency, and share real-time updates. SM contributes to building social capital, which is categorized as bonding (internal trust and cooperation) and bridging (external relationships and knowledge exchange). Effective use of SM not only supports brand awareness but also facilitates logistics transparency and crisis management. Enterprise social networks (e.g., Yammer, Salesforce Chatter) have also been used internally to increase employee collaboration, enhance coordination in logistics workflows, and promote collective problem-solving [35]. Social platforms become especially critical during disruptions (e.g., pandemics, natural disasters) when information timeliness and accuracy determine customer satisfaction.

2.1.14 Effort expectancy and technology adoption

EE refers to the degree of ease associated with a user's experience when using a system [42]. In logistics and e-commerce, high EE means that customers find it easy to place orders, track shipments, or access support. For employees, it reflects how seamlessly warehouse software or transport management systems can be learned and utilized. Lancelot Miltgen et al. [30] stated that EE is a strong predictor of BI to adopt technology. Systems with intuitive interfaces, automation, and mobile accessibility increase perceived ease of use, thereby encouraging adoption. On the contrary, overly complex or poorly designed platforms can hinder user engagement and trigger system rejection. In logistics, simplifying customer-facing digital experiences (e.g., self-service portals, mobile tracking apps) directly contributes to increased customer loyalty and reduced service costs. Internally, employee-friendly dashboards and mobile solutions can boost productivity and reduce training needs.

2.2 Previous research

From the 40 reviewed articles (see Table 1), six of them employed the variable UB [43-48]. The variable SM appeared in five articles [49-53]. The variable EE was utilized in five studies [53-57]. Meanwhile, the variable DFC appeared in as many as twenty-one articles [38, 42, 45, 51, 53, 54, 56, 58-72]. Furthermore, the variable BI was discussed in twelve articles [40, 49, 53, 55, 56, 63, 64, 66, 69, 73-76]. Lastly, the variable CX was included in seven studies [38-40, 45, 68, 77, 78].

Table 1. Summary of variables used in prior relevant studies

No.	Articles	Social Media (SM)	Effort Expectancy (EE)	Digital Facilitating Conditions (DFC)	Use Behavior (UB)	Behavioral Intention (BI)	Customer Experience (CX)
1	[49]	√				√	
2	[58]			√			
3	[59]			√			
4	[43]				√		
5	[77]						√
6	[50]	√					
7	[38]						√
8	[73]					√	
9	[74]					√	
10	[44]				√		
11	[60]			√			
12	[61]			√			
13	[54]		√	√			
14	[51]	√		√			
15	[55]		√			√	
16	[62]			√			
17	[63]			√		√	
18	[64]			√		√	
19	[56]		√	√		√	
20	[65]			√			
21	[66]			√		√	
22	[75]					√	
23	[67]			√			
24	[76]					√	
25	[68]			√			√
26	[45]			√	√		√
27	[46]				√		
28	[47]				√		
29	[69]			√		√	
30	[57]		√				
31	[70]			√			
32	[78]						√
33	[71]			√			
34	[72]			√			
35	[48]				√		
36	[52]	√					
37	[42]			√			
38	[39]						√
39	[40]					√	√
40	[53]	√	√	√		√	
41	This study	√	√	√	√	√	√

2.3 Hypothesis development

To better understand the dynamics of digital service adoption in the context of online expedition services, this study proposes a comprehensive conceptual model grounded in the UTAUT, the TAM, and complementary digital behavior theories. The model is designed to capture both the direct and indirect pathways through which key constructs, namely EE, SM, and DFC, influence BI and ultimately shape UB. It also integrates mediating and moderating mechanisms to provide a more nuanced understanding of user behavior in digital logistics platforms. Specifically, BI is posited as a central mediating variable, mediating the influence of EE, SM, and DFC on actual usage. This reflects the cognitive-behavioral pathway commonly discussed in behavioral technology models. Furthermore, CX is introduced as a moderating variable that strengthens or weakens the relationship between BI and UB, capturing the role of user satisfaction and emotional engagement in the adoption process. In addition, the construct of Age is modeled as a moderator that interacts with EE, SM, and DFC in shaping BI, acknowledging the generational and cognitive differences in technology usage. Altogether, this conceptual framework reflects the interplay between psychological perception (expectancy), external influence (social media), technological infrastructure (facilitating conditions), and personal factors (experience and age) in shaping both the intention and actual behavior of digital service users. The hypotheses derived from this framework are visually represented in Figure 1.

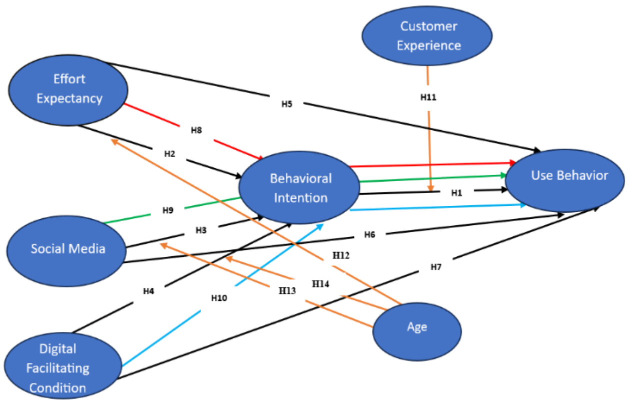

Figure 1. Conceptual model

2.3.1 Behavioral intention influences use behavior of online expedition services

BI is widely defined as the degree to which an individual is inclined to use a particular technology, as explained by scholars such as Tang et al. [79], Tian et al. [80], and Xiao and Goulias [81]. It reflects the motivational factors that capture how hard people are willing to try, or how much effort they plan to exert, to perform a behavior. In the context of technology adoption, BI is often used to predict actual user behavior. Alassafi [82] emphasized that customers' intentions play a critical role in shaping their actual behaviors. Although significant attention has been given to BI in financial technologies [83, 84], its role in expedition services remains underexplored. Given this conceptual grounding, the proposed hypothesis is:

H1: *BI significantly influences UB of online expedition services.*

2.3.2 Effort expectancy influences behavioral intention

EE is a fundamental construct in the UTAUT and TAM, reflecting the perceived ease of use associated with a system. When users perceive that a digital service is easy to use, they are more likely to adopt it. Research by Ayesha et al. [85] and Chen [86] confirmed that perceived ease of use strongly affects technology adoption decisions. Moreover, Wonglimpiyarat [87] and Moslehpour et al. [88] observed that EE influences the BI to use e-wallets and mobile banking. This suggests that users' perceptions of convenience in digital logistics platforms can directly shape their BI.

H2: *EE significantly influences BI to use online expedition services.*

2.3.3 Social media influences behavioral intention

The influence of SM on customer behavior has become increasingly significant, particularly in the context of influencer marketing. Ilieva et al. [89] emphasized the importance of collaborative strategies between marketers and influencers to improve customer engagement and purchase intention. Customized and engaging content tailored to users' interests enhances trust and encourages repeated use. Consequently, SM interactions can strongly shape BIs toward using digital platforms, including expedition services.

H3: *SM significantly influences BI to use online expedition services.*

2.3.4 Digital facilitating condition influences behavioral intention

DFC refer to the availability of organizational and technical infrastructure that supports system use. Drawing from Zacharis and Nikolopoulou [90], facilitating conditions, such as user support, accessible infrastructure, and digital literacy, enhance users' intention to engage with digital platforms. Especially in post-pandemic contexts, these factors have been instrumental in promoting the use of eLearning and financial technologies. Extending this to the logistics domain, when users perceive that supportive conditions are in place, their intention to use online expedition services increases.

H4: *DFC significantly influences BI to use online expedition services.*

2.3.5 Effort expectancy influences use behavior

Beyond influencing intention, EE may directly shape actual UB. Afan Suyanto et al. [91] argued that easier technology motivates both the intention and actual behavior of users. This dual influence is particularly relevant in digital logistics, where simplicity in using platforms can lead to higher adoption and usage rates. Therefore, EE not only acts through intention but also exerts a direct influence on user behavior.

H5: *EE significantly influences UB of online expedition services.*

2.3.6 Social media influences use behavior

SM, especially through influencer attributes, affects user decision-making and behavior. Lajnef [92] found a direct relationship between influencer characteristics and actual consumer behavior, particularly among younger demographics. The engaging nature of content on social platforms can lead directly to usage behavior, bypassing intention in some cases. This direct influence warrants empirical testing in logistics settings.

H6: *SM significantly influences UB of online expedition services.*

2.3.7 Digital facilitating condition influences use behavior

DFC can affect user behavior independently of intention. According to Chan et al. [93] and Neslin and Shankar [94], if users perceive adequate support, infrastructure, and resources, they are more likely to use a system. Age and digital literacy moderate this relationship, with older or less tech-savvy users depending more on DFC [95, 96]. Thus, such conditions directly influence user behavior in using online services.

H7: *DFC significantly influences UB of online expedition services.*

2.3.8 Behavioral intention mediates the effect of effort expectancy on use behavior

Davis [6] and Dhiman et al. [97] emphasized that BI acts as a key mediator between EE and actual use. When users find a system easy to use, they form a strong intention to use it, which in turn drives behavior. This indirect pathway highlights the role of BI in translating perceived ease of use into action.

H8: *BI significantly mediates the relationship between EE and UB.*

2.3.9 Behavioral intention mediates the effect of social media on use behavior

SM's influence on user behavior often operates through BI. As shown by Long et al. [98], influencers affect consumers' perceived norms and attitudes, which subsequently shape their BIs and eventual usage patterns. This validates the mediating role of intention in the SM–behavior link.

H9: *BI significantly mediates the relationship between SM and UB.*

2.3.10 Behavioral intention mediates the effect of digital facilitating condition on use behavior

Studies by Mansour et al. [99] and Wibowo and Sobari [100] provide evidence that DFC do not directly result in UB unless BI is activated. Infrastructure and support only lead to technology use when users are psychologically inclined to adopt it. Thus, intention serves as a crucial intervening variable.

H10: *BI significantly mediates the relationship between DFC and UB.*

2.3.11 Customer experience moderates the relationship between behavioral intention and use behavior

CX, including perceived value and emotional engagement, has been found to moderate the path from intention to behavior. Studies by Ahmed et al. [39] and Edem Amenuvor et al. [101] reveal that richer CXs enhance the strength of this relationship. Users who have positive and satisfying experiences are more likely to act on their intentions.

H11: *CX significantly moderates the relationship between BI and UB.*

2.3.12 Age moderates the relationship between effort expectancy and behavioral intention

Age is a critical moderator in digital technology adoption. As suggested by Morris et al. [102], older users focus more on effort and support. Hence, the effect of EE on intention may vary by age cohort.

H12: *Age significantly moderates the relationship between EE and BI.*

2.3.13 Age moderates the relationship between social media and behavioral intention

Generational differences also influence how users respond to SM. Younger users may be more responsive to digital influencers, while older users rely less on such cues. Therefore, the impact of SM on intention could be contingent on age.

H13: *Age significantly moderates the relationship between SM and BI.*

2.3.14 Age moderates the relationship between digital facilitating condition and behavioral intention

Finally, age may shape how users perceive and utilize digital support. While younger users may explore and adapt to systems autonomously, older users depend more on facilitating infrastructure, making the moderating effect of age significant.

H14: *Age significantly moderates the relationship between DFC and BI.*

3. METHODOLOGY

This study adopts a quantitative approach grounded in empirical data collection and analysis, aiming to examine the BI and usage behavior of online expedition service users in Jakarta. The research process began with a preliminary survey, which included field observations to capture real-time phenomena related to logistics service usage. Following this initial phase, an extensive literature review was conducted to identify relevant theoretical frameworks, including grand theory, middle-range theory, and operational theory, as well as to examine findings from previous empirical studies. These insights informed the development of the research model and the selection of study variables.

Subsequently, the core constructs were defined conceptually and operationally, and indicators were formulated for each variable. A structured questionnaire was then developed as the primary data collection instrument. Prior to full deployment, the questionnaire underwent a validity and reliability test using Pearson product-moment correlation via SPSS version 26. Items that failed to meet the required thresholds were revised or removed to ensure the instrument's psychometric integrity. The valid items were then incorporated into the final version of the questionnaire.

The study population comprises all online expedition service users across the DKI Jakarta Province. Given the population's heterogeneity and the stratified nature of service providers, a stratified proportional random sampling technique was employed. Respondents were proportionally selected from different logistics service providers based on their market share, ensuring adequate representation. A total of 323 respondents were selected, guided by the sample size recommendation of Hair et al. [103], which suggests using 5 to 10 times the number of observed indicators.

Data collection was carried out using a closed-ended questionnaire, employing a five-point Likert scale ranging from "strongly disagree" to "strongly agree" to measure respondent agreement levels. The use of this five-point internal Likert scale is justified by its simplicity, visual appeal, and statistical adequacy for large-sample studies [104-106]. Primary data were collected directly from respondents, while secondary data were sourced from relevant literature, company reports, official statistics, and academic journals.

The measurement constructs used in this study were adapted from validated instruments in prior literature, each operationalized through multiple indicators using a 5-point Likert scale. The SM variable (X1), adapted from Subagja et al. [52] includes six items (SM1–SM6) measuring perceptions of media compatibility, interactivity, social network expansion, data transparency, engagement frequency, and overall impression—highlighting the multifaceted influence of SM on user attitudes. The EE construct (X2), derived from Subhani et al. [57], consists of five items (EE1–EE5) assessing users' perceived ease of operating and mastering online freight systems, as well as task completion efficiency. Meanwhile, the DFC variable, based on Venkatesh et al. [42] and Wang and Chu [70], encompasses six indicators (DFC1–DFC6) that evaluate the availability of digital resources, user competence, system compatibility, access to support, infrastructure adequacy, and timely assistance from trained personnel. BI, serving as a mediating variable, is measured using five items (BI1–BI5) from Venkatesh et al. [42] and Subhani et al. [57], including intention to continue use, habitual usage behavior, and favorable attitudes toward online services. The CX construct (moderator) includes five items (CE1–CE5) capturing sensory, emotional, and social experiences, as well as perceived effort and system response time—critical in influencing user satisfaction and behavioral outcomes. Finally, UB, the endogenous variable, is measured through five items (UB1–UB5) based on Subhani et al. [57], covering usage frequency, intention to recommend, continued usage, loyalty across sessions, and engagement with system features. These measurement items ensure content validity and reflect the theoretical underpinnings of the UTAUT, while also integrating behavioral and experiential dimensions relevant to the context of online freight forwarding services.

To ensure rigorous analysis, the data were processed through a two-stage procedure involving descriptive and inferential statistical techniques. Descriptive statistics were used to summarize and profile the demographic and behavioral attributes of the respondents, providing a foundational understanding of the study sample. Inferential analysis was conducted using the Structural Equation Modeling (SEM) approach, operationalized through the AMOS software. This method allows simultaneous examination of multiple dependent relationships and is particularly robust for analyzing complex behavioral models involving latent constructs.

The SEM process commenced with the development of the measurement model, which evaluated the relationships between latent variables and their respective indicators. The model employed a reflective indicator approach, meaning that latent constructs were posited to influence observed variables. Construct validity was tested through confirmatory factor analysis (CFA), emphasizing convergent and discriminant validity. Convergent validity was assessed using outer loading values and the Average Variance Extracted (AVE), with acceptable thresholds of ≥ 0.7 for outer loadings and ≥ 0.5 for AVE. Discriminant validity was examined through cross-loading comparisons and Fornell-Larcker criteria, supplemented by the Heterotrait-Monotrait (HTMT) ratio to confirm construct distinctiveness.

Reliability was evaluated using both Cronbach's alpha and composite reliability (CR) scores, with thresholds set at 0.6 and 0.7 respectively. The structural model (inner model) was then assessed to determine the predictive relationships among constructs. The model's explanatory power was evaluated through R^2 values, with classifications of weak, moderate, or strong based on the magnitude of variance explained. Effect sizes (f^2) and predictive relevance (Q^2) were also calculated to capture the magnitude and relevance of the relationships. In addition, the Cross-Validated Predictive Ability Test (CVPAT), available in SmartPLS 4.0, was applied to benchmark predictive performance between SEM-PLS and indicator-average approaches, where significance was determined using Average Loss Difference (ALD) and p-values (see Figure 2).

The overall model fit was examined using the Goodness of Fit Index (GFI), computed from the geometric mean of AVE and R^2 values. A satisfactory model fit indicates that the model adequately captures the observed data structure and confirms the robustness of the proposed theoretical framework. The methodological rigor embedded in this research ensures the reliability, validity, and explanatory strength of the proposed model, thereby offering robust insights into the behavioral dynamics of online expedition service users in Jakarta.

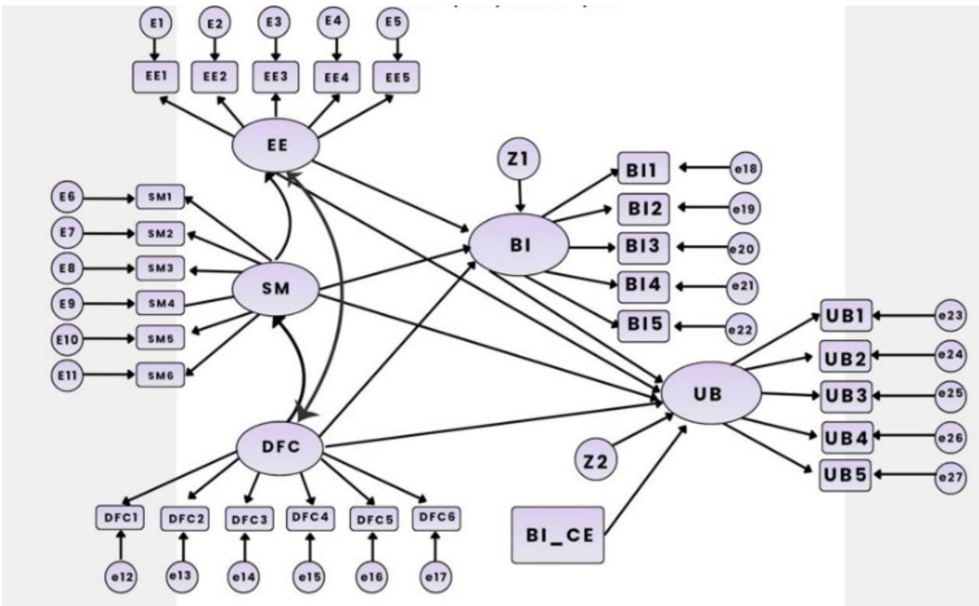

Figure 2. Structural model

4. RESULT AND DISCUSSION

4.1 Description of respondent characteristics

This study involved a total of 323 respondents, all of whom are users of online expedition services operating across the entire province of DKI Jakarta, Indonesia. The selection of Jakarta as the study area was based on its status as the nation's capital with the highest digital infrastructure and logistics activity, making it highly representative for analyzing consumer behavior in the online delivery sector. The respondents were selected using stratified proportional random sampling, ensuring a fair distribution based on the most widely used logistics service providers in the region. The demographic data gathered from respondents encompass gender, age, education level, and preferred expedition service provider, which are summarized in Table 2.

Table 2. Description of respondent characteristics

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	154	47.7
	Female	169	52.3
Age	15 – 44 years	148	45.8
	45 – 59 years	140	43.3
	≥ 60 years	35	10.8
Education	Senior High School	83	25.7
	Diploma III (D3)	28	8.7
	Diploma IV / Bachelor	110	34.1
	Master's Degree (S2)	76	23.5
	Doctoral Degree (S3)	26	8.0
Expedition Service Company	JNE	75	23.2
	J&T Express	96	29.7
	Shopee Express	46	14.2
	Tiki	12	3.7
	Sicepat	45	13.9
	Lalamove	3	0.9
	Paxel	10	3.1
	Indah Logistik Cargo	3	0.9
	Wahana Express	8	2.5
	Ninja Xpress	12	3.7
	Pos Indonesia	10	3.1

As shown in Table 2, the gender distribution among respondents is relatively balanced, with a slight dominance of female respondents totaling 169 individuals or 52.3%, while male respondents accounted for 154 individuals or 47.7%. This balance reflects the inclusive nature of online expedition services, which cater equally to both male and female consumers. In terms of age, the majority of respondents were in the younger age group of 15 to 44 years, accounting for 148 individuals (45.8%). This is followed closely by respondents aged 45 to 59 years, with a count of 140 individuals (43.3%). Meanwhile, older adults aged 60 years and above comprised a smaller portion of the sample, with 35 respondents (10.8%). This distribution indicates a strong engagement of both younger and middle-aged consumers in using online expedition services, likely due to their higher technology usage and mobility.

Regarding educational attainment, respondents with a Bachelor's degree (D IV/S-1) made up the largest group, representing 34.1% or 110 individuals. This was followed by high school graduates (SMA) at 25.7% or 83 respondents, and Master's degree holders (S-2) at 23.5% or 76 individuals. Diploma III holders constituted 8.7% (28 respondents), while those with a Doctoral degree (S-3) made up 8.0% or 26 individuals. The relatively high proportion of respondents with tertiary education suggests that online expedition services are particularly favored by individuals with higher levels of education, possibly due to their better access to and understanding of digital platforms. In terms of preferred expedition services, J&T Express emerged as the most widely used provider, cited by 96 respondents (29.7%). JNE followed as the second most popular, with 75 respondents (23.2%), and Shopee Express ranked third, used by 46 respondents (14.2%). Other service providers such as Sicepat (13.9%), Tiki and Ninja Xpress (each 3.7%), Pos Indonesia and Paxel (each 3.1%), Wahana Express (2.5%), and both Lalamove and Indah Logistik Cargo (each 0.9%) were also selected by smaller segments of the sample. These findings suggest that the respondents in this study not only represent diverse demographics but also reflect varied preferences in expedition services, which adds richness and heterogeneity to the data, an important aspect in behavioral studies involving consumer logistics choices.

4.2 Descriptive statistics

Based on the descriptive statistical analysis of all variables, SM, EE, DFC, BI, CX, and UB, the overall findings reflect a consistently positive perception among users of online delivery services in the Jakarta area. The SM variable scored an average index of 83.56, indicating that users perceive SM platforms used by expedition companies to be generally compatible, interactive, transparent, and effective in expanding social networks, although there is still room to improve users' overall impressions. EE recorded a higher average score of 84.54, suggesting strong agreement among users that the digital delivery systems are easy to use and efficient, particularly in terms of operations and transaction speed. However, ease of becoming proficient with the system remains an area that could be enhanced through user education and interface simplification. The DFC variable received an average index of 81.62, reflecting users' general satisfaction with the digital support infrastructure, such as system compatibility and access to digital resources, though improvements are needed in terms of technical support availability and personnel readiness. Meanwhile, BI scored an average of 82.80, showing that users are highly inclined to continue using and recommending online delivery services. Nonetheless, the findings suggest that forming consistent usage habits should be a strategic focus for service providers.

The CX variable achieved an average index of 81.85, highlighting that users find the service engaging, easy to use, and emotionally satisfying. However, social interaction aspects of the experience remain underdeveloped and could be improved by adding community-based or sharing features. Lastly, UB scored an average of 81.55, indicating that users frequently engage with digital delivery platforms, utilize available features, and integrate these services into their daily routines. However, efforts to increase loyalty and encourage user referrals could further enhance usage behavior. The results show that digital expedition services in Jakarta are performing well in delivering user satisfaction and functionality. Nevertheless, there is a clear opportunity for providers to strengthen social interaction, streamline usability, and invest in loyalty-driven features to ensure competitive advantage and sustained customer engagement in a highly digitalized urban environment.

4.3 Validity and reliability test

To ensure the robustness of the measurement model, a CFA was conducted on each construct using the CB-SEM approach. The analysis evaluated three key criteria: loading factor, AVE, and CR. A loading factor threshold above 0.70 was considered acceptable for establishing convergent validity, while AVE values of at least 0.50 and CR values above 0.70 were used to assess the adequacy of construct validity and internal consistency reliability. The results of the CFA are summarized in Table 3, which presents the psychometric properties for each latent variable included in the model.

As presented in Table 3, all constructs demonstrate strong psychometric properties. Most constructs exceed the minimum thresholds for AVE and CR, affirming their convergent validity and internal consistency. The CX construct, while still acceptable, shows slightly lower loading factors on two indicators and an AVE value (0.581) that, although above the minimum standard, suggests potential for refinement in future studies. Nevertheless, all constructs can be considered sufficiently valid and reliable for inclusion in subsequent structural model testing.

Table 3. Summary of validity and reliability for all constructs

Construct	Number of Indicators	Loading Factor Range	AVE	CR	Convergent Validity	Reliability
SM	6	0.84 – 0.87	0.761	0.950	Yes	High
EE	5	0.86 – 0.88	0.755	0.939	Yes	High
DFC	6	0.82 – 0.90	0.759	0.950	Yes	High
BI	5	0.75 – 0.90	0.743	0.935	Yes	High
UB	5	0.90 – 0.92	0.778	0.946	Yes	High
CX	5	0.52 – 0.97	0.581	0.867	Partially	Moderate

4.4 Assumption testing of SEM

4.4.1 Normality

In the Covariance-Based Structural Equation Modeling (CB-SEM) framework, assessing data normality is a critical prerequisite for ensuring the appropriateness of the Maximum Likelihood (ML) estimation method. Normality was evaluated by examining the z-scores (critical ratios) of skewness and kurtosis for each indicator. According to standard criteria, a univariate distribution is considered normal when the z-score lies within the range of −2.58 to +2.58, corresponding to a 0.01 significance level. If all indicators meet this requirement, the data can be assumed to follow a normal distribution and be suitable for ML estimation. However, when individual violations occur, it is advisable to further conduct Mardia's test for multivariate normality or consider bootstrapping as an alternative estimation strategy.

Table 4. Normality test results

Variable	Skew C.R.	Kurtosis C.R.
BI_CE	12.042	21.369
UB1–UB5	−7.663 to −8.286	0.471 to 1.767
BI1–BI5	−2.634 to −3.835	−0.959 to 0.013
DFC1–DFC6	−3.065 to −4.184	−0.467 to 0.979
SM1–SM6	−1.913 to −4.137	0.024 to 0.979
EE1–EE5	−2.568 to −4.225	−1.104 to 0.571
Multivariate		1.927

Source: Processed data (2025)

As shown in Table 4, while some individual indicators, such as BI_CE, exceed the recommended cut-off for univariate skewness and kurtosis, the multivariate CR is 1.927, which remains well within the acceptable range of −2.58 to +2.58. This finding indicates that the assumption of multivariate normality is sufficiently met. Therefore, despite minor deviations at the item level, the dataset can be considered appropriate for CB-SEM analysis using the ML estimation method.

4.4.2 Multicollinearity

Multicollinearity among exogenous variables in CB-SEM is assessed by examining the bivariate correlations between constructs. Following the guidelines proposed by Ghozali [107], multicollinearity is indicated when correlation coefficients exceed 0.90, which may lead to estimation instability and inflated standard errors. Therefore, acceptable correlation values among exogenous constructs should be below this threshold to confirm the independence of predictor variables in the structural model.

Table 5 shows that all correlation coefficients among exogenous variables range from 0.534 to 0.593, which are well below the 0.90 threshold. These values confirm that no multicollinearity exists among the predictors in the structural model. Hence, the model satisfies the assumption of multicollinearity independence, and further CB-SEM analysis can proceed without requiring corrective modifications to the exogenous constructs.

Table 5. Multicollinearity test results

Construct Pair	Correlation Estimate
EE ↔ SM	0.593
SM ↔ DFC	0.534
EE ↔ DFC	0.582

Source: Processed data (2025)

4.5 Goodness of fit test of the structural model

The goodness of fit test for the structural model was conducted to assess how well the theoretical model aligns with empirical data. This evaluation utilizes various fit indices, which are grouped into three main categories: absolute fit, incremental fit, and parsimony fit. Among the key indicators are the Chi-square/df (CMIN/DF), which is considered acceptable when less than 2.00; a p-value above 0.05; and other supportive indices such as the Comparative Fit Index (CFI > 0.90), Tucker-Lewis Index (TLI > 0.90), Root Mean Square Error of Approximation (RMSEA < 0.08), and GFI (GFI > 0.90). However, in SEM with large sample sizes (n > 200), the Chi-square p-value tends to be overly sensitive, often leading to statistical rejection even when the model is practically a good fit. Hence, the primary focus of model fit assessment lies in the other fit indices.

As shown in Table 6, the model demonstrates a satisfactory level of absolute fit. The Chi-square/df (CMIN/DF) value of 1.827 meets the ideal threshold of less than 2.00, indicating a good overall fit. The RMSEA (0.051) and RMR (0.039) values also fall within acceptable ranges, supporting the model's compatibility with empirical data. While the GFI (0.879) and AGFI (0.855) fall slightly below the conventional 0.90 benchmark, they are still within the "marginal fit" range, which is acceptable given the large sample size and the complexity of the model. For incremental fit indices, the structural model exhibits very strong performance. The CFI (0.968), TLI (0.964), NFI (0.932), IFI (0.968), and RFI (0.924) all exceed the 0.90 threshold, indicating that the proposed model provides a significantly better fit than the null or independent model. These results demonstrate that the model has substantial incremental validity and captures the structure of the data effectively.

Moreover, parsimony fit indices further support the model's adequacy (see Figure 3). All three indices, PNFI (0.838), PCFI (0.870), and PGFI (0.736), exceed the minimum threshold of 0.50, suggesting that the model is not only well-fitted but also efficient and parsimonious in terms of its parameter estimates. Based on these comprehensive fit assessments, it can be concluded that the structural model satisfies both statistical and theoretical requirements. Therefore, it is appropriate to proceed with hypothesis testing and interpret the structural relationships among the constructs in the context of online delivery service usage behavior.

Table 6. Goodness of fit indices of the structural model

Fit Category	No.	Fit Index	Value	Cut-off Value	Criteria
Absolute Fit	1	Chi-square/df	1.827	< 2.00	Good
	2	GFI	0.879	≥ 0.90	Marginal Fit
	3	AGFI	0.855	≥ 0.90	Marginal Fit
	4	RMR	0.039	< 0.08	Good
	5	RMSEA	0.051	< 0.08	Good
Incremental Fit	6	CFI	0.968	≥ 0.90	Good
	7	TLI	0.964	≥ 0.90	Good
	8	NFI	0.932	≥ 0.90	Good
	9	IFI	0.968	≥ 0.90	Good
	10	RFI	0.924	≥ 0.90	Good
Parsimony Fit	11	PNFI	0.838	≥ 0.50 (minimum)	Good
	12	PCFI	0.870	≥ 0.50 (minimum)	Good
	13	PGFI	0.736	≥ 0.50 (minimum)	Good

Source: Processed data (2025)

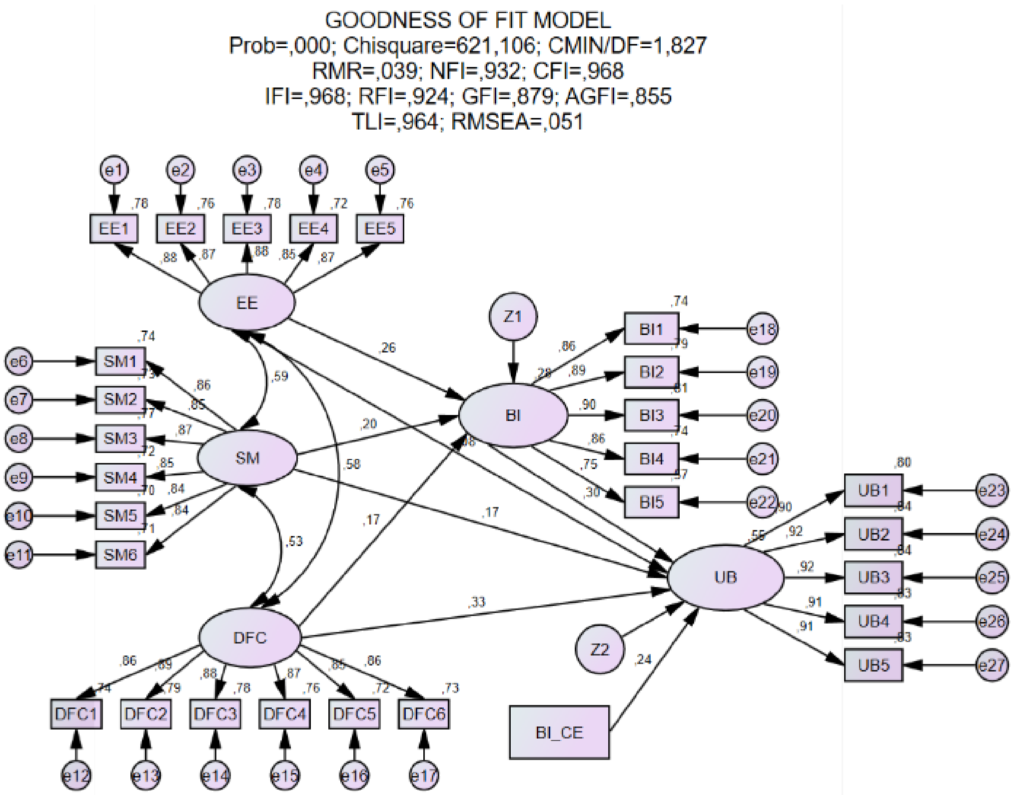

Figure 3. GoF model

4.6 Structural model

The direct effect testing using CB-SEM was conducted by examining three key statistical indicators: p-value, CR, and standardized path coefficients. A direct effect is considered statistically significant if the p-value is less than 0.05 and the CR exceeds 1.96. The path coefficient reflects the direction and strength of the relationship between constructs, where positive values indicate a direct relationship, and negative values indicate an inverse relationship. The closer the coefficient is to ±1, the stronger the effect. These results must be interpreted collectively to ensure both numerical magnitude and statistical significance. The findings reveal that most hypothesized direct relationships in the model are statistically significant. For instance, EE, SM, and DFC significantly influence BI, while BI, SM, and DFC have a significant impact on UB. However, the direct path from EE to UB was found to be non-significant. This suggests that while user expectations of ease influence intention, they do not directly drive usage behavior, implying a potential mediating role of BI. Additionally, the interaction between BI and CX significantly enhances UB, underscoring the moderating influence of experiential factors.

Table 7. Hypothesis testing results

No.	Hypothesis	Path Coefficient	P-Value	Conclusion
1	BI → UB	0.297	< 0.001	Accepted
2	EE → BI	0.255	< 0.001	Accepted
3	SM → BI	0.202	0.003	Accepted
4	DFC → BI	0.170	0.012	Accepted
5	EE → UB	0.079	0.180	Rejected
6	SM → UB	0.169	0.003	Accepted
7	DFC → UB	0.334	< 0.001	Accepted
8	EE → BI → UB (Mediated)	0.0757	0.012	Accepted
9	SM → BI → UB (Mediated)	0.0600	0.031	Accepted
10	DFC → BI → UB (Mediated)	0.0505	0.006	Accepted
11	BI * CX → UB (Interaction Effect)	0.244	< 0.001	Accepted
12	Age moderates EE → BI	0.341 vs 0.002	0.001 vs 0.989	Accepted
13	Age moderates SM → BI	0.091 vs 0.291	0.415 vs 0.001	Accepted
14	Age moderates DFC → BI	0.223 vs 0.291	0.012 vs 0.066	Accepted

Following the presentation of the comprehensive hypothesis testing summary in Table 7, further analysis was conducted to explore the indirect and moderating effects within the structural model. Indirect effects were examined using bias-corrected bootstrapping, a robust non-parametric method suitable for large samples and non-normal data distributions. The results confirmed the mediating role of BI in transmitting the effects of EE, SM, and DFC on UB. These findings indicate that users' perceptions of system ease, digital support, and social influence must first translate into a BI before manifesting as actual UB. Additionally, a Multi-Group Analysis (MGA) was performed to examine the moderating role of Age on key relationships. The analysis demonstrated significant age-based differences. For younger users, EE had a strong effect on BI, while for middle-aged and older users, SM exerted a greater influence. These differences affirm that age moderates the strength and significance of the paths from exogenous variables to BI, implying that generational differences should be considered when designing digital strategies for logistics service platforms. The results post-Table 7 not only validate the proposed theoretical framework but also emphasize the importance of mediating and moderating mechanisms in understanding digital behavior. The implications suggest that enhancing user intention, via usability, social engagement, and adequate digital infrastructure, is crucial to fostering sustained use of online expedition services, especially when tailored to demographic nuances such as age.

4.7 Discussion

This study presents a novel contribution by identifying CX as a moderating variable that strengthens the relationship between BI and UB in the context of online expedition services. This aspect has been largely underexplored in previous studies, which primarily focused on the direct impact of intention on behavior, often overlooking how user experience might influence the conversion of intention into actual usage. The findings enrich existing literature by demonstrating that a positive CX, such as omni-channel service consistency [108], application ease of use [109], perceived utilitarian value [110], and customer satisfaction fostered by credible online reviews [111], can significantly enhance the likelihood of users realizing their BI. Moreover, prior user experience has also been found to reinforce the influence of social factors on BI [110], underscoring the importance of accumulated experience in strengthening the transition from intention to actual behavior, particularly among middle-aged and older adults. Accordingly, this study not only advances theoretical understanding of digital service adoption but also offers practical insights for increasing conversion rates from intention to behavior by optimizing CX design.

The second contribution of this study lies in identifying the moderating effect of age on the relationship between EE and BI, with distinct patterns observed across different age groups. Specifically, the study reveals that EE significantly influences BI among younger users but not among middle-aged or older users. This suggests that perceived ease of technology use is more influential in shaping usage intention for younger users, who typically possess higher cognitive and psychomotor capabilities and are more familiar with modern digital interfaces. In contrast, older users may require more than just ease of use, such as perceived security, system trust, or emotional gratification, to develop strong usage intentions [112-114].

This finding extends the UTAUT2 model by asserting that age not only moderates the strength of relationships but can also alter their direction or significance. Previous studies often assumed the influence of EE on BI to be uniform across age groups. However, this research demonstrates that the effect is *age-sensitive*, robust among younger users but weaker or irrelevant among older cohorts [115, 116]. Thus, technology adoption strategies must avoid a one-size-fits-all approach and instead tailor promotional interventions, interface design, and digital education programs to age-based segments to more effectively foster BI.

The third novelty arises from the discovery that age significantly moderates the influence of SM on BI, exhibiting a unique pattern among middle-aged and older users. The study shows that the impact of SM on the intention to use online expedition services is more pronounced in middle-aged and elderly users than in younger ones. This may be attributed to the relatively higher digital literacy among younger generations, who tend to be more discerning and less easily influenced by SM content. Conversely, older users often rely on SM as a primary source of reference in forming their intentions, especially when the content is informative, persuasive, and tailored to their specific needs [117].

This finding broadens existing literature, which largely centers on youth as the main demographic for SM influence, by offering new insights that older adults are increasingly active and responsive to SM cues in decision-making processes [118, 119]. In the context of online expedition service usage, the results emphasize that SM campaigns should be age-sensitive. For older demographics, testimonial-based approaches, emotionally resonant narratives, and visually digestible content are likely to be more effective. In contrast, younger users may respond better to peer endorsements, functional value propositions, and integration with cutting-edge technologies. This novel insight enriches theoretical models of user behavior and yields practical guidance for crafting inclusive and age-segmented digital communication strategies [120, 121].

This study identifies that age moderates the relationship between DFC and BI, revealing that this relationship is stronger among younger users than among their older counterparts. For tech-savvy youth with high digital literacy, the availability of digital facilities, such as responsive expedition apps, real-time tracking systems, and accessible customer support, substantially enhances the intention to actively use such services. However, for older adults, even the availability of such infrastructure may not suffice. This is due to barriers such as lower digital literacy, the digital divide, and more prevalent cognitive and motivational limitations [114, 122, 123]. These findings introduce a new dimension to the technology adoption literature by stressing the importance of demographic considerations, particularly age, in strategies designed to promote user BI in digital services. Previous studies suggest that older individuals require more than just technological availability, they need personalized support, trust assurances, and emotional engagement to feel motivated toward adoption [124, 125]. Furthermore, frameworks such as the TAM and dual-pathway models highlight that for older users, affective motivations, social support, and perceived long-term benefits may outweigh mere functional access. Therefore, this research not only expands theoretical understanding of BI in online expedition services but also provides strategic direction for service providers to tailor their approaches based on age-specific user characteristics, thereby effectively addressing the digital divide.

5. CONCLUSION

This study concludes that BI has a strong and statistically significant influence on UB in the context of online expedition services, indicating that higher levels of intention correlate with increased likelihood of actual service usage. EE positively and significantly affects BI, suggesting that users' perceptions of ease of use and usefulness enhance their intention to adopt the service. SM exposure significantly strengthens BI, highlighting its effectiveness in shaping users' BI. Similarly, DFC positively impact BI, indicating that robust digital infrastructure enhances users' intent to use online expedition services. Although EE does not directly affect UB, it exerts an indirect effect through BI, confirming the mediating role of intention. Both SM and DFC significantly influence UB directly, with SM playing a dual role in shaping intention and behavior. Notably, BI significantly mediates the influence of EE, SM, and DFC on UB, underscoring its critical role as an intermediary. Furthermore, CX moderates the relationship between BI and UB, reinforcing the conversion of intention into behavior when users have a positive experience. Age serves as a significant moderating variable, particularly in the relationships between EE, SM, and DFC on BI. EE's influence on BI is significant among younger users but not among middle-aged and older groups. Conversely, SM exerts a stronger impact on BI among older users, while DFC shows greater influence on younger users' intentions. Among all exogenous variables, DFC demonstrates the strongest direct effect on UB. Additionally, the study finds that direct effects of exogenous variables on UB are generally stronger than indirect effects mediated through BI. These findings collectively highlight the nuanced dynamics between cognitive, technological, and experiential factors in influencing user behavior in digital service contexts, with age and experience playing pivotal moderating roles.

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