Evaluating TAM Validity and Reliability in Mobile Learning for Students with Disabilities in South African Distance Education

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Abstract
This study examined the psychometric properties of two primary domains: perceived usefulness (PU) and perceived ease of use (PEOU) in the technology acceptance model (TAM), and their value in determining mobile learning (m-learning) usage among a sample of 220 students with disabilities (SwD) enrolled in a distance education (DE) institution in South Africa. This appears to be one of the first studies in the country to establish internal consistency of the domains among SwD and confirm the two-factor structure using confirmatory factor analysis (CFA; χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039). These two constructs exhibited factor loadings (λ) ranging from .79 to .95 and produced a structure consistent with the original TAM (Davis, 1989). From a theoretical perspective, the CFA findings reinforce the construct validity of the TAM across various student populations while supporting its cross-cultural applicability in diverse educational settings. However, regression analyses suggested that PU and PEOU were not significant predictors of m-learning usage among SwD (β = .026, t = .300; p = .764; β = -.010, t = -.113, p = .910, respectively), warranting a critical review of the TAM among SwD in DE settings and giving credence to the notion that m-learning usage is deeply embedded in the structural realities of living with a disability and studying at a distance in South Africa. Nonetheless, this study contributes to the limited psychometric research on the TAM in the South African DE sector and establishes a foundation for understanding m-learning usage among SwD in developing contexts.

Keywords: Technology acceptance, students with disabilities, inclusive education, mobile learning, distance education, South Africa

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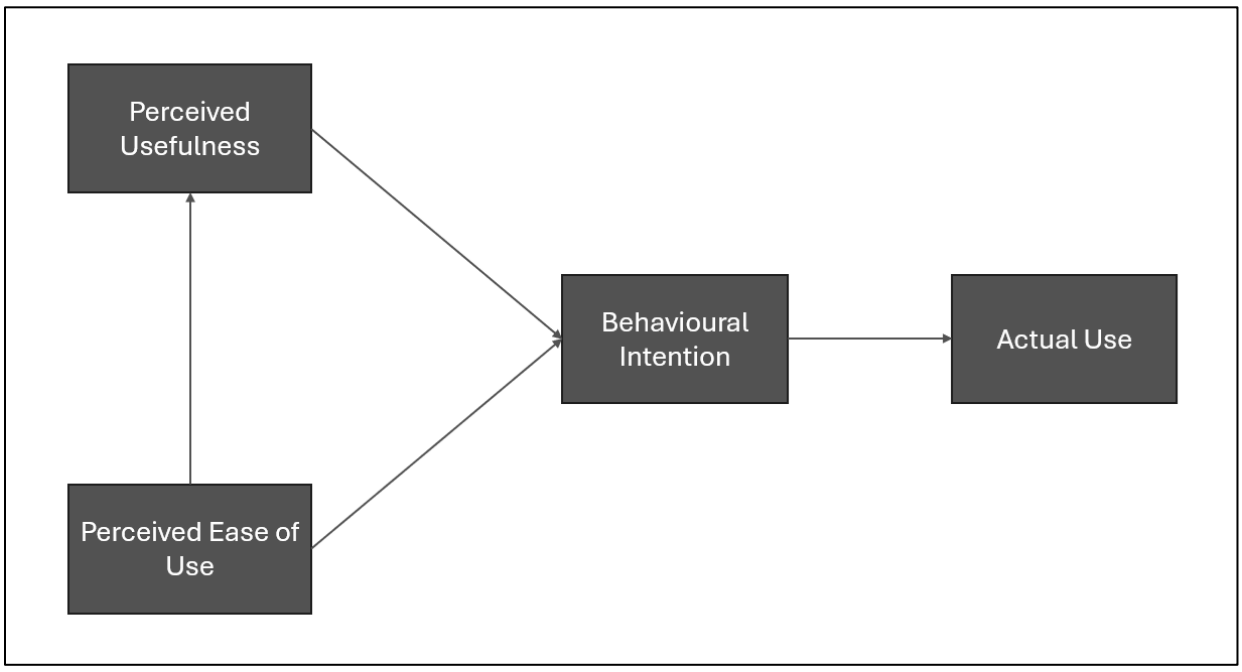
The Technology Acceptance Model (TAM), first developed by Davis (1985) and later refined by Davis (1989), has become one of the most influential frameworks for explaining information systems (IS) behaviour. Drawing on the Theory of Reasoned Action (Fishbein & Ajzen, 1975), which suggests that attitudes and subjective norms shape behavioural intentions (BI), the TAM postulates that acceptance of technology is predicted by users' BI, which is, in turn, determined by two core cognitive perceptions: the perceptions an end-user has towards the ease of use and the usefulness of the system (see Figure 1). Davis defined the latter, i.e., perceived usefulness (PU), as the degree to which the person believes that using a particular system would enhance performance, whereas the former, i.e., perceived ease of use (PEOU), is defined as the degree to which the person believes that using a particular system would be effortless. These two constructs are said to strongly influence the acceptance or use of a new IS or information technology (IT), a finding implied in the literature. Although the TAM has been extended to include social and contextual factors over the years (i.e., TAM2, Venkatesh & Davis, 2000; Unified Theory of Acceptance and Use of Technology, UTAUT, Venkatesh et al., 2003), the original TAM remains widely applied in diverse contexts due to its parsimony, explanatory power, and consistent empirical validation (Marangunić & Granić, 2015), and is thus explored in relation to mobile learning (m-learning) among students with disabilities (SwD) in the current paper.

Figure 1

The Technology Acceptance Model (Davis, 1989)



m-Learning Among SwD

M-Learning has emerged as a central modality in contemporary higher education due to its flexibility, accessibility, and potential to reduce longstanding participation barriers for diverse student groups (Gupta et al., 2021; Mustaffa & Mansor, 2015; Suner et al., 2019). Unlike

traditional e-learning delivered through desktop-bound systems, m-learning enables continuous, context-independent engagement with educational content through portable devices (Gupta et al., 2021; Murphy et al., 2014; Mustaffa & Mansor, 2015; Nichter, 2021), making it particularly valuable in settings where students have varied access to infrastructure and support (Lall et al., 2019; Milheim et al., 2021). In South Africa, where structural inequalities and resource constraints remain prevalent (Bozalek & Boughey, 2012; van Rooyen & Marais, 2018), mobile technologies often serve as students' primary means of accessing online materials, communication tools, and learning platforms (van Rooyen & Marais, 2018). For SwD, m-learning offers additional benefits, including the use of built-in accessibility features (e.g., screen readers, magnification tools, gesture-based navigation) and the ability to personalise the learning environment to meet individual functional needs (Ayoola & Mangina, 2012; Ciampa, 2014). Given these affordances, examining TAM within an m-learning context is both appropriate and necessary; the constructs of PU and PEOU become especially relevant when technology may either mitigate or exacerbate accessibility challenges (Kim et al., 2020; Lall et al., 2019).

A Chronological Review of the Psychometric Properties of the TAM's Core Constructs

Reliability

Since 1989, the psychometric properties of the TAM have been explored across various settings and populations. In the earliest of these, Davis (1989) established support for the internal consistency of the model's core constructs using various ISs (i.e., PROFS electronic mail, XEDIT file editor, Chart-Master, and Pendraw). Results from these seminal explorations revealed Cronbach's alpha coefficients (α) ranging from .91 to .98, attesting to the reliability of the constructs when applied to a diverse range of technological contexts. Since then, numerous studies have reported on the internal consistency of these core components, all of which have yielded satisfactory Cronbach's alphas ($\alpha > .70$) across various ISs and samples, as shown in Table 1 below.

Table 1

Cronbach's Alpha Coefficients of PU and PEOU

Study	Technology	PU	PEOU
Davis (1989)	PROFS electronic mail; XEDIT file editor	.97	.91
Davis (1989)	Chart-Master; Pendraw	.98	.94
Adams et al. (1992)	Email	.94	.88
Adams et al. (1992)	Voice mail	.93	.81
Chau (1996)	Microsoft Word	-	.93
Chau (1996)	Microsoft Excel	-	.94
Masrom (2007)	e-Learning system	.89	.89
Šumak et al. (2011)	Moodle	.82	.90
Ameri Shahrabi et al. (2013)	-	.89	.87

Wong et al. (2013)	Computers	.87	.97
Tarhini et al. (2013)	Blackboard	.91	.90
Bere and Rambe (2016)[a]	WhatsApp	.86	.87
Almaiah and Alismaiel (2019)	m-Learning	.85	.86
Rafique et al. (2020)	Insignia ILS	.93	.97
Pamela and Rahman (2021)	m-Learning	.79	.80
Qashou (2021)	m-Learning	.81	.77
Zhou et al. (2022)	Online education platform	.92	.87
Humida et al. (2022)	e-Learning system	.88	.77
Şahin et al. (2022)[b]	e-Learning system	.94	.91
Kabir et al. (2023)[b]	Assistive mouse controller (AMC)	.72	.79
Şahin et al. (2023)	Assistive technologies (ATs)	.84	.77
Tawafak et al. (2023)	e-Learning system	.91	.93
Kampa (2023)	m-Learning	.97	.96
Şahin and Yıldız (2024)[b]	m-Learning	.96	.95

[a] South African study; [b] Sampled SwD / Special needs; - not reported.

Construct Validity

In the seminal validation of the TAM, Davis (1989) established support for the construct validity of the dimensions using a factor- and multi-trait-multi-method (MTMM) analysis. Using a sample of 112 users from a software development company, results revealed that the items loaded distinctly onto the two aforementioned factors, a finding corroborated in a follow-up study by Davis (1989) and another by Adams et al. (1992). It was not until a year later that confirmatory factor analyses (CFA) were used to explore the validity of the scales. Using Adams et al.'s (1992) data, Segars and Grover (1993) initially reported poor fit indices (cf. Hu & Bentler, 1999) but acceptable fit after respecifying PU into usefulness and effectiveness. A similar modified TAM was examined by Chau (1996), who reported satisfactory indices (χ^2/df = 1.44, GFI = 0.94, AGFI = 0.90, NFI = 0.96, NNFI = 0.98, CFI = 0.99) among a sample of 192 Microsoft Word users and 176 Microsoft Excel users.

Later studies examined the validity of the TAM in diverse educational technology contexts. Among these, Masrom (2007) found support for the original two-factor structure among 122 e-learners in Malaysia using exploratory factor analysis (EFA) with factor loadings (λ) ranging between .60 and .77, as did Šumak et al. (2011), who revealed strong factor loadings (λ = .72 – .90) and acceptable fit indices for PU and PEOU among 235 Moodle students in Slovenia. Consistent evidence of construct validity has also been reported in developing countries, including Iran, South Africa, Lebanon, and Malaysia (Ameri Shahrabi et al., 2013; Bere & Rambe, 2016; Tarhini et al., 2013; Wong et al., 2013), providing additional corroborative evidence on the validity across different cultures.

More recently, Rafique et al. (2020) confirmed the measurement model using data from 340 university students in Pakistan. Similar to the results noted above, the measurement model attested to the model's construct validity and proved fruitful in determining BI to use a mobile library application (i.e., Insignia ILS). Zhou et al.'s (2022) study also explained substantial

variance (68.6%) in 276 university students' BI to use an online learning platform in China (λ = .83 – .91), as did Şahin et al. (2023), who extended the TAM to assistive technologies (ATs) and found that PU and PEOU exhibited robust factor loadings (λ = .76 – .85). PU and PEOU along with others in the model (i.e., self-efficacy, facilitating conditions, compatibility, enjoyment, anxiety, social influence, and personal innovativeness) accounted for 57.9% of the variance in BI to adopt ATs.

Limited Psychometric Findings Among SwD using m-Learning

Notably absent from the discourse above is the validation of the TAM among SwD or individuals with special needs, as well as its applicability to m-learning, from both a construct and predictive perspective. Although Oladejo et al. (2018) explored m-learning among SwD and its acceptance thereof, the psychometric properties are confined to a reliability index of the instrument, with no mention of validity among the said sample. It was not until a couple of years later that scholars began exploring the psychometric properties of the TAM among SwD (or special needs). Around this time, Şahin et al. (2022) sampled 1,713 university students with special needs in Turkey. Their sample was asked to rate their perceptions of using an e-learning system at the institution. In addition to the core constructs in the TAM, the authors included self-efficacy, compatibility, social influence, facilitating conditions, perceived enjoyment, and anxiety in the model. Results corroborated previous findings in the field, attesting to the reliability and validity of the core constructs (λ = .84 – .93) and, in combination with the other constructs, explained 76.9% of the variance in BI to use the e-learning system. Most recently, Şahin and Yıldız (2024) sampled 1,298 university SwD enrolled in a distance education (DE) program and ascertained the reliability and validity of the core constructs as they relate to a student's BI to adopt m-learning. Using a CFA, the authors revealed that the two core constructs in the TAM exhibit strong validity among SwD pursuing their studies at a distance (λ = .89–.95). Overall, the model (with additional constructs) explained 76.5% of the variance in SwD's BI to adopt m-learning.

The (Over) Emphasis on Behavioural Intention

The literature which concerns itself with the TAM and IS usage relies heavily on BI as a mediator, despite context, sample, or IS. While undoubtedly as a consequence of *a priori* assumptions inherent in foundational theories of human behaviour (Bandura, 1971; Fishbein & Ajzen, 1975), the overemphasis on BI limits the theory's applicability to determining actual system use. As Conner and Norman (2022) rightly indicate, measures of BI (which commonly include both a valence and an extremity component) "rarely predict all or even the majority of the variance in behaviour" (p. 2).

In an attempt to narrow this gap, a handful of scholars have explored various antecedents with direct paths to actual m-learning usage (Almaiah & Alismaiel, 2019; Althunibat et al., 2021; Alyoussef, 2021; Drwish et al., 2023; Lutfi et al., 2022; Wu et al., 2025). In the earliest of these studies, Almaiah and Alismaiel (2019) and Althunibat et al. (2021) found that satisfaction was a significant predictor of m-learning usage among university students in Jordan (β = .610, p < .001; and β = .527, p < .001; respectively). Similar results were reported by Lutfi et al. (2022), who also revealed that satisfaction was a significant factor influencing m-learning usage among university students in Saudi Arabia (β = .569, p < .001). More recently, Drwish et al. (2023) suggested that system quality (β = .320, p < .001) and service quality (β = .164, p < .001) are

significant drivers of m-learning usage, along with satisfaction ($\beta = .683$, $p < .001$). In terms of the two core constructs of the TAM (PU and PEOU), only a couple of researchers have explored these direct paths to actual m-learning usage (Drwish et al., 2023; Wu et al., 2025), both of whom have reported significant betas among university students in Saudi Arabia and China, respectively. Lamentably, these findings remain confined to traditional university students abroad, precluding any generalisability to the South African DE context.

Aim and Objectives

Given the aforementioned, the core concepts inherent in the TAM, which reportedly influence m-learning usage (PU and PEOU), should be explored and validated among SwD in a DE setting in South Africa. In doing so, indices of reliability and (construct and predictive) validity can be established, inform future praxis among similar samples, and serve as a basis for comparing studies in other developing (and developed) countries. In line with the broad aim, the research objectives are as follows:

1. To determine the extent to which the core constructs of the TAM are reliable among SwD in relation to m-learning

2. To determine the extent to which the core constructs of the TAM are valid among SwD in relation to m-learning, and

3. To determine the extent to which the core constructs of the TAM predict m-learning usage among SwD.

Methods

Research concerning vulnerable populations such as SwD needs to adhere to ethical protocols with a strong emphasis on informed consent, autonomy, and the minimisation of harm (Brown, 2015; McDonald & Kidney, 2012). As such, the anonymity and accessibility of the online questionnaire decreased the possibility of coercion while increasing participant comfort, which is essential when engaging with marginalised groups (Young-Pelton & Dotson, 2017). In addition to adhering to these ethical principles, clearance for this study was obtained from the institution's Department of Psychology and the College of Human Sciences' Ethics Committee (Ref #: 2020-PsyREC-67141242). In addition, research permission to involve SwD was granted by the institution's Research Permission Sub-Committee (RPSC; ref #: 2020_RPSC_024).

Thereafter, using a cross-sectional design and a census sampling technique, a brief explanation of the study and an invitation to the online survey were distributed via institutional email to all SwD at a South African DE institution in the 2023 academic year (N = 2,808). This was achieved by enlisting the assistance of the ICT department at the respective institution. The survey was administered in English and included demographic items, the TAM's core constructs (i.e., PU and PEOU, see Appendix A) and an item on m-learning usage (i.e., "How often do you use m-learning for your studies?"). Inclusion criteria required participants to be registered SwD and 18 years or older; exclusion criteria comprised non-consent, age below 18, or incomplete responses. Of the 247 students who started the survey, 27 were excluded due to substantial missing data. The sample consisted of individuals who completed the online survey within the allotted time and met the criteria, comprising 220 participants (n = 220), resulting in an overall response rate of 7.8%.

Participants

Demographics

Of the 220 SwD who constituted the sample, most were female (n = 148; 67.3%), undergraduate students (n = 175; 79.5%), African (n = 130; 59.1%), and reported English as their home language (n = 50; 22.8%). These frequencies, along with other descriptive statistics, are presented in the table below.

Table 2

Demographic Characteristics of the Sample (n = 220)

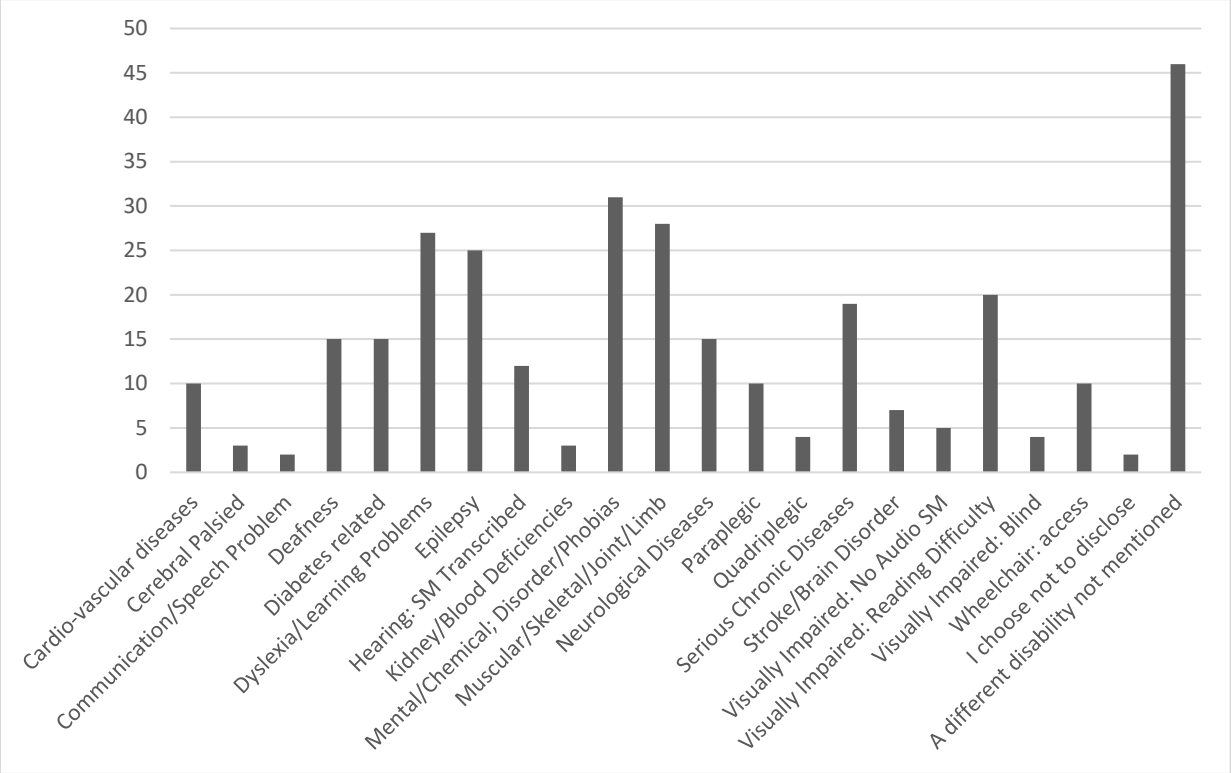
Variable	Category	*n*	%
Gender	Female	148	67.3
	Male	66	30.0
	Other / Not specified	6	2.7
Age	Range = 19-66 years ($\bar{x}$ = 33.7; SD = 10.6 years)	220	100.0
Level of study	Undergraduate	175	79.5
	Postgraduate	45	20.5

Variable	Category	*n*	%
Ethnicity	African	130	59.1
	White	63	28.6
	Mixed race	14	6.4
	Indian	11	5.0
	Other	2	0.9
Language	English	50	22.8
	isiZulu	38	17.4
	Afrikaans	37	16.9
	isiXhosa	17	7.8
	Other languages	78	35.1

Regarding the various disabilities, most of the sample indicated that their disability was not mentioned in the dropdown list contained in the online survey (20.9%; $n = 46$). Other participants noted mental or chemical disorders or phobias (14.1%; $n = 31$), followed by those who indicated a muscular/skeletal/joint/limb disability (12.7%; $n = 28$) and dyslexia or other learning problems (12.3%; $n = 27$). Less frequently reported among the sample were communication or speech problems (0.9%; $n = 2$), cerebral palsy (1.4%; $n = 3$), and/or blood/kidney deficiencies (1.4%; $n = 3$). These and other frequencies are graphically depicted below (see Figure 2).

Figure 2

Disabilities Reported Among the Sample (n = 220)



m-Learning Usage

Of the 220 SwD who comprised the sample, 147 students (66.8%) reported using m-learning daily, while 51 students (23.2%) indicated that they used it every few days. Cumulatively, eight students in the sample used mobile devices for learning once a month (1.4%; $n = 3$) or once every few months (2.3%; $n = 5$). These frequencies, along with others, are listed in Table 3 below.

Table 3

Frequency of m-Learning Usage Among the Sample

	n	**%**
Daily	147	66.8
Every few days	51	23.2
Once a week	10	4.5
Once every couple of weeks	4	1.8
Once a month	3	1.4
Once every few months	5	2.3
Total	**220**	**100.0**

Data Analysis

Following the analysis of demographic characteristics, reported disabilities, and m-learning usage, the reliability of the two constructs was tested using Cronbach's alpha and composite reliability coefficients. The measurement model of the original two-factor solution put forth by Davis (1985) was then computed and confirmed using a CFA, followed by a regression analysis, which sought to ascertain predictive validity. These analyses were performed in SPSS (version 28) and AMOS (version 29) and are presented below.

Reliability

The internal consistency of the PU and PEOU domains was assessed using Cronbach's alpha and composite reliability coefficients. Results revealed that both PU and PEOU were reliable among the sample of SwD (n = 220), yielding Cronbach's alphas (α) of .95 and .91, respectively. Further evidence of internal consistency was provided by calculating composite reliability coefficients, which were identical to the reported Cronbach's alphas and demonstrated acceptable levels of reliability (i.e.,> .70). These results are presented in Table 4.

Table 4

Reliability Coefficients of the Measurement Model

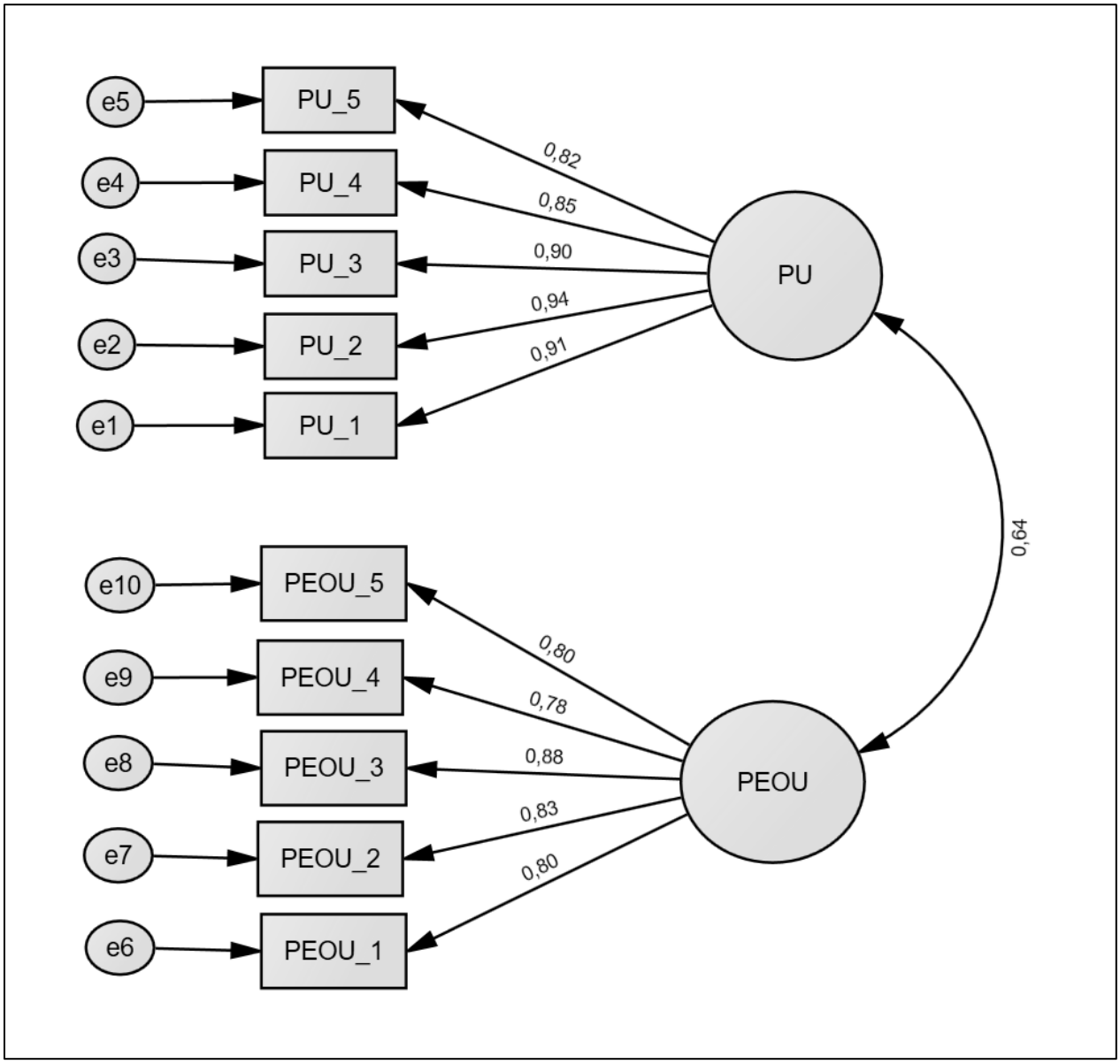
Construct	Number of items	Cronbach's alpha (α)	Composite reliability
PU	5	.95	.95
PEOU	5	.91	.91

Confirmatory Factor Analysis (CFA)

As mentioned, a CFA was performed using AMOS (version 29) to test the measurement model and assess the construct validity of the two constructs in the TAM. As part of the CFA, factor loadings (λ) were evaluated for each item, ranging from .78 ("It is easy to use m-learning to accomplish my study tasks") to .91 ("I believe that m-learning enhances my academic performance"). Moreover, the model-fit indices used to assess the model's overall goodness of fit (χ^2/df, CFI, NFI, IFI, TLI, SRMR) fell within acceptance levels (Hu & Bentler, 1999) and suggested that the two-factor solution (consisting of PU and PEOU) yielded a good fit to the data; χ^2/df = 4.17, CFI = .945, NFI = .929, IFI = .945; TLI = .927, SRMR = .051. This two-factor measurement model and the standardised estimates are depicted below.

Figure 3

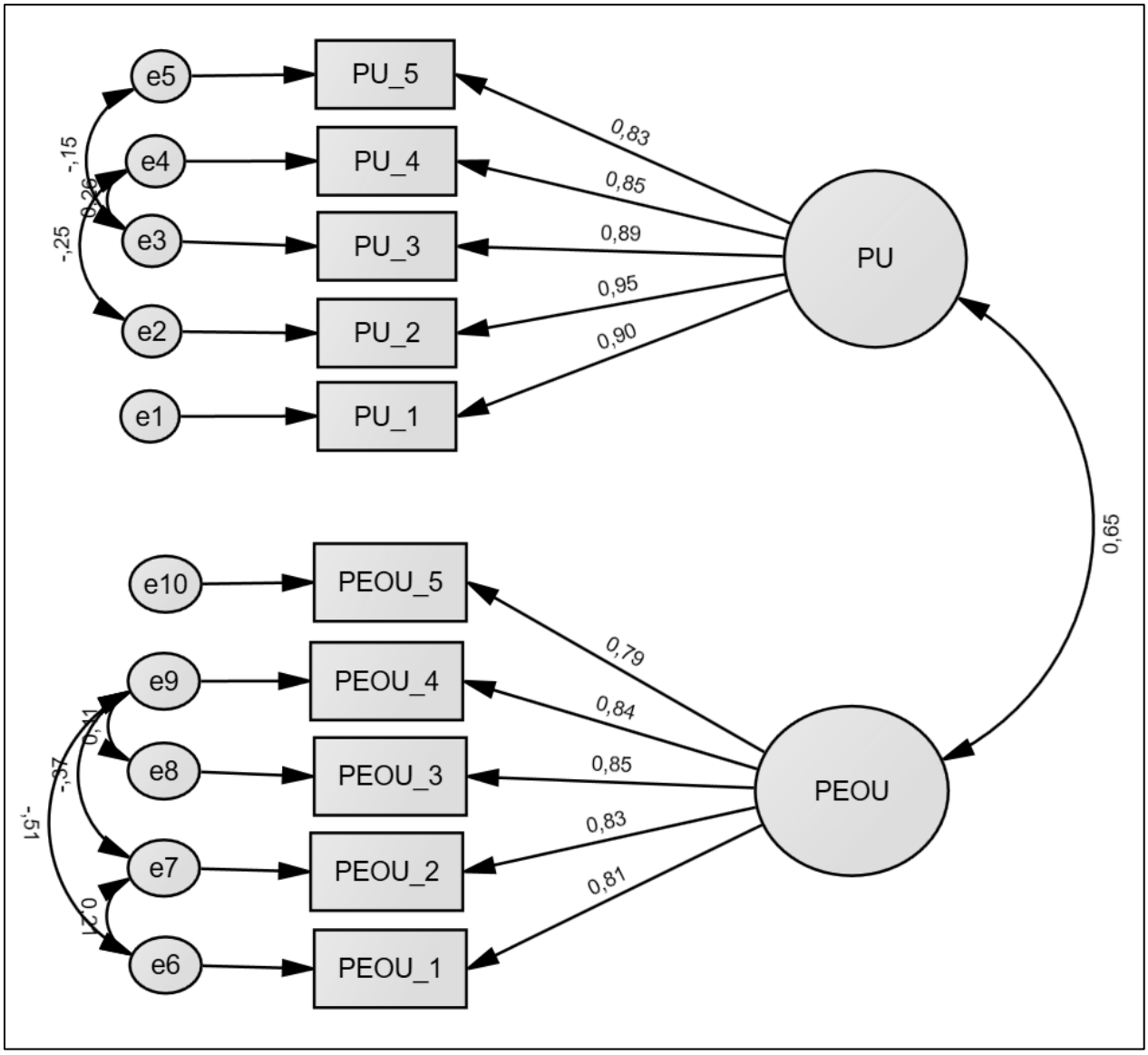
Two-Factor Measurement Model of the TAM



After considering the output from the first CFA, it was apparent that modifications to the measurement model would result in better fit. Resultantly, covariances were drawn between error terms 8 and 9, error terms 7 and 9, error terms 6 and 9, error terms 6 and 7, error terms 3 and 5, error terms 3 and 4, and error terms 2 and 3. These modifications yielded a better fit to the data than the initial model; χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039; and exhibited factor loadings ranging from λ = .79 ("My interaction with m-learning is clear and understandable") to λ = .95 ("I believe that m-learning increases my academic productivity"). The modified measurement model (along with the other λ) is depicted below.

Figure 4

Modified Two-Factor Measurement Model of the TAM



Predictive Validity

Having tested the psychometric properties of the TAM, its value in predicting m-learning usage among SwD was then explored. Using a multiple linear regression, a forced-entry method was performed where both PU and PEOU were simultaneously entered into the equation. Results from the ANOVA suggested that the model (with PU and PEOU) did not significantly predict m-learning usage among SwD (with an *F*-ratio of .049). This was corroborated by the coefficients table, which revealed non-significant betas (β) equal to .026 and -.010 (respectively), as shown below.

Table 5

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	*t*	*Sig.*	95% Confidence Interval for *B*	
		B	Std. Error	β			Lower Bound	Upper Bound
1	(Constant)	5.393	.325		16.616	<.001	4.754	6.033
	PU	.027	.091	.026	.300	.764	-.152	.207
	PEOU	-.011	.100	-.010	-.113	.910	-.209	.186

a. Dependent Variable: m-learning usage

Discussion

Establishing Reliability Among SwD

The core constructs of the TAM exhibited excellent reliability among the sample of SwD, producing Cronbach's alpha values (and identical composite reliability coefficients) of .95 for PU and .91 for PEOU. As seen in Table 1, these results are similar to many others in the field (Davis, 1989; Rafique et al., 2020; Şahin et al., 2022; Şahin & Yıldız, 2024; Tarhini et al., 2013; Tawafak et al., 2023) or higher (Bere & Rambe, 2016; Kabir et al., 2023; Şahin et al., 2023). However, most notable (and comparable) are the findings by Şahin et al. (2022) and Şahin and Yıldız (2024), which sampled SwD and explored the acceptance of e-learning and m-learning, respectively. These findings reported Cronbach's alphas ranging between .91 (PEOU; Şahin et al., 2022) and .96 (PU; Şahin & Yıldız, 2024). Collectively, these results, together with those reported in the current study, underscore the consistency of the items measuring the core constructs in the TAM among SwD in DE settings in developing countries, regardless of the manner in which the items are adapted to fit the research context, culture, language, or disability of the participants.

Establishing Construct Validity Among SwD

In addition to establishing reliability among the sample, results from the data analysis revealed strong evidence supporting the construct validity of the TAM constructs (PU and PEOU) when contextualised to m-learning among SwD in South Africa. First, the factor loadings (λ) showed a clear distinction between PU and PEOU, with loadings ranging from .79 to .95. These factors remained unchanged from the original structure (Davis, 1989) and exhibited

loadings which are comparable to numerous studies in the field (Adams et al., 1992; Bere & Rambe, 2016; Kabir et al., 2023; Rafique et al., 2020; Šumak et al., 2011; Tarhini et al., 2013; Wong et al., 2013).

Second, the initial CFA yielded a good-fitting model (CFI = .945, TLI = .927). Post-modification, model fit improved further (χ^2/df = 2.26, CFI = .982, NFI = .969, IFI = .983; TLI = .971, SRMR = .039), validating the two-factor structure of PU and PEOU. Similar indices of fit have been reported by Rafique et al. (2020), Tarhini et al. (2013), Wong et al. (2013), and Zhou et al. (2022), all of whom explored the validity of the TAM among university students in developing countries (see Table 5 below). However, it is worth noting that these studies included additional constructs in their measurement models (e.g., attitude towards the technology, social norms, quality of work life) and sampled students without disabilities, so direct comparisons should be made with caution.

Table 6

Indices of TAM Model Fit Among Students

Study	χ^2/df	GFI	AGFI	CFI	RMSEA	SRMR	NFI	TLI
Šumak et al. (2011)	1.337	.943	.915	.984	.038	-	.939	.979
Wong et al. (2013)	2.578	.944	-	.978	.072	-	-	.967
Tarhini et al. (2013)	2.697	.909	.885	.951	.055	-	.924	-
Rafique et al. (2020)	1.307	.950	.921	.992	.025	-	.948	-
Zhou et al. (2022)	-	-	-	-	-	.073	.812	-
Current	2.258	.948	.894	.982	.076	.039	.969	.971

Establishing Predictive Validity Among SwD

Results from the multiple regression analysis revealed that neither PU nor PEOU were significant predictors of m-learning usage among the current sample of SwD (β = .026, t = .300; p = .764; β = -.010, t = -.113, p = .910; respectively). These results are in stark opposition to recent findings in the field, which have suggested that the core components of the TAM have significant paths to actual m-learning usage among university students. In the first of these studies, Drwish et al. (2023) reported that PU had a significant positive impact on actual usage (β = .133, t = 2.314; p < .001) as did PEOU (β = .123, t = 1.231; p < .001). Cumulatively, the model (which included satisfaction, information quality, system quality, service quality, PU, and PEOU) was able to account for 70.0% of the variance in m-learning usage among undergraduate and postgraduate students in Saudi Arabia. Similar results have been reported by Wu et al. (2025), who suggested that PU has a significant influence on actual m-learning *usage* among university students in China (β = .591, t = 8.049; p < .001). Considering these differences, it is essential to note that both studies (i.e., Drwish et al., 2023; Wu et al., 2025) sampled students from traditional, face-to-face universities without disabilities—nuances that cannot be overlooked and require further exploration.

Limitations and Implications

This study, like all others, is subject to limitations. First, the current study sought only to determine the reliability of the core constructs in the TAM (PU and PEOU) along with the construct and predictive validity. Future research endeavours should explore the convergent and divergent/discriminant validity of these two domains among a sample of SwD in a DE institution in South Africa. Such insights would add to the limited psychometric evidence of the TAM in the country's DE sector. Second, the focus on PU and PEOU is a notable limitation. Future studies would benefit from the exploration of other facets reportedly known to influence m-learning usage (such as satisfaction and system- and service quality; Althunibat et al., 2021; Drwish et al., 2023; Lutfi et al., 2022) or other factors known to reduce the intention-behaviour gap (such as goal dimensions or basis of intention; Conner & Norman, 2022). Third, the focus on SwD precludes any generalisations to the general DE student population. As a result, future research endeavours could explore the value of PU and PEOU in determining m-learning usage among DE students without a disability.

Conclusion

Despite these limitations, this appears to be one of the first studies to establish the psychometric properties of the core components of the TAM (PU and PEOU) and explore their predictive validity in relation to m-learning usage among SwD in a DE institution in South Africa. Overall, the results revealed favourable psychometric properties that strengthen the cultural validity of the TAM and provide additional support for its robustness among SwD pursuing their studies at a DE institution. However, given the stark results revealed in the regression analysis, which suggested that the core components inherent in the TAM are not indicative of technology usage among SwD, DE practitioners involved in inclusive practices and curriculum design should exercise caution when implementing or adopting systems based solely on their PU and PEOU. Rather, attention should be paid to the structural and disability-specific barriers in South Africa, including device and data constraints, unstable internet- and power connectivity, and imperfect integration with ATs. In parallel, the continuous refinement of platforms should be informed and co-designed with students with diverse disability profiles, ensuring that inclusive practices are grounded in actual usage rather than assumed acceptance.

Declarations

Ethics Board Approval

Ethical clearance for this study was obtained from the institution's Department of Psychology at the College of Human Sciences' Ethics Committee (Ref #: 2020-PsyREC-67141242). In addition, research permission to involve SwD was granted by the institution's Research Permission Sub-Committee (RPSC; ref #: 2020_RPSC_024).

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AI Use Statement

Generative artificial intelligence (AI) was used in the preparation of this manuscript for grammar, style refinement, and brevity using ChatGPT, Version 5.1. The AI tool was not used to generate, analyse, or interpret research data, nor to create original scholarly content. All content was reviewed, verified, and approved by the authors, who take full responsibility for the accuracy and integrity of the work.

Conflicts of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

Abbreviation	Item
PU_1	I believe that m-learning enhances my academic performance.
PU_2	I believe that m-learning increases my academic productivity.
PU_3	I believe that m-learning enhances my learning effectiveness.
PU_4	I believe that m-learning enhances my learning efficacy.
PU_5	I believe that m-learning is useful for my studies.
PEOU_1	Learning to use m-learning is very simple.
PEOU_2	It's easy for me to become skilful at using m-learning.
PEOU_3	I think using m-learning is easy.
PEOU_4	It is easy to use m-learning to accomplish my study tasks.
PEOU_5	My interaction with m-learning is clear and understandable.