

UNDERSTANDING CONGOLESE STUDENTS' BEHAVIOURAL INTENTIONS TOWARD LEARNING MANAGEMENT SYSTEMS: AN EXTENDED TAM APPROACH

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Highlights:

- Perceived usefulness, ease of use, and social norms all significantly shape Congolese students' behavioural intentions toward LMS adoption, with usefulness emerging as the strongest driver.
- Behavioural intention fully mediates the relationship between these perceptual factors and actual LMS usage, reaffirming intention as the most direct determinant of technology use.
- The extended TAM model demonstrates moderate explanatory power (42% of variance in intention, 34% in usage), offering practical insights for designing inclusive and resilient digital education strategies in emerging economies.

Abstract:

This study empirically validates a technology acceptance model (TAM)-based framework for predicting technology adoption, integrating core constructs—perceived usefulness (PU), perceived ease of use (PEOU), and social norms (SN)—to examine their influence on behavioural intention and actual usage. Using partial least squares structural equation modelling (PLS-SEM), the measurement model demonstrated strong reliability and validity, while the structural model confirmed all hypothesised relationships. PU emerged as the most influential predictor of intention, and behavioural intention fully mediated the link between perceptual antecedents and usage. The model explained 42.3% of the variance in intention and 34.3% in usage, with Q² values confirming substantial predictive relevance. These findings contribute to the literature by reaffirming the centrality of intention in technology adoption and by highlighting the complementary role of social norms in shaping user behaviour. The study offers theoretical and practical insights for designing inclusive digital strategies, particularly in emerging economies.

Keywords: Technology Acceptance Model (TAM); perceived usefulness; perceived ease of use; social norms; behavioural intention; technology adoption; PLS-SEM; digital literacy; structural equation modelling; emerging economies.

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1. Introduction

The global expansion of information and communication technologies (ICTs) has transformed the educational landscape, challenging traditional pedagogies and driving the rise of digital platforms in higher education (Munabi et al., 2020).

In developed countries, learning management systems (LMS) such as Google Classroom and Moodle have become integral tools for managing and delivering educational content. According to the OECD (Bo, 2025), platforms like Google Classroom are widely adopted due to their seamless integration with productivity suites, enabling real-time collaboration and feedback. Moodle, by contrast, is valued for its open-source flexibility and adaptability to diverse institutional needs (Balaskas et al.,

2025). These systems support asynchronous learning and flipped classroom models, which have been shown to enhance student engagement and autonomy (Wang et al., 2025). Rather than serving purely administrative functions, LMS platforms now play a central role in shaping digital pedagogy and assessment strategies.

However, in many developing countries, including the Democratic Republic of the Congo (DRC), LMS adoption faces infrastructural, financial, and pedagogical barriers. Limited internet access remains a major constraint, particularly in rural and peri-urban areas, where connectivity is unreliable and expensive (World Bank, 2020). Digital literacy among students and faculty is often low, further complicating the effective use of platforms like Moodle or Google Classroom (Tshimanga, 2023). Institutional support is also inconsistent, with many

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universities lacking strategic ICT policies or sufficient funding to sustain LMS deployment (Kalumendo, 2022a). These challenges collectively hinder the integration of digital platforms into higher education, despite growing awareness of their pedagogical potential.

This picture has started to change. The ongoing conflict in eastern DRC, particularly in North Kivu, has forced universities in affected areas to shift some operations online, accelerating the need for digital learning infrastructures (Zaidi, 2025). In response to these pressures, the Ministry of Higher and University Education has recently adopted a more progressive stance. In 2024, it formally recognised online and blended learning as legitimate modalities for academic delivery (Ministère de l'Enseignement Supérieur et Universitaire, 2025). This policy milestone marks a significant shift in national strategy, supporting broader integration of digital tools across the sector and aligning Congolese higher education with global trends in flexible learning (World Bank, 2020).

Like in other countries (Akkan and Eminoglu Kucuktepe, 2024) affected by the COVID-19 pandemic, higher education institutions in the Democratic Republic of the Congo (DRC) were compelled to experiment with virtual instruction amidst widespread health-related disruptions (Ndejjo et al., 2023). Although national regulations had previously remained ambiguous regarding distance education, many universities began adopting e-learning platforms to maintain academic continuity (Matete et al., 2023). This reactive shift laid the groundwork for more sustained digital engagement, especially as institutional actors recognised the pedagogical and logistical value of LMS platforms (Munabi et al., 2020). Coupled with recent policy reforms that formally legitimise online and blended learning modalities, the sector now finds itself at a critical juncture (Ministère de l'Enseignement Supérieur et Universitaire, 2025). The convergence of crisis-driven adaptation and progressive regulation raises an urgent and timely question: how do Congolese students perceive LMS platforms, and what factors shape their behavioural intentions toward sustained usage?

Anchored in the extended Technology Acceptance Model (TAM), this study investigates the influence of perceived usefulness, perceived ease of use, and subjective norms on students' behavioural intentions and their subsequent actual use of learning management system (LMS) platforms. These constructs have been widely validated in Sub-Saharan African contexts, where LMS adoption is shaped by both individual perceptions and institutional pressures (Bervell and Umar, 2017; Jiang et al., 2025). Data will be collected from students across six Congolese universities with prior LMS experience, ensuring empirical relevance and contextual depth.

This research fills a critical gap. To date, few studies have empirically examined LMS adoption in Congolese higher education, particularly under conditions of displacement, infrastructural fragility, and digital transition (Kalumendo, 2022a; Kalumendo, 2022b; Kalumendo et al., 2025). By foregrounding student perspectives in a high-conflict, policy-shifting environment, this study offers grounded insights that can guide future strategies for inclusive and resilient digital education in the DRC. It also contributes to

the broader discourse on technology acceptance in post-crisis educational reform (García et al., 2024; Rosli et al., 2022).

2. Literature review and hypothesis development

The integration of Learning Management Systems (LMS) in higher education has become a critical dimension of digital transformation, particularly in response to global shifts in pedagogical delivery and institutional resilience (Alotaibi, 2024; Bajger et al., 2025). Across the globe, research on technology adoption models—most notably the Technology Acceptance Model (TAM) introduced by (Davis, 1989)—has guided scholarly understanding of how and why users engage with new technologies. The model identifies two core determinants of usage behaviour: perceived usefulness (PU) and perceived ease of use (PEOU), both of which have been consistently validated across educational contexts (Jiang et al., 2025; Saif et al., 2024). In extended forms, TAM has incorporated additional constructs such as subjective norms (Venkatesh and Davis, 2000), behavioural intention, and facilitating conditions (Marchewka and Kostiwa, 2014) to better reflect socio-cultural and contextual complexities, especially in resource-constrained or post-crisis environments (Munabi et al., 2020).

2.1. Perceived usefulness and behavioural intention

Perceived usefulness (PU) refers to the extent to which individuals believe that using a particular technology will enhance their performance (Davis, 1989). In the context of Learning Management Systems (LMS), PU reflects students' perceptions of how digital platforms contribute to their academic success—whether through improved access to course materials, streamlined communication, or greater flexibility in learning. A growing body of research confirms that PU is a strong predictor of behavioural intention to use LMS platforms. For example, Barz et al. (2024) found that PU significantly influenced students' willingness to adopt LMS tools in higher education settings. Similarly, Zulherman and Zaelani (2023) demonstrated that PU plays a central role in shaping LMS engagement among university students, validating its relevance in post-pandemic digital learning environments.

Hypothesis 1 (H1): Perceived usefulness positively influences students' behavioural intention to use Learning Management Systems.

2.2. Perceived ease of use and behavioural intention

Perceived ease of use (PEOU) refers to the extent to which a user believes that interacting with a system will be free of effort (Davis, 1989). In the context of Learning Management Systems (LMS), this construct captures students' perceptions of how intuitively and efficiently they can navigate digital platforms for academic purposes. PEOU has proven particularly critical in developing contexts, where digital literacy and prior exposure to

educational technologies may be limited (Rhema and Miliszewska, 2014). Systems perceived as easy to operate are more likely to be embraced, especially when students face infrastructural constraints or lack formal ICT training. Alharbi and Drew (2014) further confirms that usability plays a decisive role in shaping students' intention to adopt LMS tools, reinforcing the importance of interface simplicity and user support in the acceptance of technology.

Hypothesis 2 (H2): Perceived ease of use positively influences students' behavioural intention to use Learning Management Systems.

2.3. Social norms and behavioural intention

Subjective norms—defined as the perceived social pressure to perform or not perform a certain behaviour—introduce a socio-psychological dimension to the Technology Acceptance Model (TAM) (Ajzen, 1991). In educational environments, students' behavioural intentions are often shaped by peer influence, instructor expectations, and institutional advocacy. These social cues can reinforce or discourage engagement with digital platforms, especially in contexts where technology adoption is still emerging. Chu and Chen (2016) found that subjective norms significantly influenced learners' attitudes toward e-learning systems, particularly when institutional support was visible. Similarly Hussein (n.d.), demonstrated that peer and faculty endorsement of LMS platforms positively affected students' intention to use them, underscoring the importance of social validation in technology uptake.

Hypothesis 3 (H3): Subjective norms positively influence students' behavioural intention to use Learning Management Systems.

2.4. Behavioural intention and actual usage

While behavioural intention does not guarantee action, it is widely acknowledged as its strongest predictor of actual technology use (Abbad, 2021). In educational settings, intention often aligns with opportunity and access; students who intend to use LMS platforms are more likely to translate that intention into actual usage—particularly when system availability, institutional support, and digital infrastructure are sustained. This relationship

has been validated across multiple TAM-based studies, where behavioural intention consistently mediates the link between attitudinal constructs and observable engagement with digital (Zulherman and Zaelani, 2023).

Hypothesis 4 (H4): Behavioural intention positively influences the actual usage of Learning Management Systems by students.

Summary Conceptual Model

The theoretical model (Figure 1) for this study builds on these four hypotheses, positing that perceived usefulness, perceived ease of use, and social norms influence behavioural intention, which in turn affects actual system usage. This model will be tested using structural equation modelling (PLS-SEM), a rigorous method for assessing both direct and indirect effects among variables.

3. Methodology

3.1. Research design

This study adopted a quantitative research design and employed the Extended Technology Acceptance Model (TAM) to investigate the factors influencing students' adoption and usage of Learning Management Systems (LMS). The model integrated three key constructs—perceived usefulness, perceived ease of use, and subjective norms—as predictors of behavioural intention. Behavioural intention was then modelled as a mediating variable influencing actual system usage. This structure reflects established TAM extensions validated in educational technology research, particularly in developing contexts where socio-psychological and infrastructural factors shape digital engagement (Chu and Chen, 2016; Zulherman and Zaelani, 2023).

3.2. Population and sampling

The target population for this study comprised university students enrolled in ten higher education institutions across three provinces of the Democratic Republic of Congo: North Kivu, Ituri, and Kasai-Central. All participants had prior experience using at least one Learning Management System (LMS), most commonly Google Classroom, as part of their academic coursework. This criterion ensured that respondents could provide meaningful reflections on LMS adoption and usage.

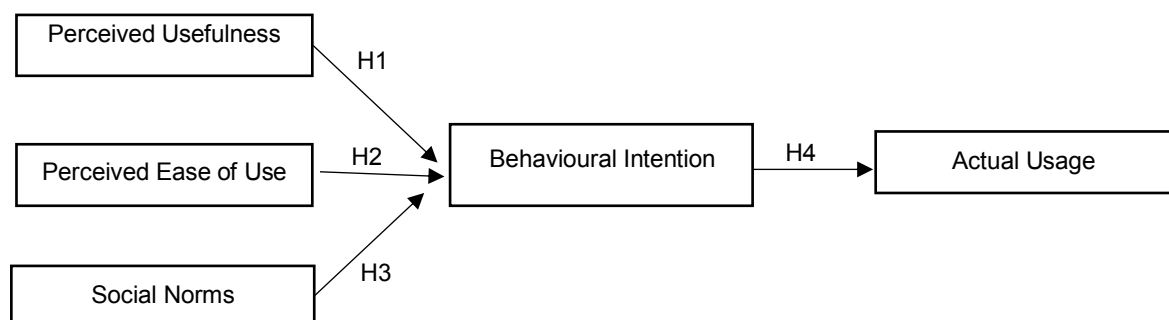


Figure 1: Conceptual Model.

Participants were recruited using purposive sampling from six Congolese universities that had prior experience with Learning Management Systems (LMS). These universities were selected according to four criteria: (1) prior institutional LMS deployment (evidence of at least one semester of LMS use), (2) geographic representation across provinces affected by both conflict and policy change (North Kivu, Ituri, Kasai-Central), (3) institutional size and diversity of disciplines (to capture undergraduate students across STEM and social sciences), and (4) accessibility and willingness of local administrators to facilitate data collection. Within each selected university, students were sampled through convenience/purposive approaches targeting classes that used LMS in the preceding academic terms. A total of 400 valid responses were collected, exceeding the minimum sample size recommended for structural equation modelling (SEM) using SmartPLS. According to (Hair et al., 2021), a sample of 200 or more is generally sufficient to achieve statistical power and model stability when estimating complex path relationships.

3.3. Instrumentation

Data were collected using a structured questionnaire developed in French, the primary language of instruction across the participating universities. The instrument was designed to measure five core constructs derived from the Extended Technology Acceptance Model (TAM): perceived usefulness, perceived ease of use, subjective norms, behavioural intention, and actual system use. Each construct was operationalised using a minimum of three items, adapted from validated TAM instruments. Responses were recorded on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), ensuring consistency in measurement and facilitating structural equation modelling (SEM) analysis.

3.4. Data collection procedure

The questionnaire was administered using KoboToolbox, a platform specifically designed for data collection in low-resource and offline environments. This choice ensured accessibility across diverse institutional settings, with data gathered both online and offline depending on campus infrastructure and connectivity. Before participation, students provided informed consent, and the study adhered to established ethical protocols, including confidentiality safeguards and assurances of voluntary participation.

3.5. Data analysis

Structural Equation Modelling (SEM) was conducted using SmartPLS version 4, a variance-based approach well-suited for exploratory research and complex models with latent constructs (Hair et al., 2021). The measurement model was assessed for internal consistency reliability using Cronbach's Alpha and Composite Reliability (CR), both of which are standard indicators for evaluating construct stability (Sarstedt et al., 2017). Convergent validity was examined through the Average Variance Extracted (AVE), while discriminant validity was confirmed

using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, as recommended for PLS-SEM applications (Henseler et al., 2015).

The structural model was evaluated using path coefficients, coefficient of determination (R^2), and predictive relevance (Q^2), which collectively assess the explanatory and predictive power of the model. Bootstrapping with 5000 subsamples was employed to test the statistical significance of all hypothesised relationships, ensuring robustness in parameter estimation.

4. Results

The psychometric properties of the constructs were assessed to establish the adequacy of the measurement model. Reliability and convergent validity indices are presented in Table 1. All constructs achieved Cronbach's alpha (α) and Composite Reliability (CR) values exceeding the recommended threshold of 0.70, indicating satisfactory internal consistency (Nunnally and Bernstein, 1994; Hair et al., 2019). For instance, Perceived Ease of Use (PEU) and Perceived Usefulness (PU) recorded CR values of 0.914 and 0.900, respectively, reflecting excellent construct reliability. Furthermore, all Average Variance Extracted (AVE) values surpassed the 0.50 benchmark, thereby confirming convergent validity (Fornell and Larcker, 1981).

Table 1: Reliability and convergent validity indices.

Construct	n items	Cronbach alpha	Composite Reliability_CR	AVE
PEU	5	0.88	0.91	0.68
PU	3	0.83	0.90	0.75
SN	3	0.77	0.87	0.69
INT	3	0.85	0.91	0.77
USAGE	3	0.84	0.90	0.76

As shown in Table 2, all outer loadings exceeded the recommended threshold of 0.70, indicating strong indicator reliability and confirming that each item contributed meaningfully to its respective latent construct.

Table 2: Outer Loadings.

Construct	Item	Loading_with_latent
PEOU	PEOU1	0.84
PEOU	PEOU2	0.81
PEOU	PEOU3	0.84
PEOU	PEOU4	0.82
PEOU	PEOU5	0.82
PU	PU1	0.87
PU	PU2	0.86
PU	PU3	0.87
SN	SN1	0.81
SN	SN2	0.84
SN	SN3	0.84
INT	INT1	0.88
INT	INT2	0.88
INT	INT3	0.88
USAGE	USAGE1	0.88
USAGE	USAGE2	0.87
USAGE	USAGE3	0.86

(Hulland, 1999; Hair et al., 2019). High outer loadings suggest that the observed variables share substantial variance with their underlying theoretical dimensions, thereby supporting the reflective measurement model structure (Diamantopoulos and Siguaw, 2006). According to Hair et al. (2019), loadings above 0.70 are considered ideal, as they demonstrate that over 50% of the variance in the indicator is explained by the latent variable. The consistent strength of loadings across all items reinforces the construct validity of the instrument and supports its suitability for structural equation modelling using PLS-SEM. they were retained (Hair et al., 2021).

4.1. Discriminant validity

Discriminant validity was evaluated using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, as recommended for reflective measurement models in PLS-SEM (Henseler et al., 2015; Hair et al., 2021). As shown in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (diagonal values) was consistently greater than its correlations with other constructs (off-diagonal values), thereby satisfying the Fornell–Larcker criterion (Fornell and Larcker, 1981). This indicates that each construct shares more variance with its own indicators than with those of other constructs, supporting discriminant validity.

Table 3: Fornell–Larcker criterion.

Construct	PEU	PU	SN	INT	USAGE
PEU	0.825				
PU	0.643	0.865			
SN	0.213	0.155	0.832		
INT	0.565	0.598	0.225	0.880	
USAGE	0.394	0.438	0.190	0.586	0.871

Complementarily, Table 4 reports the Heterotrait–Monotrait (HTMT) ratios, all of which were below the conservative threshold of 0.85, thereby confirming discriminant validity (Henseler et al., 2015). The HTMT criterion is considered a more robust and reliable alternative to traditional methods such as the Fornell–Larcker criterion, particularly in detecting discriminant validity issues in variance-based structural models (Franke and Sarstedt, 2019). Values below 0.85 suggest that the constructs are empirically

distinct and not excessively correlated, reinforcing the conceptual separation of latent variables within the model (Hair et al., 2021).

Table 4: HTMT Values.

Construct	PEU	PU	SN	INT	USAGE
PEU	1	0.749	0.256	0.651	0.457
PU	0.749	1	0.192	0.71	0.524
SN	0.256	0.192	1	0.276	0.234
INT	0.651	0.71	0.276	1	0.691
USAGE	0.457	0.524	0.234	0.691	1

Collectively, these results confirm that each latent construct is empirically distinct from the others, satisfying the requirements for discriminant validity (Fornell and Larcker, 1981; Henseler et al., 2015). Taken together, Tables 1–4 provide robust evidence of measurement model adequacy, demonstrating high internal consistency reliability, strong indicator loadings, satisfactory convergent validity, and clear discriminant validity. These findings affirm the psychometric soundness of the instrument and its suitability for structural equation modelling using PLS (Hair et al., 2019).

4.2. Structural model evaluation

Path coefficients and hypothesis testing

The structural relationships (Figure 2) among the latent constructs were examined using bootstrapping procedures with 2000 subsamples, following best practices for significance testing in partial least squares structural equation modelling (PLS-SEM) (Hair et al., 2021). Table 5 presents the estimated path coefficients, standard errors, t-statistics, p-values, and 95% bias-corrected confidence intervals. All hypothesised relationships were statistically supported, thereby validating the proposed theoretical model.

- **PEOU → INT:** Perceived ease of use exerted a positive and statistically significant influence on behavioural intention ($\beta = 0.309$; $p < 0.01$). This suggests that when users perceive the system as user-friendly, their intention to adopt it increases, consistent with the Technology Acceptance Model (TAM) (Davis, 1989).

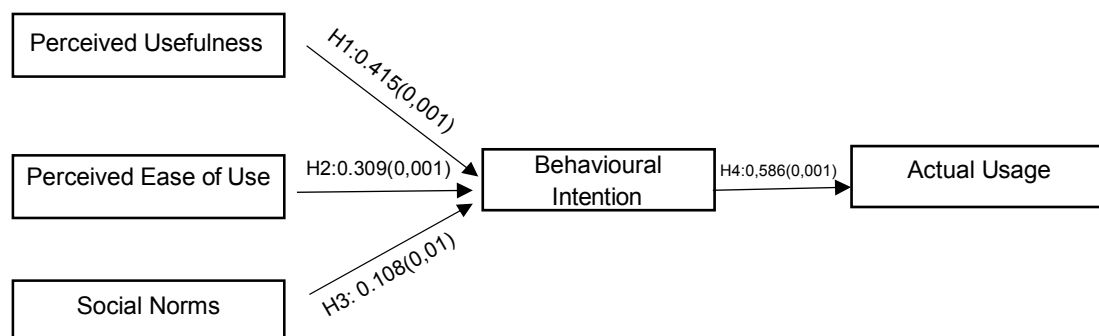


Figure 2: Structural Model.

- **PU → INT:** Perceived usefulness demonstrated the strongest effect on behavioural intention ($\beta = 0.415$; $p < 0.001$), reaffirming its central role in technology adoption. This outcome aligns with TAM extensions that emphasise the instrumental value of technology in shaping user intentions (Venkatesh and Davis, 2000).
- **SN → INT:** Social norms were positively and significantly associated with behavioural intention ($\beta = 0.108$; $p < 0.05$), albeit with a smaller effect size. This finding highlights the influence of peer and organisational expectations, in line with the extended TAM and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks (Venkatesh et al., 2003).
- **INT → USAGE:** Behavioural intention emerged as the sole and significant predictor of actual system use ($\beta = 0.59$; $p < 0.001$). No other direct paths to usage were specified or tested in the model. This substantial coefficient reinforces the theoretical proposition that intention is the most proximal determinant of usage behaviour, a foundational tenet of intention-based models such as TAM and UTAUT (Ajzen, 1991; Venkatesh et al., 2003).

Table 5: Path Coefficients.

Hypothesis	Path	β (Beta)	t-value	p-value
H1	PU → INT	0.415	8.22	0.001
H2	PEOU → INT	0.309	5.93	0.001
H3	SN → INT	0.108	2.56	0.01
H4	INT → USAGE	0.586	14.68	0.001

4.3. Coefficient of determination (R^2)

As reported in Table 6, the structural model accounts for 42.3% of the variance in behavioural intention (INT) and 34.3% in actual usage (USAGE). These R^2 values reflect moderate explanatory power, as per (Chin, 1998) classification, which considers values around 0.33 as indicative of acceptable model strength in behavioural and social sciences. The findings affirm that perceived usefulness (PU), perceived ease of use (PEOU), and social norms (SN) are salient predictors of intention and, indirectly, of usage. However, the residual unexplained variance suggests that the model may benefit from the inclusion of additional constructs to capture the multifaceted nature of technology adoption.

Specifically, variables such as habit, facilitating conditions, and perceived behavioural control have been shown to enhance predictive accuracy in extended frameworks like UTAUT and the Theory of Planned Behaviour (Ajzen, 1991; Venkatesh et al., 2003). Habit, for instance, reflects the automaticity of repeated behaviour and has demonstrated incremental validity in explaining continued usage. Facilitating conditions (Limayem et al., 2007)—such as access to infrastructure, technical support, and organisational readiness—may also moderate the intention–usage link, particularly in resource-constrained environments. Thus, while the current model offers a parsimonious and theoretically grounded explanation,

future research should consider integrating these complementary dimensions to improve its explanatory scope and contextual relevance.

Table 6: Coefficient of Determination.

Endogenous	R^2
INT	0.4234
USAGE	0.3432

4.4. Predictive relevance (Q^2)

As reported in Table 7, the Q^2 values obtained via cross-validated redundancy were 0.406 for behavioural intention (INT) and 0.339 for actual usage (USAGE), both substantially above zero. These values indicate that the model possesses meaningful predictive relevance for its endogenous constructs, as per the guidelines established by Stone (1974) and Geisser (1974). In the context of PLS-SEM, Q^2 values above 0.25 are generally interpreted as indicative of strong predictive accuracy (Hair et al., 2019), particularly when assessing behavioural outcomes in technology adoption research.

The use of blindfolding procedures to generate Q^2 statistics provides a robust test of the model's out-of-sample predictive capability, complementing the explanatory power indicated by R^2 values. The results suggest that the latent predictors—namely perceived usefulness, perceived ease of use, and social norms—offer not only theoretical relevance but also practical utility in forecasting user intentions and behaviours. This reinforces the model's applicability in real-world settings and supports its deployment in future empirical studies seeking to understand technology acceptance dynamics.

Table 7: Predictive Relevance.

Construct	Q^2
INT	0.4057
USAGE	0.3387

5. Discussion

The findings offer robust empirical support for the theoretical propositions underpinning the Technology Acceptance Model (TAM) and its subsequent extensions. Among the examined constructs,

Perceived Usefulness (PU) emerged as the most influential determinant of behavioural intention, reaffirming its foundational role in shaping user attitudes toward technology adoption (Davis, 1989; Venkatesh et al., 2003). This result underscores the primacy of instrumental value—users are more likely to engage with a system when they perceive it as enhancing task performance or productivity. The salience of PU has been consistently validated across diverse domains, including e-learning (Al-Gahtani, 2016; Alshammari and Alkhawaldi, 2025), educational AI (Yang, 2025), and GenAI-supported learning environments (Hsiao and Tang, 2025).

Perceived Ease of Use (PEU) also exerted a significant positive effect, suggesting that usability perceptions remain critical, particularly in environments where digital literacy, resource constraints, or prior exposure to technology may vary. This aligns with prior studies emphasising the role of intuitive design and low cognitive load in facilitating adoption (Venkatesh et al., 2003; Gefen et al., 2003). In contexts such as the Democratic Republic of the Congo, where infrastructural and educational disparities may influence user experience, PEU becomes a particularly salient construct for inclusive technology deployment.

The positive, albeit modest, effect of Social Norms (SN) on intention further illuminates the role of normative pressures in shaping individual behaviour. This influence is especially pronounced in collectivist or hierarchical organisational cultures, where peer endorsement, managerial expectations, and institutional mandates may guide adoption decisions (Venkatesh et al., 2003; Srite and Karahanna, 2006). The inclusion of SN enriches the explanatory scope of TAM by accounting for socio-contextual dynamics that extend beyond individual cognition, a perspective increasingly advocated in culturally sensitive adoption models (Straub et al., 1997).

Crucially, the structural model revealed a strong and exclusive path from behavioural intention (INT) to actual usage (USAGE), confirming the mediating role of intention in translating perceptions into action. This finding aligns with intention-based frameworks such as TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behaviour (Ajzen, 1991), all of which posit intention as the proximal antecedent of behaviour. The strength of this path reinforces the predictive validity of the model and supports its application in both academic and practical settings.

Taken together, the results highlight a coherent interplay between cognitive evaluations (PU, PEU), social influence (SN), and volitional behaviour (INT → USAGE), offering a parsimonious yet theoretically robust framework for understanding technology acceptance. The model's empirical validity and predictive strength affirm its relevance for guiding digital transformation initiatives, particularly in emerging economies where adoption is shaped by a blend of individual perceptions and collective expectations.

6. Conclusion

This study provides a theoretically grounded and empirically validated model for understanding technology adoption through the lens of the Technology Acceptance Model (TAM). By integrating core constructs—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Social Norms (SN)—the research demonstrates that behavioural intention serves as a critical mediating mechanism between user perceptions and actual system usage. The measurement model exhibited strong reliability and validity, while the structural model confirmed all hypothesised relationships with statistical significance.

The prominence of PU as the strongest predictor of intention reaffirms its centrality in shaping adoption decisions, particularly in contexts where perceived functional benefits drive engagement. The significant role of PEOU highlights the importance of usability and design simplicity, especially in environments with varying levels of digital literacy. Although SN exerted a comparatively modest influence, its inclusion underscores the relevance of collective expectations and social pressures in shaping individual behaviour.

Importantly, the model explained a substantial proportion of variance in both intention and usage, and demonstrated strong predictive relevance through Q² statistics. These findings contribute to the broader literature by validating TAM in a contextually sensitive manner and by reinforcing the theoretical proposition that intention is the most proximal determinant of technology use.

In sum, the study offers a parsimonious yet powerful framework for predicting technology adoption, with implications for both academic inquiry and practical implementation. It provides a foundation for future research to explore additional behavioural, contextual, and cultural variables that may further enhance explanatory power and applicability across diverse settings.

6.1. Implications

The findings of this study offer both theoretical and practical implications. Theoretically, the validated model reinforces the enduring relevance of TAM constructs—particularly Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—in predicting behavioural intention, while demonstrating the added value of integrating Social Norms (SN) to capture socio-contextual influences. This aligns with calls for culturally sensitive extensions of TAM and UTAUT, especially in non-Western and resource-constrained environments (Straub et al., 1997; Srite and Karahanna, 2006). The results confirm that technology adoption in such contexts is shaped not only by individual perceptions but also by social expectations and collective behavioural patterns.

Practically, the study provides specific, actionable strategies for policymakers, system designers, and institutional leaders seeking to foster effective and inclusive digital adoption:

- 1. Strengthen Perceived Usefulness (PU).** Institutions should ensure that students clearly see the academic value of digital systems. This can be achieved by integrating graded LMS activities into every course, showcasing features that directly improve learning efficiency (e.g., faster feedback, centralized resources), and providing short demonstrations at the beginning of the semester. Making usefulness visible increases motivation to adopt the platform.
- 2. Improve Ease of Use (PEOU).** System designers and IT teams should simplify LMS interfaces and ensure compatibility with low-end devices and low-bandwidth environments common in the DRC. Offering quick-start guides, brief orientation sessions, and step-by-step tutorials during the first week

of classes can significantly reduce initial barriers. Streamlined navigation and mobile-friendly design further encourage consistent use.

3. **Leverage Social Norms (SN).** Since social influence plays a meaningful role, institutions can promote digital adoption by creating supportive peer and instructor ecosystems. Appointing LMS “champion” instructors, establishing student digital ambassadors, and publicly recognising departments that effectively use digital tools help create positive normative pressure. Organisational endorsement—such as official communication emphasising LMS use as an institutional standard—further strengthens adoption.
4. **Support Inclusive Digital Strategies.** To ensure equitable access, universities should implement targeted measures such as device-loan programmes, campus Wi-Fi hotspots, and low-data content formats. Training local IT staff to provide timely support and using analytics to identify students who struggle with system use enable more responsive and inclusive interventions.

Collectively, these practical insights demonstrate that digital transformation in emerging economies requires addressing not only technological factors but also cultural expectations, resource limitations, and the broader social environment. By aligning system design and institutional practices with these behavioural drivers, universities can meaningfully enhance digital adoption and improve learning outcome

6.2. Limitations

Despite its contributions, the study is subject to several limitations. First, the model excluded potentially influential constructs such as habit, facilitating conditions, and trust, which may further explain variance in usage behaviour. Second, the use of cross-sectional data limits the ability to capture temporal dynamics or infer causality. Third, although the study aimed to validate the extended TAM in a Congolese context, demographic data (e.g., age, gender, year of study) were not collected, which prevented the inclusion of demographic characteristics as control variables or the examination of subgroup differences. This absence restricts the ability to assess how demographic variations might influence the studied relationships. Fourth, the generalisability of the findings may be constrained by sample characteristics and institutional context. Finally, while subjective norm (SN) was included, other cultural dimensions—such as power

distance or uncertainty avoidance—were not explicitly modelled, which may influence behavioural outcomes in culturally diverse settings.

6.3. Future Research Directions

Building on these findings, future research should consider several avenues for extension. First, incorporating additional constructs such as habit, perceived behavioural control, and facilitating conditions may enhance the model's explanatory and predictive power (Ajzen, 1991; Venkatesh et al., 2003). Second, longitudinal designs would allow for the examination of behavioural evolution over time, capturing sustained usage patterns and post-adoption dynamics. Third, exploring moderating effects—such as age, gender, digital literacy, or institutional support—could reveal subgroup-specific adoption mechanisms and inform targeted interventions.

Moreover, applying the model across diverse technological domains (e.g., e-health, mobile finance, AI-supported learning) and regional contexts would test its robustness and adaptability. Finally, integrating qualitative approaches—such as interviews or ethnographic methods—could provide deeper insights into the socio-cultural and emotional dimensions of technology acceptance, complementing the quantitative findings and enriching theory development.

Statements and Declarations

Author contributions: All authors contributed to the conception and design of the study. Material preparation, data collection, and analysis were carried out by Rodrigue Kalumendo, Paluku VAGHENI, Tiabaki TANDELE and Ntumba Malu Pierre. Rodrigue Kalumendo drafted the initial version of the manuscript. All authors provided feedback on earlier drafts and approved the final version for submission.

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Declarations, Ethics approval, and consent to participate: This study did not require formal ethical approval, as it involved non-sensitive, anonymous survey data collected from adult participants. All respondents were informed of the research's purpose and participated voluntarily. Informed consent was obtained before participation, and no personally identifiable information was collected. The study adhered to ethical principles of confidentiality, autonomy, and responsible data handling throughout the research process.

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