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The technology acceptance model for digitalised logistics in low-income countries: The case of Ethiopia

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ABSTRACT

Digitalisation is transforming logistics operations worldwide. However, low-income countries continue to face significant barriers to adoption, including limited infrastructure and resources. In Ethiopia, supply chains remain inefficient due to inadequate technological integration. The technology acceptance model (TAM) has been used by several researchers to explain the usage and adoption of technologies. However, this framework has rarely been applied to digital logistics in the context of low-income countries. This study empirically investigated the intention of stakeholders in Ethiopian supply chains to adopt digital technologies using a modified version of TAM. Data were collected through an extensive survey of logistics professionals. The results indicated that, beyond perceived usefulness and ease of use, external factors such as infrastructure availability, human resource capacity, technological accessibility and supportive policies, significantly influence stakeholders' intention to adopt digital technologies. The study emphasises the importance of awareness-raising initiatives and the development of digital strategies to support successful digital transformation in low-income countries. These findings offer valuable insights for policymakers and practitioners seeking to better understand the relationship between technology adoption, user perceptions and enabling conditions.

1. Introduction

Digitalisation has become a key component of modern life, transforming how businesses operate and deliver goods and services (Mhlanga & Ndhlovu, 2023). In the logistics sector, digital technologies play a crucial role in enhancing operational efficiency, enabling real-time tracking and tracing, improving planning, and supporting sustainable supply chain practices. Successful companies worldwide have integrated digital tools into their operations to reduce losses, improve productivity and maintain competitiveness.

Digitalisation is a key enabler for achieving the core logistics objectives of delivering the right product, to the right customer, in the right quantity, at the right time, place, condition and price (Egorov, Levina, Kalyazina, Schuur, & Gerrits, 2021). Digital technologies help create efficient logistics systems, giving firms a notable competitive advantage through better planning, optimisation and management. They also support companies in managing their fleets, monitoring driver behaviour during transportation (Hopkins & Hawking, 2018) and controlling their inventories (Kelepouris, Pramatari, & Doukidis, 2007). Another key benefit of digitalisation in supply chains is end-to-end traceability (Kelepouris et al., 2007; Lin et al., 2020), allowing consumers to have more confidence in the products they purchase (Kshetri, 2018). By improving connectivity across supply chains, digitalisation becomes a key driver of productivity and economic growth (Deichmann, Goyal, & Mishra, 2016; Jang, 2021; Tesfachew, 2022).

Despite its proven benefits, many low-income countries continue to lag behind in adopting digital technologies in logistics (Tadesse, Kine, Gebresenbet, Tavasszy, & Ljungberg, 2022), contributing to a growing digital divide between developed and least-developed nations (United Nations, 2020). Several challenges hinder the adoption of digital technologies in these countries, including limited access, lack of awareness, resistance from stakeholders, skill gaps, inadequate infrastructure, financial constraints, data privacy and security concerns and absence of supportive policies (Abdinoor & Mbamba, 2017; Ahikiriza et al., 2022; Ben Hassen, El Bilali, & Baya Chatti, 2024; Díaz-Arancibia et al., 2024; Ghobakhloo & Tang, 2013; Mhlanga & Ndhlovu, 2023; Musa, 2006; Pappa, Iliopoulos, & Massouras, 2018; Tadesse, Gebresenbet, Tavasszy, & Ljungberg, 2021; Tesfachew, 2022; United Nations, 2020; Uy,

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Limnirankul, Kramol, Hoang Gia, & Nguyen Thi, 2025).

This research was motivated by the need to better understand the behavioural reasons behind the slow uptake of digital technologies in logistics within low-income countries. Existing literature reveals a lack of empirical research that explores the human and organisational factors influencing digital technology adoption in this context. Identifying these behavioural drivers can help policymakers, logistics firms, and development partners develop targeted strategies to overcome adoption barriers and accelerate digital transformation.

To examine these behavioural drivers, this study adopts the Technology Acceptance Model (TAM) developed by Davis (1989). TAM is a widely accepted framework to explain users' behaviour concerning technology adoption (Pappa et al., 2018) due to its robustness (Venkatesh & Davis, 2000), It has been used extensively across various sectors, including logistics. For instance, TAM has been applied by Bienstock and Royne (2010) to examine the adoption of information technology (IT) in the logistics sector. Other studies have used it to model the adoption of specific technologies such as blockchain (Bracci, Tallaki, Ievoli, & Diplotti, 2021; Chowdhury, Rodriguez-Espindola, Dey, & Budhwar, 2022), the Internet of Things (IoT) (Gao & Bai, 2014), mobile e-commerce (Abdinoor & Mbamba, 2017), Global Positioning System (GPS) devices (Chen & Chen, 2011), electric cargo vehicles (Ngoc, Nishiuchi, & Nhu, 2023) and digital traceability solutions (Pappa et al., 2018).

The study of technology adoption and diffusion is an important step towards understanding how new technologies are perceived by users in different regions and from different economic backgrounds (Musa, 2006). This can be achieved with behavioural models such as TAM, which can aid decision-makers promote the most beneficial technologies and address barriers to adoption (Ngoc et al., 2023; Pappa et al., 2018). However, empirical evidence from the logistics sector in low-income countries remains limited.

The objective of this study was therefore to model the behavioural intention of stakeholders in low-income countries to adopt digital technologies, using TAM as a theoretical framework. Ethiopia was used as a case study due to its status as one of the world's low-income countries with limited digitalisation in logistics. Despite being one of Africa's fastest growing economies and the second most populous country in the continent, Ethiopia continues to face high logistics costs, low Information and Communication Technology (ICT) adoption and fragmented supply chains. By focusing on Ethiopia, this research aims to provide insights that are also relevant to other low-income countries with similar constraints. The research question that this paper addresses is "*What are the most significant factors influencing the behavioural intention of stakeholders in low-income countries to adopt digital technologies?*"

The remainder of this paper is structured as follows: Section 2 presents the theoretical foundation and outlines the hypotheses that form the conceptual model. Section 3 describes the methodology, Section 4 reports the results and Section 5 discusses the findings. Section 6 presents the conclusion, implications and recommendations.

2. Theoretical background and hypotheses

2.1. Model for technology adoption

Originally developed from the constructs of the Theory of Planned Behaviour, TAM was introduced by Davis (1989) to assess the behavioural intention of users to adopt new computers. Since its introduction, TAM has widely been applied across diverse fields to explain technology adoption from a behavioural perspective. In recent times, the model has been utilised to examine the adoption of emerging digital technologies for various contexts.

For instance, Ma et al. (2025) applied TAM to assess the adoption of artificial intelligence (AI) by users. Their findings indicated adoption was more prevalent in urban areas and among individuals with higher education levels. Wibowo et al. (2024) applied TAM to explore factors influencing digital entrepreneurship in Indonesia. Mastour, Yousefi, and Niroumand (2025) used the model to examine the acceptance of e-learning platforms in the healthcare industry in Iran. Other applications of TAM include the adoption of drones for delivery (Edwards, Subramanian, Chaudhuri, Morlacchi, & Zeng, 2024), digital transformation in the maritime industry (Gündoğan & Keçeci, 2024) and augmented reality for online shopping (Lai, Leong, Khoo, & Sidhu, 2025).

While TAM remains a widely used and validated model, recent studies have called for its contextual adaptation to better reflect modern technologies and socio-economic settings. Mogaji, Viglia, Srivastava, and Dwivedi (2024), for example, examined the suitability of TAM in today's technological landscape and emphasised the importance of incorporating cultural norms and industry-specific factors to enhance the model's relevance.

Building on these insights, this study applied TAM to examine behavioural intentions towards adopting digital technologies in low-income countries, using Ethiopia as a case study. Following Davis's original formulation, this study investigated the core constructs such as perceived usefulness (PU), perceived ease of use (PEU), and attitude (AT) towards technology. However, recognising the complexity of adoption in low-income contexts, this study incorporated additional factors such as accessibility, human resources (HR), policies, finance and infrastructure, which are crucial to understanding technology adoption and diffusion in such settings.

2.2. Perceived usefulness

PU is defined as the perspective of users regarding the usefulness of the technology in helping them carry out their desired tasks. It reflects the potential increase in productivity by users brought about by using the technology (Davis, 1989; Moon & Kim, 2001) and the resultant potential time saving (Chen & Chen, 2011; Moon & Kim, 2001). Additionally, it is explained by improved job performance (Davis, 1989; Moon & Kim, 2001), the possibility of users achieving their goals more quickly (Chen & Chen, 2011) and improved customer satisfaction (Díaz-Arancibia et al., 2024).

The usefulness of a technology might also be reflected in terms of the economic benefit stakeholders might gain as a result of its adoption since economic benefit is one of the strongest drivers for the adoption of digital technologies in low-income countries (Tadesse et al., 2021). Beyond economic gains, digitalisation may offer social benefits, such as job creation and environmental advantages, including reduced emissions.

Based on this and according to the theory developed by Davis (1989), the following hypotheses for the usefulness of technology are proposed:

H1: The usefulness of digitalisation has a positive impact on stakeholders' attitudes towards implementing digital technologies in logistics.

H2: The usefulness of digitalisation has a positive impact on stakeholders' behavioural intentions to adopt digital technologies in logistics.

2.3. Perceived ease of use

PEU, meanwhile, explains how easy the technology is to use, according to the perspective of potential users (Davis, 1989). It is explained by the ease with which users learn how to use the technology (Chen & Chen, 2011; Moon & Kim, 2001), the amount of time required by users to learn to use the technology (Chen & Chen, 2011), and the possibility of using the technology without the aid of experts (Moon & Kim, 2001). This construct is critical, as users may be discouraged from adopting technologies perceived as complex or time-consuming (Autry, Grawe, Daugherty, & Richey, 2010).

The hypotheses regarding the ease of use for digitalisation are presented below according to the theory developed by Davis (1989):

H3: The ease of use of digitalisation has a positive impact on stakeholders' attitude towards implementing digital technologies for their logistics activities.

H4: The ease of use of digitalisation has a positive impact on the usefulness of digitalisation.

2.4. Accessibility, HR, policies, finance and infrastructure

To enhance TAM's applicability in low-income countries, Mogaji et al. (2024) suggest incorporating context-specific variables. Musa (2006) also argues that the original TAM does not fully capture the unique characteristics of technology adoption in low-income countries.

One of the determining factors for the adoption of digital technologies in low-income countries is the presence of adequate resources. Mathieson, Peacock, and Chin (2001) added the variable perceived resources (PR) to TAM because the authors believed that the absence of the right resources could dissuade users from adopting technologies. Infrastructure, finance and HR are all resources that are needed if low-income countries intend to successfully adopt digital technologies for their logistics activities (Tadesse et al., 2021). However, it is important to see the separate impact that each type of resource has on technology adoption.

The adoption of digital technologies in low-income countries is also determined by policy frameworks (Tadesse et al., 2021). The policies put forward by officials should promote digitalisation, while also considering the country's local contexts (Tesfachew, 2022).

Niehm, Tyner, Shelley, and Fitzgerald (2010) state that the decision to adopt a new technology is affected by the exposure and access users have to the technology. Therefore, accessibility is another factor that affects the adoption of technologies in low-income countries (Musa, 2006; Tadesse et al., 2021). Accessibility can also refer to the presence of the right training and capacity-building programmes that stakeholders might need if they intend to adopt new technologies (Niehm et al., 2010).

Therefore, the following hypotheses are presented based on the above factors:

H5: Accessibility, HR, policies, finance and infrastructure positively influence the perceived usefulness of digital technologies in logistics.

H6: Accessibility, HR, policies, finance, and infrastructure positively influence the perceived ease of use of digital technologies in logistics.

H7: Accessibility, HR, policies, finance, and infrastructure positively influence stakeholders' attitudes towards adopting digital technologies in logistics.

2.5. Attitude

The behavioural intention towards adopting technology is dependent on the users' attitude (AT) to the technology (Davis, 1989). It is explained by how users think that the technology is beneficial for them and their inclination to use the technology (Chen & Chen, 2011). When users have a positive attitude to a technology, they tend to have a behavioural intention (BI) to adopt the technology in the future. This is explained by the likelihood of users recommending the technology to other users and their willingness to use the technology for their activities (Chen & Chen, 2011).

Therefore, the following hypothesis is presented for the relationship between AT and BI following the hypothesis of Davis (1989):

H8: Stakeholders' attitudes towards digitalisation positively influence their behavioural intention to adopt digital technologies in logistics.

The proposed conceptual model illustrating the hypothesised relationships is presented in Fig. 1.

3. Methodology

This study adopted a case study approach, selecting Ethiopia due to its ongoing national efforts towards digitalisation and the persistent challenges that have hindered technology adoption. These conditions make Ethiopia a suitable case for applying TAM and assessing behavioural factors influencing technology adoption in low-income countries.

The methodology comprises three main components: questionnaire design, sampling and data collection, and data analysis using Structural Equation Modelling (SEM). A structured questionnaire was developed and reviewed by experts for clarity and contextual relevance prior to launching the main survey. The quality and reliability of the data were checked before applying SEM to test the hypothesis and examine the relationships between the variables.

3.1. Questionnaire design

The questionnaire used in this survey consisted of four sections. The first section introduced the study, explaining its purpose, assuring participants of confidentiality and obtaining their informed consent. Screening questions were used in the second section to determine whether respondents were familiar with digital technologies. In the third section, respondents were asked to measure the model constructs presented in Table 1, using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In the final section of the questionnaire, the respondents' socio-demographic characteristics, including their age, years of work experience and company size, were collected.

3.2. Pilot study

A pilot study was conducted to evaluate the clarity, language and applicability of the questionnaire to the Ethiopian context. Based on expert feedback, ambiguous items were revised prior to the main survey to enhance the questionnaire's validity.

Content validity of the questionnaire was assessed through consultation with experts in both academia and those working in the industry. These experts evaluated each questionnaire item to evaluate its relevance and alignment with the study objectives. The study experts were also asked to comment on the clarity and wording of each question to assess face validity. This helped to flag ambiguous questions or overly technical terms and instead to replace them with widely understood language.

Based on the feedback from experts, instructions were clarified, questions reworded and some questionnaire items removed. These ensured that the questionnaire was understandable and appropriate for the target group.

3.3. Data collection

This study targeted stakeholders across different levels of the Ethiopian supply chain sector, including importers, exporters, shippers, manufacturers, transport operators, processors, wholesalers and retailers. Convenience sampling was employed for data collection, which is commonly used when the population size is large or not precisely known (Chen & Chen, 2011; Pappa et al., 2018).

The questionnaire was designed in English using Google Forms and administered online via email and social media platforms to ensure broad accessibility and efficient distribution. A reminder was sent to respondents where needed. Data collection took place between January 2023 and April 2023, resulting in a total of 425 responses, which is well above the sample size requirement set by Kline (2011). The collected responses were later analysed using RStudio.

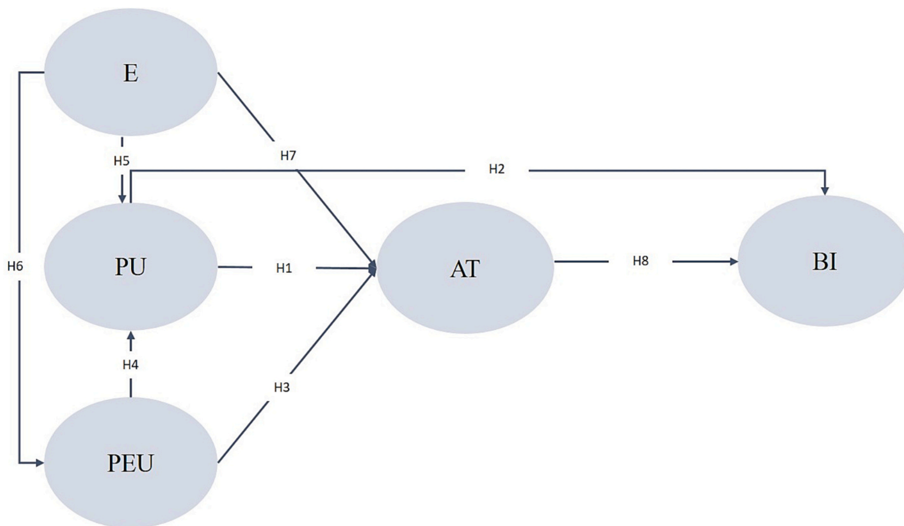

Fig. 1. Hypotheses on the effects of perceived usefulness (PU), perceived ease of use (PEU) and external facilitating conditions (E) on attitude (AT) and behavioural intent (BI) concerning the adoption of digital technologies for logistics in low-income countries.

3.4. Bias assessment

To assess non-response bias, a wave analysis was conducted by conducting early responses and late responses (Atif, Richards, & Bilgin, 2012). Independent *t*-tests were conducted for each variable. The results indicated that all variables except AT2, BI1 and BI2 had no statistically significant differences ($p > 0.05$), indicating that non-response bias is unlikely to have affected the results.

For AT2, BI1 and BI2, differences between early and late responses were statistically significant, indicating that non-response bias might be present. Following this, the effect size for these variables were checked with Cohen's d and were found to be small (<0.2), indicating minimal practical impact (Piasta & Justice, 2010).

Harman's single factor test was used to check for common bias. The results indicated the first factor accounted for 40.14 % of the total variance, which is below the recommended threshold of 50 % (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). This shows that there was no common method bias in this study.

3.5. Data analysis and modelling

The study used SEM for data analysis, as it is one of the most common and widely used methods for analysing TAM (Ullman & Bentler, 2012). SEM is distinct from other statistical techniques in its capacity to analyse both latent and observed variables simultaneously. According to Kline (2011), SEM has two main goals: to understand covariance among observed variables and to explain these covariances as much as possible. SEMs are analysed by first constructing a measurement model and then using the values of the measurement model to build the structural model.

3.5.1. Pre-analysis

Prior to conducting the main analysis, sample adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) test, and the data's suitability for factor analysis was checked using Bartlett's test of sphericity (χ^2). Cronbach's alpha reliability test was used to check the reliability and internal consistency of the collected sample (Kline, 2016). All tests indicated that the data were appropriate for further analysis.

3.5.2. Evaluation of the measurement model

The first step in evaluating the measurement model was Exploratory Factor Analysis (EFA). This step is essential for identifying underlying relationships among observed variables and determining the number of factors to retain for the analysis. Following EFA, the measurement model was constructed using confirmatory factor analysis (CFA).

The validity and reliability of the measurement model were assessed through several statistical checks. Cronbach's alpha was used to evaluate internal consistency. Item communality and Average Variance Extracted (AVE) were calculated to determine the proportion of variance explained by each observed variable and its corresponding latent construct.

Discriminant validity was assessed using the Fornell-Larcker criterion, which involves comparing the square roots of the AVEs with the inter-construct correlations. Discriminant validity is confirmed when the square root of the AVE for each construct is greater than its correlations with other constructs (Ab Hamid, Sami, & Mohmad Sidek, 2017).

3.5.3. Evaluation of the structural model

The validity of the structural model was assessed using the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardised Root Mean Square Residual (SRMR). Additionally, the evaluation of the structural model was undertaken by observing the *p*-values for each relationship. The hypotheses were accepted if the p-value was less than 0.05 (Li, Paudel, & Guo, 2021).

4. Results

This section presents the findings of the study, beginning with descriptive statistics of the respondents and the measured variables. The results of the measurement and structural models using CFA and SEM are then presented, providing insights into the relationships among the constructs and test the study's hypotheses.

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the respondents and their companies. As indicated, the majority of the respondents (36.2 %) had between 10 and 20 years of experience in the logistics and supply chain sector. Just over half of the respondents (51.5 %) had a postgraduate degree and 54.1 % were under the age of 35.

Following the standard enterprise classification of Ethiopia, companies with 100 employees or fewer are classified as small and medium-sized enterprises (SMEs), whereas companies with more than 100 employees are classified as large enterprises (Oshora, Desalegn, Gorgenyi-Hegyes, Fekete-Farkas, & Zeman, 2021). Based on this classification,

Table 1
The constructs for the technology acceptance model (TAM).

Construct	Items	Wording	Adopted from
PU	PU1	Using digital technologies increases my productivity	(Davis, 1989), (Moon & Kim, 2001)
	PU2	Digital technologies can save time	(Chen & Chen, 2011), (Moon & Kim, 2001)
	PU3	Using digital technologies improves my job performance	(Davis, 1989), (Moon & Kim, 2001)
	PU4	Using digital technologies helps me reach my goals faster	(Chen & Chen, 2011)
	PU5	Overall I find digital technologies very useful	(Chen & Chen, 2011)
PEU	PEU1	Learning to use digital technologies is easy	(Chen & Chen, 2011), (Moon & Kim, 2001)
	PEU2	I spend a lot of time learning to use digital technologies	(Chen & Chen, 2011)
	PEU3	It is impossible to use digital technologies without expert help	(Moon & Kim, 2001)
	PEU4	Overall, it is easy to use digital technologies	(Chen & Chen, 2011)
E	Infrastructure	Infrastructure is important for me to adopt digital technologies for my logistics activity	(Tadesse et al., 2021)
	Accessibility	Accessibility is important for me to adopt digital technologies for my logistics activity	(Tadesse et al., 2021)
	Affordability	Affordability is important for me to adopt digital technologies for my logistics activity	(Tadesse et al., 2021)
	Policies	Policies are important for me to adopt digital technologies for my logistics activity	(Tadesse et al., 2021)
	HR	HR is important for me to adopt digital technologies for my logistics activity	(Tadesse et al., 2021)
AI	AT1	Using digital technologies is beneficial for me	(Chen & Chen, 2011)
	AT2	I would like to use digital technologies	(Chen & Chen, 2011)
BI	BI1	I recommend others to use digital technologies	(Chen & Chen, 2011), (Moon & Kim, 2001)
	BI2	I would be willing to use (or continue to use) digital technologies for my job	(Chen & Chen, 2011), (Moon & Kim, 2001)

Table 2
Descriptive statistics of the characteristics of the respondents ($n = 425$).

Variable	Frequency	Percent (%)	Variable	Frequency	Percent (%)
Experience			Age		
<5	108	25.4	<35	230	54.1
5 to 10	140	32.9	35 to 50	185	43.5
10 to 20	154	36.2	>50	9	2.1
>20 years	23	5.4	Enterprise size		
Education			SME	155	36.5
High school diploma	1	0.2	Large	267	62.8
Bachelor's degree	205	48.2			
Master's degree or higher	219	51.5			

36.5 % of the respondents worked for SMEs, 62.8 % were employed in large enterprises and 0.7 % chose not to disclose the size of their organisation.

Table 3 shows the descriptive statistics of the measured variables. The means for the measured variables ranged from 3.55 to 4.74, while the standard deviations ranged from 0.64 to 1.00.

4.2. *Sampling adequacy and reliability*

The overall KMO value for the entire dataset was 0.89, while the KMO values for the individual variables were all above the recommended threshold of 0.6. Bartlett's test of sphericity yielded a statistically significant chi-square value of 0.000 indicating that the dataset was suitable for factor analysis.

Furthermore, the reliability was assessed using Cronbach's alpha value, which was found to be 0.878. This value indicates that the data were internally consistent and reliable.

4.3. *Evaluation of the measurement model*

The evaluation of the measurement model was conducted using CFA. The initial factor analysis showed that PEU2 and PEU3 did not load sufficiently on the latent variable PEU, and were therefore removed from the final model.

Table 4 shows the factor loadings, item communalities, composite reliabilities and AVE on all five factors after PEU2 and PEU3 were removed. As can be seen from Table 4, each measured variable demonstrated acceptable loadings (above 0.7) on its subsequent factor. The values for item communality for all the observed variables were more than 0.4, indicating that an adequate amount of variance was explained by each observed variable (Costello & Osborne, 2005). The composite reliabilities for all latent variables, except for PEU, exceeded the recommended threshold of 0.7, indicating good internal consistency and reliability. Although the composite reliability of PEU was slightly lower than 0.7, Hair, Babin, and Krey (2017) note that values between 0.6 and 0.7 are generally acceptable. The values of AVE for all constructs were more than 0.5, confirming convergent validity.

Discriminant validity was assessed using the Fornell-Larcker criterion. As shown in Table 5, all the construct correlations are less than the square root of AVE for each corresponding construct, satisfying the Fornell-Larcker criterion.

4.4. *Evaluation of the structural model*

Running the SEM resulted in the coefficients for the paths that are indicated in Fig. 2. The CFI value for the model was 1.000, the TLI value was 1.000, the RMSEA value was 0.005 and the SRMR value was 0.042. A CFI value above 0.90, TLI value above 0.95, and RMSEA and SRMR values below 0.08 indicate that a model is a good fit. All these values were within acceptable limits, indicating that the estimated model was acceptable.

Table 6 summarises the hypothesis testing results. The results showed that the hypotheses for all paths were accepted, except for H2, which shows the relationship PU → BI (p-value = 0.485). This indicates that the effect of perceived usefulness on behavioural intention is fully mediated by attitude.

5. Discussion

This section presents a discussion of the key findings in relation to the TAM developed by Davis (1989). In particular, it reflects on how TAM variables interact with contextual factors and facilitating conditions in shaping digital technology adoption in Ethiopia's logistics sector. While TAM emphasises user perceptions, the findings of this study show that affordability, infrastructure, policy support, human resource capacity and economic factors, strongly shapes perception and subsequent behaviours.

Table 3
Descriptive statistics of the indicators (n = 425).

	Mean	SD	Infrastructure	Affordability	Policies	HR	Access	PU1	PU2	PU3	PU4	PU5	PEU1	PEU2	PEU3	PEU4	AT1	AT2	BI1	BI2
Infrastructure	4.52	0.88	1																	
Affordability	4.19	1	0.52	1																
Policies	4.12	1	0.58	0.63	1															
HR	4.26	1	0.53	0.63	0.65	1														
Accessibility	4.35	0.96	0.53	0.61	0.64	0.77	1													
PU1	4.62	0.74	0.34	0.32	0.33	0.26	0.26	1												
PU2	4.74	0.67	0.3	0.31	0.29	0.24	0.29	0.82	1											
PU3	4.64	0.73	0.3	0.32	0.33	0.24	0.28	0.77	0.84	1										
PU4	4.62	0.73	0.34	0.34	0.36	0.29	0.33	0.79	0.84	0.86	1									
PU5	4.67	0.73	0.32	0.31	0.34	0.29	0.32	0.77	0.82	0.76	0.8	1								
PEU1	3.61	0.94	0.07	0.08	0.06	0.1	0.09	0.21	0.23	0.26	0.28	0.24	1							
PEU2	3.15	0.96	0.12	0.03	0.05	0	0.03	0.14	0.13	0.17	0.19	0.16	0.11	1						
PEU3	2.8	1.11	0.09	0.04	0.1	0.1	0.04	0.1	0.07	0.13	0.11	0.04	0.08	0.25	1					
PEU4	3.55	0.93	0.07	0.07	0.07	0.1	0.13	0.14	0.15	0.14	0.19	0.16	0.53	0.15	0.02	1				
AT1	4.62	0.64	0.35	0.27	0.28	0.28	0.26	0.53	0.52	0.51	0.53	0.49	0.26	0.1	0.07	0.24	1			
AT2	4.63	0.66	0.27	0.28	0.25	0.24	0.24	0.5	0.52	0.46	0.5	0.47	0.27	0.1	0.03	0.26	0.84	1		
BI1	4.55	0.69	0.28	0.24	0.24	0.22	0.23	0.42	0.44	0.44	0.45	0.44	0.2	0.19	0.07	0.23	0.69	0.66	1	
BI2	4.6	0.66	0.29	0.24	0.25	0.25	0.29	0.44	0.46	0.47	0.47	0.48	0.22	0.17	0.07	0.26	0.68	0.71	0.84	1

Table 4
Summary of the measurement model.

Latent variable	Indicator	Loadings	Item communality	Composite reliability	AVE
E	Accessibility	0.892	0.755	0.900	0.707
	HR	0.880	0.777		
	Policies	0.845	0.719		
	Affordability	0.804	0.667		
	Infrastructure	0.776	0.572		
PU	PU1	0.919	0.813	0.939	0.880
	PU2	0.974	0.885		
	PU3	0.936	0.855		
	PU4	0.954	0.877		
	PU5	0.907	0.809		
PEU	PEU1	0.830	0.763	0.695	0.603
	PEU4	0.718	0.776		
AT	AT1	0.955	0.795	0.874	0.909
	AT2	0.952	0.800		
BI	BI1	0.927	0.816	0.869	0.901
	BI2	0.971	0.826		

Table 5
Discriminant validity assessment.

	Square root of AVE	PU	PEU	E	AT	BI
PU	0.938	1.000				
PEU	0.777	0.388	1.000			
E	0.841	0.501	0.143	1.000		
AT	0.953	0.725	0.449	0.414	1.000	
BI	0.949	0.661	0.401	0.375	0.888	1.000

5.1. *Role of external facilitating conditions*

The structural model revealed that external factors significantly influence PU. Without the presence of facilitating conditions (i.e. HR, access, infrastructure, finance and policies), stakeholders are unlikely to adopt new technologies. These factors also have a direct effect on AT, indicating that facilitating conditions not only shape how stakeholders perceive a technology's usefulness but also influence their overall attitude towards its use. These findings align with those of Dakduk, Santalla-Banderali, and Ribamar Siqueira (2020), who found in their study on mobile commerce adoption behaviour in Ecuador that the facilitating conditions have a direct effect on users' behavioural intention to adopt new technologies. Similar conclusions were drawn by Mastour et al. (2025) in their study on the adoption of e-learning platforms by healthcare professionals in Iran and by Uy et al. (2025), who investigated digital technology adoption by smallholder farmers in Vietnam.

5.1.1. *Human resources*

One of the key factors contributing to the adoption of digital technologies in low-income countries is the availability of skilled labour (Abdinoor & Mbamba, 2017; Díaz-Arancibia et al., 2024). Although investing in technology is essential for implementation, it must be accompanied by the skills and resources required for successful implementation (Kittipanya-Ngam & Tan, 2020). However, studies have shown that existing workforces often resist digitalisation (Autry et al., 2010), fearing the loss of their jobs as digital tools tend to replace low-skill jobs (Ghobakhloo & Fathi, 2020).

Stakeholders upstream in the supply chain, such as smallholder farmers, are particularly disadvantaged regarding access and ability to use new technologies. Uy et al. (2025) indicated that smallholder farmers in Vietnam have not yet adopted digital applications for their farming activities. This digital divide between urban and rural population, along with resistance to change, could be mitigated by training and education programs aimed at enhancing skills and knowledge (Ghobakhloo & Fathi, 2020; Uy et al., 2025).

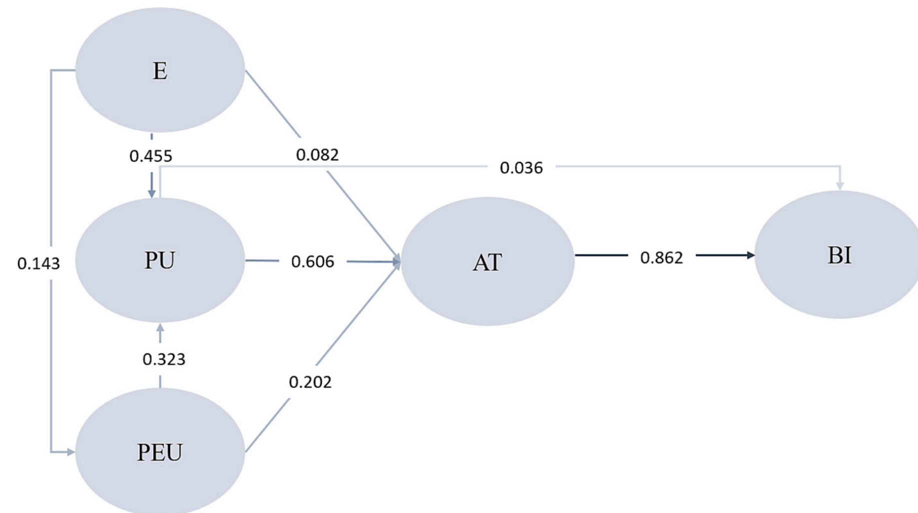

Fig. 2. Estimations of the structural model.

Table 6
Hypothesis test results for the structural model.

Hypothesis	Regression path	p-value	Hypothesis verification
H1	PU → AT	0.000	Accepted
H2	PU → BI	0.485	Rejected
H3	PEU → AT	0.000	Accepted
H4	PEU → PU	0.000	Accepted
H5	E → PU	0.000	Accepted
H6	E → PEU	0.000	Accepted
H7	E → AT	0.003	Accepted
H8	AT → BI	0.000	Accepted

5.1.2. *Accessibility*

Technologies that are readily available tend to have a higher likelihood for adoption. One of the main barriers to technology adoption in low-income countries is limited access to the technology. Most new technologies that promote digitalisation are not readily available in low-income countries (Musa, 2006). This lack of access also explains the low adoption rates of digital technologies in low-income countries.

Beyond access to the technology, stakeholders also need access to the necessary training and manuals for operating it. Both availability of the technology and the supporting training are crucial determinants of successful adoption (Niehm et al., 2010). Technologies that are both accessible and user-friendly are more likely to become successful after adoption (Niehm et al., 2010).

5.1.3. *Infrastructure*

The adoption of technologies is facilitated by the presence of infrastructure (Abdinoor & Mbamba, 2017; Díaz-Arancibia et al., 2024; Mastour et al., 2025). Critical infrastructure components such as uninterrupted internet access in both rural and urban areas is essential for digitalisation (Jang, 2021; Lechman & Popowska, 2022).

The level of a country's digitalisation is measured by the number of ICT subscriptions the country has and the intensity of use of ICT (Jang, 2021). According to a report by the United Nations (2020), only 19.1 % of individuals in low-income countries have access to the internet. Burundi is the country with the lowest internet penetration rate, at a value of 5.8 %, while Ethiopia has an internet penetration rate of 16.7 % (World Bank, 2023). This low internet penetration rate inhibits digitalisation, especially in rural areas where access to internet services is limited (Deichmann et al., 2016).

In addition to ICT access, reliable power supply is vital for digitalisation. However, power blackouts are common in many low-income countries, even in areas where electricity is available, leading to reduced productivity (Tesfachew, 2022).

5.1.4. *Affordability*

Financial constraints are a major barrier to technology adoption in low-income countries (Díaz-Arancibia et al., 2024). An earlier study on the adoption of e-commerce solutions for small businesses in Iran shows that affordability presented a challenge (Ghobakhloo & Tang, 2013). The study by Ahikiriza et al. (2022) on Ugandan dairy farmers reveals that farmers are more inclined to adopt affordable mobile-based solutions. Pappa et al. (2018) indicate that farmers in Greece are more likely to adopt new technologies if the costs of adopting them are manageable.

The present study further confirms that affordability significantly influences the digitalisation of Ethiopia's logistics sector. Therefore, investing in affordable digital solutions is important since the added cost of adopting new technologies can dissuade users from adopting them (Abdinoor & Mbamba, 2017). Firms can do this by initially adopting cheaper and easily accessible technologies for certain supply chain activities (Fall, Orozco, & Akim, 2020; Ghobakhloo & Fathi, 2020), and then subsequently implementing the technology in the rest of the supply chain, depending on how successful the initial implementation has been.

5.1.5. *Support policies*

Without the right policies that nurture digitalisation, it might become challenging and sometimes nearly impossible for firms to adopt new technologies in their supply chains. Policies should not only be directed towards improving ICT infrastructure, but should also try to develop a conducive environment that facilitates digital transformation (Díaz-Arancibia et al., 2024; Paul, Upadhyay, & Dwivedi, 2020).

Moreover, successful digitalisation initiatives require collaboration between public and private sectors to ensure effective policy implementation (Tesfachew, 2022). Policies should also consider the rural population (Paul et al., 2020), since ensuring that they are as connected as the urban population is vital for digitalisation in supply chains (Suominen, 2017). This is especially important in low-income countries where the economy is dependent on smallholder farmers living in rural areas.

5.2. *Usefulness and ease of use*

The usefulness of technology, expressed in terms of PU, motivates users to start using the technology or continue using it (Vukovic, Pivac, & Kundid, 2019). The findings of this study showed that attitudes towards the use of digitalisation in logistics was affected more by PU than by PEU and E. The findings of this study are consistent with those of others including Bracci et al. (2021), Chowdhury et al. (2022), Gao and Bai (2014) and Venkatesh and Davis (2000), where they also state that PU is a strong determinant of users' attitudes to the adoption of new technologies.

Ghobakhloo and Tang (2013) also found that small businesses in Iran were more likely to adopt e-commerce in their businesses if the advantages that they obtain from adopting the technology are beneficial to them. Similarly, Tadesse et al. (2021) also show that the main contributor for technology adoption in low-income countries is the economic benefit stakeholders might potentially gain as a result of adopting the technology. This suggests that users are more likely to adopt a technology if they perceive it to not only enhance performance but also yield economic returns.

According to Davis (1989), in some instances users tend to be behaviourally inclined towards adopting a new technology without having any positive or negative attitude towards it, but only based on the usefulness of the technology. However, the findings in this study indicated that PU was not a significant direct predictor of BI. This indicates that in the context of this study, it is only the attitude that has a direct effect on users' behaviour towards the adoption of new technologies. Other researchers have also found the relationship between PU and BI to be insignificant, including Chen and Chen (2011), Chi (2018) and Ngoc et al. (2023).

An effect of PEU on AT was observed in this study. When users are aware of how to operate a new technology, their attitude to the technology becomes positive. In addition, stakeholders who have already implemented digital technologies in their supply chains are less likely to face issues related to ease of use compared with stakeholders who have not yet started implementing digital technologies (Ahikiriza et al., 2022). Their awareness may make them perceive the technology to be easy to use. Furthermore, PEU was found to be a significant predictor of PU, indicating that technologies that are easy to use are perceived as useful by stakeholders. This confirms earlier results obtained by several researchers. For instance, Ngoc et al. (2023) found in their study on users' intentions to use electric cargo vehicles in Vietnam that users who perceive the vehicles as easy to use are likely to accept them. Chen and Chen (2011) also had similar findings in their study of users' intentions towards adopting in-vehicle GPS systems.

Finally, as expected, the present study indicated that AT was a significant predictor of BI. When users have a positive attitude to digitalisation, this will change their behaviour, leading to the decision to accept the technology. The acceptance of digitalisation eventually leads to its adoption in supply chains (Autry et al., 2010).

5.2.1. *Awareness*

The model showed that the perception of a new technology significantly affected users' likelihood of adoption. The study by Abdinoor and Mbamba (2017) shows that one of the contributors to users adopting technologies in Tanzania is awareness. Similarly, Ahikiriza et al. (2022) show in their study on Ugandan dairy farmers that once farmers are aware of the uses of the technology, their perception of the technology changes, which in the end might affect their intention to use the technology in future. This suggests that users are likely to adopt new technologies when they have information about how the technology works and the potential benefits of adopting the technology (Fall et al., 2020). Therefore, initiatives, such as training and capacity-building programmes, should be implemented by both public and private actors to positively influence users' perceptions of digital technologies, particularly by increasing awareness of their benefits and applicability (Ahikiriza et al., 2022; Mastour et al., 2025; Uy et al., 2025).

6. Conclusions

The assessment of factors that drive the adoption of digital technologies in low-income countries can be undertaken using TAM, a framework widely favoured by researchers for its robustness and simplicity. This study applied TAM to model the acceptance behaviour of stakeholders in Ethiopia towards digital technologies in low-income countries.

The findings confirmed that, consistent with previous literature, PU and PEU had a significant effect on the attitude of stakeholders in low-income countries to the adoption of digital technologies. In addition to PU and PEU, this study identified several external factors, including HR, accessibility, infrastructure, financial resources and policy frameworks, as important contributors to technology adoption.

The results indicated that users' attitudes towards digital technologies were the most significant determinant for technology adoption. This finding highlights the importance of awareness creation and capacity-building initiatives. By enhancing stakeholders' understanding of the benefits of digitalisation, specifically in enhancing logistics performance, adoption rates may increase.

6.1. *Practical contribution*

This study offers practical implications for policymakers, academics, and industry practitioners, including business managers and supply chain leaders. For policymakers, the findings highlight key areas in need of intervention, such as infrastructure development and skills training, to create an enabling environment for technology adoption.

From a business and management perspective, logistics firms and supply chain managers can leverage these insights to prioritise investments in user-friendly digital technologies and capacity-building initiatives within their organisations. Understanding that stakeholders' attitudes strongly influence adoption, managers should focus on awareness campaigns and training programs to demonstrate the tangible benefits of digitalisation on operational efficiency and cost reduction.

Furthermore, businesses can adopt a phased approach to digitalisation by starting with affordable and accessible technologies before scaling up to more advanced systems, thereby reducing financial risk and increasing acceptance among employees and partners. Collaboration between industry players and academic institutions can also facilitate the development of relevant digital skills, ensuring the workforce is well-prepared to operate emerging technologies effectively.

6.2. *Theoretical contribution*

Theoretically, this study advances the technology adoption literature by extending the TAM framework to include external factors that are particularly relevant to low-income countries. Even if TAM has been widely studied, its application in contexts characterised by infrastructural constrains and limited institutional capacity is underexplored.

By integrating context- specific factors into the existing TAM framework, this study demonstrates the influence external factors have on PU, PEU and BI. This insight highlights the importance of framing TAM frameworks to fit socio-economic conditions.

Future scholars can build on this extended framework by testing it across other low-income countries and exploring sector-specific drivers for technology adoption. In doing so, this study lays the groundwork for more advanced adoption models in low-income countries.

6.3. *Limitations and directions future research*

This study was conducted as a case study in Ethiopia, focusing on stakeholders in the logistics and supply chain sector. Future research should conduct comparative studies across multiple low-income countries to identify context-specific and cross-regional drivers of technology adoption.

Additionally, further studies should examine the perspectives of upstream supply chain actors, who may have different needs, barriers, and levels of awareness regarding digitalisation. Research focusing on specific technologies would also offer valuable insights into how individual digital technologies are perceived and adopted by stakeholders.

In addition, future research should study the relationship between the socio-demographic characteristics of the population and their behavioural intention to adopt digital technologies. Finally, the long-term success of digitalisation in low-income countries depends on the development of clear national or sectoral digitalisation roadmaps. Future studies could explore best practices from middle- and high-income countries and propose adaptable strategies tailored to the local constraints and opportunities present in low-income contexts. A well-defined digital strategy would support the transformation of supply chains, enhancing both efficiency and global competitiveness.

CRediT authorship contribution statement

Mahlet Demere Tadesse: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Girma Gebresenbet:** Writing – review & editing, Supervision, Conceptualization. **David Ljungberg:** Writing – review & editing, Supervision. **Lóránt Tavasszy:** Writing – review & editing, Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

None.

Data availability

Data will be made available on request.

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