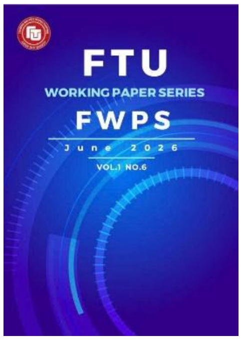

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MỨC ĐỘ SẴN SÀNG ỨNG DỤNG AI TRONG GIAO HÀNG CHẶNG CUỐI B2B: NGHIÊN CỨU CÁC DOANH NGHIỆP VỪA VÀ NHỎ TẠI VIỆT NAM

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Tóm tắt

Bài nghiên cứu được thực hiện nhằm đánh giá mức độ sẵn sàng của các doanh nghiệp vừa và nhỏ B2B tại Việt Nam trong việc áp dụng trí tuệ nhân tạo (AI) vào giao hàng chặng cuối (LMD) thông qua việc tích hợp mô hình TAM và TOE. Phương pháp định lượng được sử dụng với các kỹ thuật như thống kê mô tả, Cronbach's Alpha, EFA, CFA và PLS-SEM. Kết quả cho thấy tồn tại khoảng cách giữa kỳ vọng của lãnh đạo và năng lực số của nhân sự. Cảm nhận dễ sử dụng (PEOU) là điều kiện tiên quyết để hình thành cảm nhận hữu ích (PU). Lãnh đạo chuyển đổi đóng vai trò quan trọng trong việc thúc đẩy sự sẵn sàng, trong khi SMEs vẫn bị hạn chế bởi ngân sách và nguồn lực. Nghiên cứu đề xuất giải pháp thực tiễn là triển khai các công cụ AI chi phí thấp, dễ sử dụng như Abivin vRoute, kết hợp lộ trình áp dụng theo giai đoạn và tận dụng hỗ trợ bên ngoài. Kết quả nhấn mạnh rằng sự sẵn sàng AI phụ thuộc vào cả yếu tố công nghệ và tổ chức.

Từ khoá: AI, giao hàng chặng cuối, B2B, SMEs Việt Nam, mức độ sẵn sàng

AI READINESS IN B2B LAST-MILE DELIVERY: EVIDENCE FROM VIETNAMESE SMES

Abstract

This study examines the readiness of B2B SMEs in Vietnam to apply Artificial Intelligence (AI) in last-mile delivery (LMD) by integrating the TAM and TOE frameworks. A quantitative approach is applied using descriptive statistics, Cronbach's Alpha, EFA, CFA, and PLS-SEM. The results reveal a gap between leadership expectations and employees' digital capabilities. Perceived Ease of Use (PEOU) is a prerequisite for Perceived Usefulness (PU), while Transformational Leadership plays a critical role in driving readiness. SMEs also face significant budget and resource constraints. The study recommends practical solutions, including adopting low-cost, user-friendly AI tools such as Abivin vRoute, implementing a phased approach, and leveraging external support. Findings highlight that AI readiness depends on both technological and organizational factors.

Keywords: AI, last-mile delivery, B2B, Vietnamese SMEs, readiness

1 Introduction

1.1 Rationale

A subfield of computer science known as artificial intelligence (AI) refers to intelligence that has been produced by humans and is capable of learning, reasoning, and making decisions that are intrinsically linked to human intelligence (Tran Minh Tam, 2019; Boute & Udenio, 2023). In logistics, AI is particularly valuable due to the need for efficiency and optimization. Last-mile delivery (LMD) refers to the final and deciding stage of the transport process, where products are moved from a warehouse or a distribution center to the hands of final consumers (Risher et al., 2020). LMD is the most costly and sophisticated phase, which can cover 13% to 75% of overall supply chain costs based on the situation, half of the cost of logistics on average (Paulo Rita and Ricardo F. Ramos, 2022)

In Vietnam, these challenges are pronounced for B2B SMEs, accounting for 97% of enterprises but lack scale, infrastructure, resources (Anh Tuan, 2021). Issues like low delivery density, failed deliveries, rising e-commerce demand increase costs, reduce competitiveness. Using AI's machine learning algorithms and data optimization offers potential to optimize LMD through improved routing and resource allocation (Shuaibu et al., 2025). However, its adoption among Vietnamese B2B SMEs remains limited. Therefore, this study assesses B2B SMEs' readiness to adopt AI in LMD by examining their resources, environmental context, awareness, providing theoretical and practical insights.

1.2 Research objectives

The authors established the following targets in order to achieve those previously described objectives:

i. Using the TAM-TOE frameworks, determine how prepared B2B Vietnamese SMEs are to apply AI for last-mile delivery.

ii. To suggest a particular AI solution for last-mile delivery operational bottlenecks.

1.3 Research question

The study's primary goals are to assess Vietnamese SMEs' level of preparedness for implementing AI in last-mile delivery operations. The study's questions are as follows:

i. How prepared are B2B SMEs in Vietnam's industry to use AI for last-mile delivery?

ii. What types of AI can B2B SMEs explore for adoption?

1.4 Research method

In this study, the authors would apply quantitative methods. Statistical tools such as SPSS, STATA, and SmartPLS would be used to preprocess, code, and analyze quantitative data from online surveys. Additionally, a variety of analytical methods are used, such as Cronbach's Alpha to evaluate scale reliability, Exploratory Factor Analysis (EFA) to find underlying factor structures, Confirmatory Factor Analysis (CFA) to validate the measurement model, and descriptive statistics to summarize data characteristics. Lastly, the research model is tested, correlations between variables are examined, and the importance of the suggested hypotheses is assessed using partial least squares structural equation modeling (PLS-SEM).

2 Literature review and research gap

2.1 Literature review

AI is recognized as a transformative force enhancing logistics competitiveness. However, existing studies vary in context and often lack a specific focus on AI implementation in last-mile delivery, particularly within SMEs.

Le and Nguyen (2025), in *"Application of Artificial Intelligence in Logistics Enterprises in Vietnam: A New Direction in the Industrial Revolution 4.0",* examine AI adoption in Vietnam's logistics sector, highlighting its benefits, challenges, and general recommendations. However, the study treats logistics firms as a homogeneous group without distinguishing SMEs from large enterprises and remains at a macro level, lacking specific analysis of AI application in functions such as last-mile delivery, where SMEs face unique constraints. Nguyen (2025), in *"Challenges and Opportunities of Omni-Channel Integration in Last Mile Delivery Services for E-commerce in Vietnam",* analyzes LMD integration in Vietnam's e-commerce sector, outlining key challenges, opportunities, and strategies. However, the study relies mainly on literature review, lacks empirical evidence, and does not focus on SMEs, resulting in limited firm-level insights.

Alkhodair and Alkhudhayr (2025), in *"Harnessing Industry 4.0 for SMEs: Advancing Smart Manufacturing and Logistics for Sustainable Supply Chains",* examine challenges and enablers of AI adoption in SMEs' logistics. However, the study focuses mainly on mid-stream activities and lacks specific analysis of last-mile delivery, where distinct challenges exist. Uzozie (2022), in *"Innovating Last Mile Delivery Post-Pandemic: A Dual-Continent Framework for Leveraging Robotics and AI",* highlights differences in AI adoption between developed and emerging countries. However, the study remains general and lacks specific insights into the Vietnam context.

2.2 Research gap

Previous studies highlight AI's potential in logistics and address SMEs, LMD, or Vietnam separately. However, few integrate all three - AI, SMEs, and last-mile delivery - in the Vietnamese context, creating a key research gap. Existing research often focuses on logistics broadly or mid-stream activities, overlooking LMD-specific challenges and SMEs' constraints and still focus on SMEs context rather than investigating specific type – B2B. Moreover, many studies rely on qualitative or descriptive approaches without a structured framework, leading to limited empirical evidence. Therefore, this study addresses these gaps by examining B2B SMEs' readiness to adopt AI in LMD in Vietnam using an integrated TOE-TAM approach.

3 Theoretical framework

3.1 Conceptual research model

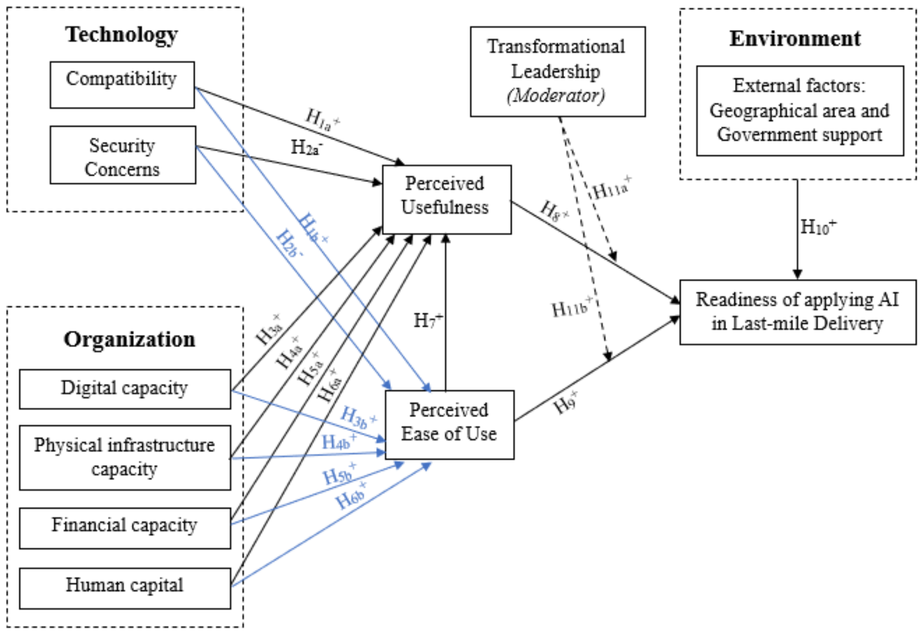

Figure 1. Conceptual research model

Source: The authors' compilation, 2025

3.2 Research hypothesis

Based on the literature review and foundational theories, the hypotheses are proposed:

- **Hypothesis 1a (H_{1a}):** Compatibility has a positive effect on Perceived usefulness of AI in LMD.
- **Hypothesis 1b (H_{1b}):** Compatibility has a positive effect on Perceived ease of use of AI in LMD.
- **Hypothesis 2a (H_{2a}):** Security Concerns have a negative effect on Perceived Usefulness of AI in LMD.
- **Hypothesis 2b (H_{2b}):** Security Concerns have a negative effect on Perceived Ease of Use of AI in LMD.
- **Hypothesis 3a (H_{3a}):** Digital capacity has a positive effect on Perceived usefulness of AI in LMD.
- **Hypothesis 3b (H_{3b}):** Digital capacity has a positive effect on Perceived ease of use of AI in LMD.
- **Hypothesis 4a (H_{4a}):** Physical infrastructure capacity has a positive effect on Perceived usefulness of AI in LMD.
- **Hypothesis 4b (H_{4b}):** Physical infrastructure capacity has a positive effect on Perceived ease of use of AI in LMD.

- **Hypothesis 5a (H_{5a}):** Financial capacity has a positive effect on Perceived usefulness of AI in LMD.
- **Hypothesis 5b (H_{5b}):** Financial capacity has a positive effect on Perceived ease of use of AI in LMD.
- **Hypothesis 6a (H_{6a}):** Human capital has a positive effect on perceived usefulness of AI in LMD.
- **Hypothesis 6b (H_{6b}):** Human capital has a positive effect on Perceived ease of use of AI in LMD.
- **Hypothesis 7 (H_7):** Perceived ease of use has a positive effect on Perceived usefulness of AI in LMD.
- **Hypothesis 8 (H_8):** Perceived usefulness has a positive effect on Readiness for applying AI in LMD.
- **Hypothesis 9 (H_9):** Perceived ease of use has a positive effect on Readiness for applying AI in LMD.
- **Hypothesis 10 (H_{10}):** External factors, including geographical area and government support, has a positive effect on Readiness for applying AI in LMD.
- **Hypothesis 11a (H_{11a}):** Transformational leadership reinforces the relationship between Perceived usefulness and Readiness for applying AI in LMD
- **Hypothesis 11b (H_{11b}):** Transformational leadership reinforces the relationship between Perceived ease of use and Readiness for applying AI in LMD.

3.3 The underpinning theories

3.3.1 Technology-Organization-Environment (TOE) framework

Following Tornatzky & Fleischer (1990), the TOE framework explains technology adoption through three contexts: technological, organizational, and environmental. Technological factors include infrastructure, skills, and perceived usefulness; organizational factors involve firm size, structure, and management support; while environmental factors cover competition, partners, and regulation. Widely applied across technologies and industries, TOE is flexible but limited as a classification tool and may require complementary theories. Despite this, its holistic and adaptable nature makes it suitable for analyzing the readiness of B2B Vietnamese SMEs to adopt AI in last-mile delivery.

3.3.2 Technology Acceptance Model (TAM)

Developed by Davis (1989), the Technology Acceptance Model (TAM) explains technology adoption through two factors, including perceived usefulness (PU) and perceived ease of use (PEOU). Derived from TRA and TPB, it links user perceptions to behavioral intention and actual usage. Although criticized for simplicity and reliance on self-reported measures, TAM has been widely validated across technologies, including AI. Its flexibility and compatibility with other frameworks, such as TOE, make it suitable for analyzing SMEs' acceptance of AI in LMD.

4 Research methodology

4.1 Research paradigms and research approach

For this study, the authors adopt pragmatism as it emphasizes practical problem-solving and actionable knowledge (Saunders et al., 2023). This is suitable with the aim of the study. It also uses deductive approach, developing its hypothesis from existing theories so as to assess the subject of the research. The study would use TOE framework and TAM framework together and quantitative methods are also used to generalize findings and practical implications

4.2 Measurement of variables

Table 1: Variables

Variables	Code	Measurement	Unit of measurement	Expectation
Compatibility	C	Five-point Likert scale	Score	+
Security Concerns	SC	Five-point Likert scale	Score	-
Digital Capacity	DC	Five-point Likert scale	Score	+
Physical Infrastructure Capacity	PIC	Five-point Likert scale	Score	+
Financial Capacity	FC	Five-point Likert scale	Score	+
Human Capacity	HC	Five-point Likert scale	Score	+
Perceived Usefulness	PU	Five-point Likert scale	Score	+
Perceived Ease of Use	PEOU	Five-point Likert scale	Score	+
Transformational Leadership	TL	Five-point Likert scale	Score	+
Environment	E	Five-point Likert scale	Score	+
Readiness	R	Five-point Likert scale	Score	+

Source: The authors' compilation, 2025

4.3 Data collection and analysis techniques

4.3.1 Data collection method

The authors use homogeneous techniques for sampling, focusing on a specific group with the same features: Vietnamese B2B SMES. The data collection is from 15 December 2025 to 15 March 2026 and the authors get 124 valid responses. Besides, a cross-sectional design is adopted, in which data are collected at a single point in time, enabling a cost-effective and time-efficient approach that aligns with the study’s short-term scope.

4.3.2 Data analysis techniques

Table 2: Data analysis techniques

Data analysis technique	Purpose
Descriptive Statistics	Provide initial overview of the dataset by examining its key characteristics. This step serves as a foundation before proceeding to more inferential or multivariate analyses.
Cronbach’s Alpha Reliability	Assess the internal consistency of measurement scales prior to applying techniques such as EFA or CFA.
Exploratory Factor Analysis - EFA	Evaluate the extent to which the empirical data aligns with the theoretical framework established in previous studies.
Confirmatory Factor Analysis - CFA	Beyond validating the measurement model through outer loadings, analyze the direction and strength of relationships between constructs in the structural model using path coefficients.
Partial Least Squares Structural Equation Modeling - PLS-SEM	Examine the proposed hypotheses by testing the statistical significance of the relationships, typically through the interpretation of P - values.

Source: The authors' compilation, 2025

5 Findings and analysis

5.1 Pilot Testing

Over a two-week period, 31 valid responses within the target population are tested:

Table 3: Reliability results

Construct	Explain	Number of items	Cronbach's Alpha
DI	Digital Infrastructure	7	0.935
PI	Physical Infrastructure	5	0.878
ODT	Operational and Data Transparency	6	0.924
SDCW	Skills and Digital Capabilities of the Workforce	4	0.869
UCG	Urban Constraints and Geography	5	0.902
UCGS	Upgrading Capabilities via Government Support	4	0.857

Source: The authors' compilation, 2026

The general information section was revised for greater clarity and to reduce response bias, with added industry examples such as textiles, consumer goods or cosmetics and an "Others" option. Some items were rewarded to avoid overlapping, particularly the question on AI investment in last-mile delivery.

Following the pilot test with around 31 valid responses, Cronbach's alpha indicated redundancy in several variables ($\alpha > 0.90$), so the scales were refined. Based on interview findings, the study removed and added constructs in line with TAM and TOE (Technology, Organization, Environment, PU, PEOU, TL, Readiness) and included one attention-check question; invalid responses were excluded.

5.2 Analysis results of B2B

5.2.1 Descriptive statistics analysis

The results show very high score rates for PEOU (3.625) and PU (3.581). Similarly, the moderating variable TL (3.580) and external factor E (3.592) also recorded high values. This reflects B2B leaders have a positive attitude toward AI, along with strong expectations about its potential in last-mile delivery. In contrast, the resource-related factors scored lower, with C at 3.393, FC at 3.403, and DC at 3.441. HC and PIC also received relatively low scores of 3.495 and 3.519, respectively. These findings indicate although management support is strong, businesses encounter notable internal resource barriers, leading to an overall readiness score of 3.514. All variables had standard deviations ranging from 0.620 to 0.969. The skewness values (from -0.970 to -0.601) and kurtosis values (from -0.490 to 0.735) fell within the acceptable range of -1 to +1, confirming that the data is normally distributed and suitable for PLS-SEM analysis.

5.2.2 Using Cronbach's Alpha, EFA and CFA to analyze Reliability

All constructs exhibit strong internal consistency in terms of dependability according to Cronbach's Alpha, with α values that range from 0.744 to 0.881 (>0.7). The majority of item-total corrections are more than 0.5. Despite having a score of 0.333, item E5 nonetheless meets the minimum criteria and is kept maintaining content validity.

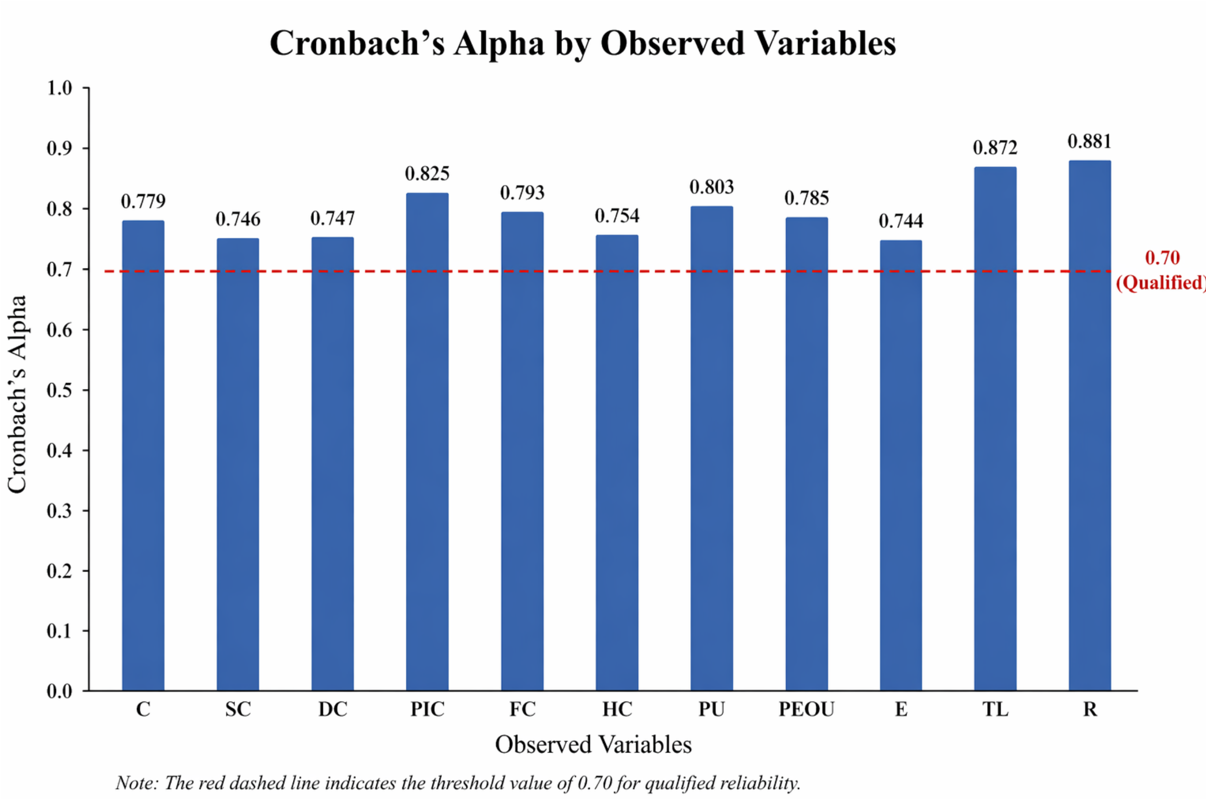

Figure 2: The result of B2B from Cronbach Testing

Source: The authors' compilation, 2026

The data are very appropriate for factor analysis in terms of convergent validity of EFA, as shown by significant Bartlett's Tests of Sphericity (Sig. = 0.000) and KMO values ranging from 0.655 to 0.887 (>0.5). For every construct (Eigenvalue > 1), all observable variables converge into a single underlying factor. The total variance explained and factor loadings (ranging from 0.588 to 0.864) all meet acceptable thresholds, confirming the unidimensionality and convergent validity of the measurement scales.

Table 4: Results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests

Construct	KMO	Bartlett's Chi-Square	df	Sig.

C	0.771	129.240	6	0.000
SC	0.686	82.894	3	0.000
DC	0.655	82.796	3	0.000
PIC	0.710	118.919	3	0.000
FC	0.698	104.729	3	0.000
HC	0.676	82.956	3	0.000
PU	0.782	145.415	6	0.000
PEOU	0.767	129.339	6	0.000
E	0.786	148.944	15	0.000
TL	0.884	341.810	21	0.000
R	0.887	385.627	21	0.000

Source: The authors' compilation, 2026

Considering CFA, the measurement model was evaluated using SmartPLS and demonstrated adequate reliability, validity, and fit for structural analysis. Internal consistency was confirmed with Cronbach's $\alpha > 0.7$ and Composite Reliability (CR) ranging from 0.825 to 0.909. Indicator reliability was acceptable; while outer loadings varied (0.474 - 0.869), lower items were retained to preserve content validity. Convergent validity was established, as most Average Variance Extracted (AVE) values exceeded 0.5, and constructs with slightly lower AVEs still maintained satisfactory CRs. Discriminant validity was supported by the Fornell-Larcker criterion, cross-loadings, and HTMT ratios, with minor HTMT deviations being theoretically justified. Finally, the model exhibited a good fit (SRMR = 0.068 < 0.08), despite a modest NFI (0.618), which is acceptable given its supplementary role in PLS-SEM. Hence, the tables synthesized by the authors (2026) were shown below:

Table 5: Matrix of outer loadings

	C	DC	E	FC	HC	PEOU	PIC	PU	R	SC	TL	TL x PEOU	TL x PU
C1	0.790												
C2	0.788												
C3	0.719												
C4	0.803												
DC1		0.867											
DC2		0.798											
DC3		0.780											
E1			0.722										
E2			0.686										
E3			0.696										
E4			0.632										
E5			0.474										
E6			0.756										

FC1				0.848									
FC2				0.811									
FC3				0.862									
HC1					0.832								
HC2					0.811								
HC3					0.811								
PEOU1						0.771							
PEOU2						0.814							
PEOU3						0.793							
PEOU4						0.741							
PIC1							0.869						
PIC2							0.854						
PIC3							0.860						
PU1								0.857					

PU2								0.745					
PU3								0.766					
PU4								0.803					
R1									0.728				
R2									0.681				
R3									0.745				
R4									0.738				
R5									0.855				
R6									0.819				
R7									0.787				
SC1										0.841			
SC2										0.792			
SC3										0.808			
TL1											0.722		

TL2											0.735		
TL3											0.717		
TL4											0.779		
TL5											0.789		
TL6											0.785		
TL7											0.739		
TL x PEOU												1.000	
TL x PU													1.000

Table 6: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
C	0.779	0.783	0.858	0.601
DC	0.749	0.757	0.856	0.666
E	0.746	0.764	0.825	0.445
FC	0.793	0.796	0.879	0.707
HC	0.754	0.757	0.859	0.669
PEOU	0.785	0.787	0.861	0.609
PIC	0.826	0.826	0.896	0.742

PU	0.804	0.811	0.872	0.630
R	0.882	0.885	0.909	0.588
SC	0.747	0.756	0.855	0.663
TL	0.872	0.873	0.901	0.567

Table 7: Validity of discrimination. Matrix of the heterotrait-monotrait ratio (HTMT)

	C	**DC**	**E**	**FC**	**HC**	**PEOU**	**PIC**	**PU**	**R**
C									
DC	1.035								
E	0.393	0.485							
FC	0.932	1.057	0.384						
HC	0.865	1.047	0.494	1.002					
PEOU	0.879	0.872	0.397	0.881	0.810				
PIC	0.900	1.048	0.432	1.010	0.983	0.802			
PU	0.859	0.889	0.392	0.846	0.815	1.014	0.790		
R	0.836	0.905	0.591	0.841	0.897	0.837	0.862	0.802	
SC	0.819	0.857	0.433	0.832	0.963	0.824	0.856	0.822	0.811
TL	0.881	0.922	0.497	0.884	0.936	0.901	0.893	0.847	0.895
TL x PEOU	0.691	0.709	0.369	0.663	0.731	0.761	0.645	0.768	0.686
TL x PU	0.639	0.638	0.375	0.598	0.687	0.797	0.629	0.694	0.641

Table 8: Model fit. Fit summary

	SRMR	d_ULS	d_G	Chi-square	NFI
Saturated model	0.063	4.426	2.937	1681.859	0.621
Estimated model	0.068	5.150	3.008	1695.611	0.618

5.2.3 PLS-SEM analysis

Firstly, the measurement model demonstrated satisfactory reliability and validity. The majority of outer loadings for constructs C, DC, FC, HC, PIC, PEOU, and PU exceeded the 0.70 threshold, indicating robust representation. Readiness (R) showed acceptable reliability, with item loadings ranging from 0.681 to 0.855. Construct E exhibited the weakest performance, with several indicators (E2, E3, E4, E5) falling below 0.70. Overall, despite localized limitations within construct E, the measurement quality of the model is adequate for subsequent structural analysis.

The structural model exhibits strong explanatory power, with R^2 values reaching 70.7% for PU, 70.6% for R, and 58.9% for PEOU.

Table 9: Coefficient of Determination

Constructs	PEOU	PU	R
R-square	0.589	0.707	0.706
R-square adjusted	0.567	0.689	0.691

Besides, path analysis reveals that PEOU is significantly driven by FC (β = 0.293), C (β = 0.283), and SC (β = 0.248), whereas DC, HC, and PIC show no significant impact ($p > 0.05$). Notably, external variables do not directly affect PU; rather, PU is strongly and directly driven by PEOU itself (β = 0.549, p = 0.000). This indicates that users must perceive the system as easy to use before recognizing its usefulness. For the outcome variable Readiness (R), TL (β = 0.473) and E (β = 0.191) serve as the strongest direct predictors. Although PU and PEOU lack direct effects on R, this is explained by the moderation role of TL. Specifically, TL negatively moderates the PEOU → R relationship (β = -0.367), meaning that as TL increases, users' reliance on ease of use decreases. Conversely, TL positively moderates the PU → R relationship (β = 0.304), amplifying the impact of perceived usefulness on Readiness when TL is high.

Table 10: Path Coefficients

Relationship	Original sample	Sample mean	STDEV	T stat	P values
C -> PEOU	0.283	0.278	0.123	2.307	0.021
DC -> PEOU	0.055	0.063	0.142	0.387	0.699
FC -> PEOU	0.293	0.286	0.117	2.499	0.012
HC -> PEOU	-0.008	0.015	0.123	0.063	0.950
PIC -> PEOU	-0.002	0.005	0.130	0.016	0.987
SC -> PEOU	0.248	0.226	0.126	1.971	0.049
C -> PU	0.080	0.078	0.107	0.745	0.456
DC -> PU	0.164	0.165	0.110	1.493	0.135
SC -> PU	0.116	0.103	0.086	1.344	0.179
FC -> PU	0.028	0.031	0.121	0.233	0.816
HC -> PU	0.016	0.019	0.124	0.132	0.895
PIC -> PU	-0.015	-0.002	0.138	0.107	0.915
PEOU -> PU	0.549	0.542	0.108	5.098	0.000
E -> R	0.191	0.195	0.058	3.265	0.001
PEOU -> R	0.226	0.226	0.129	1.756	0.079
PU -> R	0.007	0.040	0.151	0.045	0.964
TL -> R	0.473	0.448	0.108	4.373	0.000

TL x PEOU -> R	-0.367	-0.342	0.151	2.438	0.015
TL x PU -> R	0.304	0.285	0.150	2.029	0.043

After thorough analysis, the authors reach the results as below:

Table 11: Results of hypothesis verification

Hypothesis		Result
H1a	Compatibility has a positive effect on Perceived usefulness of AI in LMD.	Rejected
H1b	Compatibility has a positive effect on Perceived ease of use of AI in LMD.	Accepted
H2a	Security Concerns have a negative effect on Perceived Usefulness of AI in LMD.	Rejected
H2b	Security Concerns have a negative effect on Perceived Ease of Use of AI in LMD.	Accepted
H3a	Digital capacity has a positive effect on Perceived usefulness of AI in LMD.	Rejected
H3b	Digital capacity has a positive effect on Perceived ease of use of AI in LMD.	Rejected
H4a	Physical infrastructure capacity positively influences Perceived usefulness of AI in LMD.	Rejected
H4b	Physical infrastructure capacity has a positive effect on Perceived ease of use of AI in LMD.	Rejected
H5a	Financial capacity has a positive effect on Perceived usefulness of AI in LMD.	Rejected

H5b	Financial capacity has a positive effect on Perceived ease of use of AI in LMD.	Accepted
H6a	Human capital has a positive effect on perceived usefulness of AI in LMD.	Rejected
H6b	Human capital has a positive effect on Perceived ease of use of AI in LMD.	Rejected
H7	Perceived ease of use has a positive effect on Perceived usefulness of AI in LMD.	Accepted
H8	Perceived usefulness has a positive effect on Readiness for applying AI in LMD.	Rejected
H9	Perceived ease of use has a positive effect on Readiness for applying AI in LMD.	Rejected
H10	External factors, including geographical area and government support, has a positive effect on Readiness for applying AI in LMD.	Accepted
H11a	Transformational leadership reinforces the relationship between Perceived usefulness and Readiness for applying AI in LMD.	Accepted
H11b	Transformational leadership reinforces the relationship between Perceived ease of use and Readiness for applying AI in LMD.	Accepted

Source: The authors' compilation, 2026

6 Discussion and further research

6.1 Discussion

The quantitative findings for B2B SMEs highlight a clear gap between relatively positive perceptions of AI and only moderate Readiness (mean = 3.514). This gap can be explained by structural constraints rather than perception alone.

Consistent with the model results, C → PEOU → PU is supported, but the absence of direct effects from PEOU and PU to Readiness reinforces that ease of use acts as a precondition, not a driver. Given the limited digital capability of LMD personnel, firms only recognize AI's usefulness after it is perceived as simple and intuitive. This implies that overly complex AI solutions are unlikely to translate into actual adoption.

At the same time, TL → Readiness ($\beta = 0.473$) and its moderating role confirm that leadership is the key mechanism bridging perception and action in B2B firms. Even when AI is seen as useful, Readiness does not materialize without strong leadership to drive change, reduce resistance, and guide implementation. This explains why PU and PEOU are statistically insignificant as direct predictors.

Finally, the significance of E → Readiness alongside the non-significance of most internal resources (DC, HC, PIC) reflects SMEs' structural limitations. Budget constraints and weak internal capabilities limit their ability to act independently, making external support and basic facilitating conditions more critical.

Overall, B2B readiness is not perception-driven but leadership- and resource-dependent, where simple, compatible technologies, strong managerial direction, and external support jointly determine whether AI adoption can move forward.

6.2 Recommendations

6.2.1 Recommendations for specific AI

Based on the findings, this study recommends Abivin vRoute as the primary AI solution for Vietnamese SMEs in B2B sector. This locally developed, low-cost platform optimizes routes, provides real-time tracking, and increases delivery density using only Excel input and standard Android phones - directly addressing high last-mile costs and failed deliveries without requiring heavy infrastructure investment. Complementary tools such as Routific or Zalo OA chatbots can be added for ETA prediction at minimal cost (< 0.5 - 1% of revenue). A simple phased approach is advised: start with Abivin's basic package, followed by predictive features for higher-readiness firms. Policymakers should subsidize 50 - 70% of software costs under the 2026 - 2030 Digital Transformation Program and offer free training.

6.2.2 Recommendations for Vietnamese SMEs' owners and managers

For B2B SMEs, AI readiness is mainly driven by Compatibility, Human Capital, and Transformational Leadership, but constrained by limited internal resources.

First, firms should prioritize human capital development by improving employees' digital and AI-related skills through basic training and practical guidance. This is essential because PEOU acts as a prerequisite for recognizing AI's usefulness. Second, transformational leadership is critical. Managers need to clearly communicate AI's benefits, motivate employees, and actively drive change, as leadership is the key factor translating positive perceptions into actual readiness.

Third, given resource limitations, SMEs must leverage external support (e.g., partnerships, technical assistance) to complement internal weaknesses and reinforce leadership efforts. Finally, firms should enhance compatibility by either adjusting workflows or adopting simple, well-fitted AI solutions rather than complex systems.

6.2.3 Recommendations for the government

For B2B SMEs, the effectiveness of government support depends largely on implementation quality. Although Decision 33/QĐ-TTg provides comprehensive support, procedures should be simplified and standardized to reduce barriers such as unclear criteria and complex application processes. Establishing a centralized platform with clear guidelines would improve SMEs' access to these supports.

In addition, promoting provincial-level innovation competitions can encourage AI adoption by creating accessible opportunities for B2B SMEs to network, gain technical support, and exchange knowledge.

6.3 Limitations and further research

This study has several limitations. First, the sample size remains relatively small, particularly with regard to valid qualitative data from interviews. Although the research scope is limited to Vietnam, the number of collected responses is still modest due to time and access constraints. Second, data were gathered at a single point in time using a cross-sectional design. Given the rapid evolution of AI technology, the findings may quickly become outdated. Consequently, the study cannot capture long-term changes or confirm whether the observed readiness level is sustainable or merely temporary. Finally, the cross-sectional approach limits the ability to establish causal relationships, especially concerning the role of transformational leadership in actual AI adoption.

Future studies should address these limitations by collecting a larger sample size over an extended period through longitudinal research to better observe the dynamic nature of AI readiness. Researchers could also narrow the focus to specific AI applications in last-mile delivery such as route optimization, autonomous vehicles, or predictive analytics rather than general AI technology. In addition, more practical-oriented research is encouraged to develop and test concrete implementation solutions tailored for Vietnamese SMEs in B2B context, thereby providing actionable recommendations for both academics and practitioners.

The datasets generated and analyzed during the present study are available from the corresponding author upon reasonable request. The authors hereby formally declare that they assume full responsibility for the accuracy, integrity, and authenticity of the survey data, as well as for all statistical analyses and empirical testing results reported in this manuscript.

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Appendix A. Questionnaire

SECTION A: BASIC INFORMATION
1. Which company are you currently working for? 2. What is your current position?
SECTION B: GENERAL INFORMATION ABOUT THE COMPANY
1. What industry is your company currently operating in? 2. Approximately how many employees does your company have? □ Under 10 employees □ From 10 to 100 employees □ From 100 to 200 employees □ Over 200 employees
SECTION C: B2B SMEs
I. BUSINESS OPERATIONS OVERVIEW:

General Information and Financial Situation

1. What is the approximate size of your current customer base?
   - ☐ Under 10
   - ☐ From 10 to 50
   - ☐ From 50 to 100
   - ☐ From 100 to 200
   - ☐ Over 200
2. What is the average monthly revenue growth rate of your company?
   - ☐ <5%
   - ☐ 5–10%
   - ☐ 10–25%
   - ☐ 25%

General Information on Last-Mile Delivery (LMD)

1. Which last-mile delivery model does your company primarily use?
   - ☐ Delivery by truck drivers
   - ☐ Delivery by motorbike couriers
   - ☐ Order consolidation with customer self-pickup
   - ☐ Drone delivery
   - ☐ Autonomous delivery robots
   - ☐ Crowdsourced delivery (using independent individuals)
   - ☐ Ride-sharing combined with goods delivery
2. What is your company's return rate?
   - ☐ Under 1%
   - ☐ From 1% to 5%
   - ☐ From 5% to 10%
   - ☐ Over 10%
   - ☐ Not measured
3. Has your company previously implemented any initiatives to improve last-mile delivery efficiency?
   - ☐ Yes
   - ☐ No
4. If yes, what initiatives have been implemented?
5. Does your company plan to improve last-mile delivery operations (in terms of process, budget, or service quality) in the near future?
   - ☐ Yes

☐ No

6. If yes, which aspects does your company aim to improve?

☐ Delivery speed
☐ Cost efficiency
☐ Customer experience
☐ Others: ________________________________

Tangible Resources

1. How many employees are involved in last-mile delivery operations?

☐ Under 10
☐ From 10 to 50
☐ From 50 to 100
☐ From 100 to 200

2. What types of vehicles does your company currently use for last-mile delivery?
3. What types of technologies are currently applied in your last-mile delivery operations?
4. Your company's expected investment in AI for last-mile delivery is approximately:

☐ <1% of total costs
☐ 1–3% of total costs
☐ 5% of total costs
☐ 5% of total costs

Intangible Resources

1. What is the level of technological proficiency of last-mile delivery staff in using software and management systems?
2. Does your company provide internal training programs for last-mile delivery staff?

☐ Yes
☐ No

3. Which sales channels does your company mainly use? Which channel generates the most orders?

Challenges

1. Does your company face difficulties delivering to areas with rough terrain or narrow roads?

☐ Yes
☐ No

2. Does your firm face difficulties in optimizing vehicle load capacity and volume, as well as in handling transportation for large orders?

- Yes
- No

3. Does your company experience situations where "large orders delay smaller ones," causing operational inefficiencies?

- Yes
- No

II. READINESS

Note: Please rate your level of agreement with the following statements on a scale from 1 to 5:

1 – Strongly disagree; 2 – Somewhat disagree; 3 – Neutral; 4 – Somewhat agree; 5 – Strongly agree

Compatibility (C)					
C1. The firm believes that using AI is compatible with its current last-mile delivery processes.	1	2	3	4	5
C2. The adoption of AI technology at present is compatible with the firm's technical capabilities.	1	2	3	4	5
C3. The use of AI is consistent with the firm's current business values and objectives.	1	2	3	4	5
C4. AI technology can be seamlessly integrated with the firm's existing management systems (ERP, WMS…).	1	2	3	4	5
Security Concerns (SC)					
SC1. Concerns about exposure of trade secrets and confidential data.	1	2	3	4	5
SC2. Perceived security risks in partner-integrated networks.	1	2	3	4	5
SC3. Increased risk of unauthorized access, malware, and ransomware.	1	2	3	4	5
Digital Capacity (DC)					

DC1. The firm has digitized document-handling processes (invoices, red invoices, related paperwork).	1	2	3	4	5
DC2. The firm has systems to monitor quality for high-value or special-requirement shipments.	1	2	3	4	5
DC3. The firm has sufficient resources and systems (e.g., WMS, ERP, CRM, HRM, TMS) to support AI in LMD, enabling resource and route optimization.	1	2	3	4	5
Physical Infrastructure Capacity (PIC)					
PIC1. The firm has sufficient server and network infrastructure to support AI in LMD.	1	2	3	4	5
PIC2. The firm has well-located warehouse facilities to simplify last-mile operations.	1	2	3	4	5
PIC3. The firm has adequate transportation and logistics equipment (forklifts, machinery, handling devices) to support distribution.	1	2	3	4	5
Financial Capacity (FC)					
FC1. The firm has a clear financial plan to upgrade infrastructure and equipment for AI in LMD.	1	2	3	4	5
FC2. The firm has sufficient financial resources to invest in AI technologies for last-mile delivery operations.	1	2	3	4	5
FC3. Top management is willing to allocate budget for digital transformation.	1	2	3	4	5
Human Capacity (HC)					
HC1. The firm's employees have sufficient digital skills and receive adequate training to work with modern logistics technologies.	1	2	3	4	5
HC2. Employees are proficient in using digital systems such as ERP, CRM, HRM, WMS, TMS, and POS in their daily work.	1	2	3	4	5

HC3. Employees have a positive attitude toward the implementation of AI in last-mile logistics operations.	1	2	3	4	5
Perceived Usefulness (PU)					
PU1. AI improves efficiency and productivity while reducing time and resource usage.	1	2	3	4	5
PU2. AI enables flexible responses to delivery disruptions such as traffic, address changes, and weather.	1	2	3	4	5
PU3. AI helps reduce delivery and last-mile logistics operating costs.	1	2	3	4	5
PU4. AI enables real-time analysis and information for better tracking and delivery management.	1	2	3	4	5
Perceived Ease of Use (PEOU)					
PEOU1. The use of AI in last-mile delivery does not impose significant pressure or difficulty on employees.	1	2	3	4	5
PEOU2. A user-friendly interface improves accessibility and usability.	1	2	3	4	5
PEOU3. A user-friendly system reduces training costs and reliance on specialized staff.	1	2	3	4	5
PEOU4. The application of AI in last-mile delivery does not disrupt the firm’s existing workflows.	1	2	3	4	5
External Factors (E)					
E1. Delivery routes are affected by poor infrastructure in some regions.	1	2	3	4	5
E2. Regional logistics infrastructure differences affect digitalization and AI adoption.	1	2	3	4	5
E3. Difficult terrain increases operational and delivery costs.	1	2	3	4	5

E4. Firms face challenges accessing government support due to complex procedures.	1	2	3	4	5
E5. Government digital transformation policies are not well-suited to the firm's needs.	1	2	3	4	5
E6. Lack of clear SME-focused policies increases AI adoption risk.	1	2	3	4	5
Transformational Leadership (TL)					
TL1. Top management shows strong commitment to digital transformation and AI adoption, taking responsibility for related investments.	1	2	3	4	5
TL2. Employees trust the long-term vision and technology-related decisions of top management.	1	2	3	4	5
TL3. Top management clearly communicates the importance of AI in the firm's overall development strategy.	1	2	3	4	5
TL4. Top management helps employees understand the role of AI in their future work and career development.	1	2	3	4	5
TL5. The firm actively encourages innovation, learning, and adaptation to new AI technologies.	1	2	3	4	5
TL6. Employees are encouraged to experiment with AI solutions despite risks.	1	2	3	4	5
TL7. Leadership supports employees during AI implementation.	1	2	3	4	5
Readiness (R)					
R1. The firm believes that adopting AI in last-mile delivery will significantly improve revenue and optimize delivery costs.	1	2	3	4	5
R2. The firm considers AI adoption in delivery as a key strategic priority in the near future.	1	2	3	4	5

R3. The firm's current technical infrastructure is ready for AI application in last-mile delivery.	1	2	3	4	5
R4. The firm's physical infrastructure is ready for AI application in last-mile delivery.	1	2	3	4	5
R5. The firm is willing to invest financial resources in adopting AI for last-mile delivery.	1	2	3	4	5
R6. The current workforce is ready to adapt work processes to implement AI in last-mile delivery.	1	2	3	4	5
R7. The firm has a capable leader responsible for successfully driving AI adoption in last-mile delivery.	1	2	3	4	5

Appendix B. Descriptive statistics analysis of B2B constructs variables

No.	Observed Variables	Mean	Std. Deviation	Skewness	Kurtosis	Results
1	C	3.393	0.846	-0.750	-0.370	Qualified
2	SC	3.457	0.854	-0.702	-0.460	Qualified
3	DC	3.441	0.902	-0.816	-0.306	Qualified
4	PIC	3.519	0.968	-0.798	-0.251	Qualified
5	FC	3.403	0.918	-0.601	-0.416	Qualified
6	HC	3.495	0.881	-0.826	-0.132	Qualified

7	PU	3.581	0.847	-0.887	-0.253	Qualified
8	PEOU	3.625	0.809	-0.970	-0.105	Qualified
9	E	3.593	0.620	-0.783	0.735	Qualified
10	TL	3.580	0.787	-0.942	-0.168	Qualified
11	R	3.514	0.794	-0.690	-0.490	Qualified

Source: The authors' compilation, 2026