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Mobile learning acceptance among pre-service teachers in the Global South: a TPACK-based structural equation modelling approach

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ABSTRACT

Despite sustained efforts to integrate mobile learning into teacher education, technology acceptance models remain largely perception-driven rather than competence-based. This study challenges that paradigm by examining how pre-service teachers' Technological Pedagogical Content Knowledge (TPACK) shapes their acceptance of mobile learning. Guided by TPACK and the Technology Acceptance Model (TAM), data were collected via a 49-item electronic questionnaire administered to 292 S-year Bachelor of Education students. Partial least squares structural equation modelling revealed that pedagogical knowledge is the strongest predictor of TPACK. In contrast, pedagogical content knowledge was non-significant, highlighting that mobile learning competence is anchored in pedagogy rather than content expertise. The model explained 63.5% of the variance in TPACK, 22.8% in perceived ease of use (PEOU), 44.3% in perceived usefulness (PU), and 44.8% in behavioural intention (BI). TPACK significantly influenced PEOU and BI, indicating that pre-service teachers' pedagogical capability drives mobile learning acceptance more strongly than perceptions of utility or usability. Theoretically, the study reframes mobile learning adoption as epistemic rather than psychological, positioning pedagogical design, not perception, as the core of digital competence. In practice, the findings underscore the need for pedagogy-first training that equips pre-service teachers to teach with technology rather than merely fostering positive attitudes. In integrating TPACK and TAM, this research advances the understanding of competence-led mobile learning adoption.

1. Introduction

The global proliferation of mobile devices has transformed connectivity, with 95% of the population now living in areas with mobile-cellular network coverage [1,2] (International Telecommunication Union (ITU), 2025). Ownership has surged, with most adults possessing multiple devices [3]. As of 2025, approximately 4.88 billion people, equivalent to 78.42% of the global population, own smartphones, projected to reach 7.12 billion by the end of 2025 (ITU, 2025). Mobile device usage continues to expand, with 15 billion active devices recorded in 2021 and an expected increase to 18.22 billion by 2025. Given projections of a global population ranging from 8.1 billion in 2025 to 9.74 billion by 2050 [3,4], mobile device penetration is expected to deepen, creating a hyper-connected society in which individuals use mobile devices for everyday tasks, including education. By 2050, advances in artificial intelligence, augmented reality, and adaptive learning technologies will further personalise education, making mobile learning (m-learning) a central component of future pedagogies.

However, despite this global expansion, the integration of mobile technologies into higher education remains uneven, particularly in the Global South. Structural inequalities such as limited digital infrastructure, inconsistent connectivity, and disparities in digital competence constrain the effective pedagogical use of mobile devices [5,6]. In many developing regions, including sub-Saharan Africa, access to mobile devices does not necessarily translate into meaningful educational integration. This disconnect is especially critical in teacher education, where pre-service teachers should be equipped not only as users of technology but as future facilitators of digitally enriched learning environments. Recent studies, such as those by Tang et al [7] and Wijaya et al [8], highlight increasing engagement with emerging technologies among pre-service teachers, emphasising the importance of understanding factors that influence their adoption and effective use. Pre-service teachers, therefore, represent a pivotal group in this transition, as they simultaneously experience m-learning as students while being expected

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to integrate such technologies into their future teaching practices.

Although existing research highlights the potential of mobile devices to enhance access, interactivity, and learner engagement [9,10], much of this work remains descriptive and technologically deterministic, often overlooking the knowledge structures required for effective pedagogical integration. In particular, there is limited empirical understanding of how pre-service teachers in the Global South develop the integrated knowledge needed to incorporate mobile technologies into teaching and learning meaningfully. The Technological Pedagogical Content Knowledge (TPACK) framework [11] provides a robust theoretical lens for examining this integration, as it conceptualises the interplay between technological, pedagogical, and content knowledge domains. While TPACK has been widely applied in studies of technology integration, there remains a lack of model-driven, quantitative investigations of the structural relationships among its components in the context of m-learning in Global South teacher education settings. Furthermore, few studies have employed advanced analytical approaches, such as structural equation modelling, to validate these relationships and explain how different knowledge domains interact with affective factors to influence m-learning acceptance.

To address this gap, this study develops and tests a TPACK-based structural equation model to examine the relationships among pre-service teachers' TPACK and m-learning acceptance. The model further incorporates Technology Acceptance Model (TAM) factors, demonstrating how TPACK knowledge domains interact with perceived usefulness and perceived ease of use to influence pre-service teachers' acceptance of m-learning under conditions of constraint and opportunity. The findings contribute to theory by extending TPACK into the domain of m-learning and by offering a validated, integrative model that can inform future research.

2. Background

Defined as the use of mobile devices, such as smartphones and tablets, to support flexible, interactive, and personalised learning [12], m-learning is characterised by key attributes such as portability, contextual relevance, social interactivity, and personalisation [10,13]. These features enable continuous learning beyond the classroom, which El-Hussein & Cronje [14], p.13] term "breaking the classroom walls", fostering authentic learning experiences through real-world interactions. For example, mobile apps allow students to collect and analyse virtual experimental data in real-time [9,15], promote collaboration through digital platforms, and facilitate peer discussions, mentorship, and knowledge sharing [12]. Additionally, the availability of customisable apps further enhances individualisation [16], enabling students to tailor their learning experiences to their specific learning needs.

Despite these benefits, the pedagogical effectiveness of mobile devices hinges on teachers' acceptance and how well they are leveraged into teaching. As Mishra and Koehler [11] and Amjad et al [1] observed, increased technology accessibility in the classroom does not guarantee enhanced learning outcomes. Instead, teachers must possess the necessary knowledge to blend these technologies with pedagogy and subject content [11,17,18]. In teacher education, m-learning plays a crucial role in fostering this knowledge among pre-service teachers, preparing them to utilise mobile technologies as pedagogical instruments in their future classrooms. With this understanding, several studies have examined various aspects of m-learning, such as pre-service teachers' perceptions [12,19,20], their intentions [21–23] and its impact on students' academic performance [9,10,24]. However, empirical evidence on pre-service teachers' acceptance of and knowledge of using mobile devices as pedagogical resources remains scarce.

Although pre-service teachers may demonstrate basic digital competence, current research suggests that many lack the knowledge to effectively integrate mobile learning (m-learning) into their teaching and learning spaces [22]. For this purpose, the TPACK framework [11] provides a comprehensive model for understanding how teachers integrate technology into their teaching, emphasising the interplay between three core knowledge areas: technological knowledge (understanding and using mobile devices), pedagogical knowledge (applying effective mobile teaching strategies), and content knowledge (mastery of subject content). On the other hand, the TAM [25] offers insights into technology acceptance. This study, thus, explores the impact of TPACK on pre-service teachers' acceptance of m-learning. Grasping these factors could be a crucial step toward enhancing teacher preparation and supporting the meaningful and impactful use of mobile devices in the present and future classroom. After the introduction and background, the article presents the conceptual framework, develops the research model and hypotheses, outlines the methodology, reports the results and discusses their implications, and concludes with limitations and directions for future research.

3. Conceptual framework

3.1. Integrating TPACK and TAM for m-learning adoption

Understanding pre-service teachers' adoption of m-learning requires a framework that captures both their professional knowledge for technology integration and their acceptance of technology use. To achieve this, the present study integrates the TPACK framework with the TAM to provide a theoretically grounded explanation of how knowledge and perceptions jointly shape m-learning adoption. TPACK, rooted in Shulman's (1986) concept of Pedagogical Content Knowledge (PCK), conceptualises teachers' professional knowledge as the dynamic interaction of Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) [11] as shown in Fig. 1. These domains and their intersections (PCK, TCK, TPK, and TPACK) represent the knowledge required for effective technology integration in teaching. Widely adopted, TPACK provides a robust lens for analysing teachers' technology integration. In the context of m-learning, TPACK is particularly relevant as it captures pre-service teachers' ability to align mobile technologies with pedagogical strategies and subject content. This study adopts TPACK as a set of antecedent knowledge constructs, as it explains what teachers know about integrating technology into teaching practice. In pre-service teacher education, TPACK functions as both a diagnostic

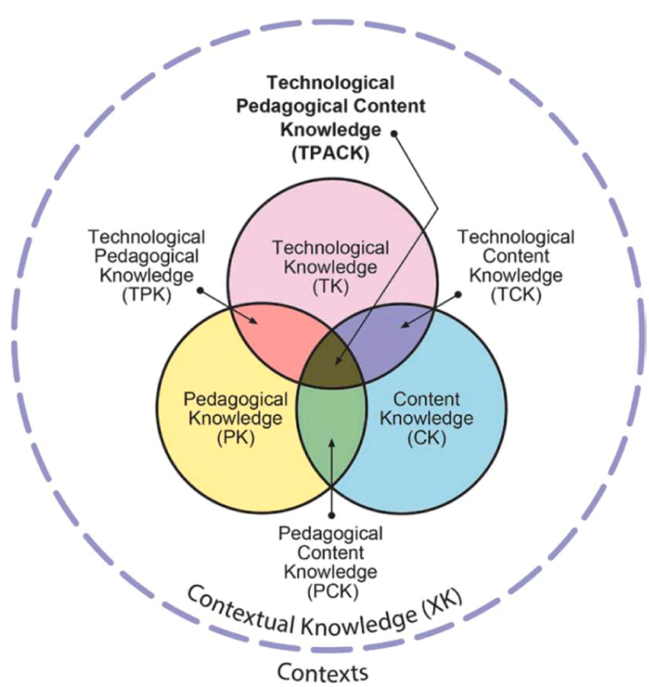

Fig. 1. Updated TPACK model. Adopted from Petko et al [[17], p.4].

and developmental tool. Although pre-service teachers are often digitally adept, they may lack effective pedagogical strategies for utilising technology meaningfully. Hence, teacher education must deliberately foster TPACK for mobile and technology-rich learning environments.

However, possessing knowledge alone does not guarantee technology adoption. The Technology Acceptance Model (TAM) complements TPACK by explaining why individuals choose to use technology. TAM posits that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are key determinants of Behavioural Intention (BI) to use a technology [25,26]. In m-learning contexts, PEOU reflects the extent to which pre-service teachers perceive mobile technologies as easy to use. In contrast, PU reflects the extent to which they believe these technologies enhance their learning and teaching performance.

3.2. Conceptual linkage between TPACK and TAM

This study conceptualises TPACK as a foundational determinant of TAM variables, thereby establishing a knowledge → perception → intention pathway. Specifically, the study hypothesises that pre-service teachers with stronger technological, pedagogical, and content knowledge are more likely to perceive m-learning technologies as both useful and easy to use. For instance, TK enhances familiarity with mobile tools, PK supports effective pedagogical use, and CK ensures alignment with subject matter. The integration of these domains (TPACK) therefore directly shapes perceptions of usability (PEOU) and utility (PU). Furthermore, consistent with TAM, PEOU is expected to positively influence PU, as technologies perceived as easier to use are more likely to be considered useful. Both PEOU and PU, in turn, influence BI's adoption of m-learning. Through this integration, TPACK extends TAM by embedding pedagogical and professional knowledge into the acceptance process. TAM's robustness has been confirmed across numerous m-learning studies [27–29], yet it has been criticised for its limited contextual sensitivity in educational settings [30,31]. Specifically, TAM does not fully account for the pedagogical, institutional, and sociocultural factors that shape teachers' technology use [26]. This limitation is particularly pronounced in teacher education, where mobile technologies are used not only as learning tools but also as resources requiring pedagogical alignment.

To address the limitations of TAM in teacher education, this study integrates TPACK as a theoretical antecedent to TAM constructs. Pre-service teachers' TPACK represents their professional capacity to design and implement m-learning. This professional knowledge is theorised to shape acceptance beliefs by influencing both Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Pre-service teachers with stronger TPACK are likely to find m-learning technologies easier to operate (higher PEOU) and more beneficial for their learning and teaching outcomes (higher PU). These perceptions, in turn, drive Behavioural Intention (BI) to adopt m-learning, consistent with TAM. Integrating TPACK and TAM thus establishes a 'knowledge → perception → intention' pathway, providing a theoretically grounded explanation for how professional knowledge translates into m-learning acceptance. This integration is reflected in the conceptual framework (Fig. 2) and the study's hypotheses, ensuring that the structural model captures both cognitive (TPACK) and attitudinal (TAM) determinants of m-learning adoption.

4. Model development and hypotheses

In this study, we integrated TPACK components as external antecedent variables in TAM to examine the extent to which pre-service teachers' TPACK influences their acceptance of m-learning. Based on this integrated framework, the study proposes a structural model in which TPACK domains (TK, PK, CK and/or composite TPACK) function as exogenous variables and TAM constructs (PEOU and PU) function as mediating variables while BI represents the outcome variable. This integrative TPACK-TAM approach is particularly relevant in Global South contexts, where disparities in digital competence, infrastructural constraints, and sociocultural factors amplify the need to consider both knowledge capacity and technology perceptions. Building on prior research that underscores the relevance of TPACK in shaping technology integration and acceptance [32–34], we proposed the research model illustrated in Fig. 2 below.

First, as noted by Joo et al [35] and Cheng et al [36], empirical investigations into the relationship between TPACK and the TAM remain limited. TPACK refers to the integrated knowledge required to teach effectively with technology [11]. For example, a pre-service teacher with strong TPACK might develop a mobile-supported science lesson using video analysis applications for field investigations grounded in inquiry-based learning principles and aligned with curriculum standards. Despite the growing importance of m-learning in teacher education, existing research has yet to examine how pre-service teachers' TPACK influences their acceptance and adoption of m-learning. To address this gap and extend the theoretical boundaries of TPACK and TAM, we incorporate TPACK components as external antecedents in the proposed model and formulate the following three core hypotheses.

H1. TPACK positively influences PEOU of m-learning.

H2. TPACK positively influences PU of m-learning.

H3. TPACK positively influences BI to use m-learning.

Second, the relationships among the individual knowledge domains, TK, PK, CK, and TPACK, have shown inconsistencies across existing studies. Some studies report strong, positive relationships, suggesting that well-developed TK, PK, and CK significantly enhance TPACK [37,38]. For instance, Koh et al [37] identified TK as the strongest predictor of TPACK among Singaporean pre-service teachers. Conversely, Chai et

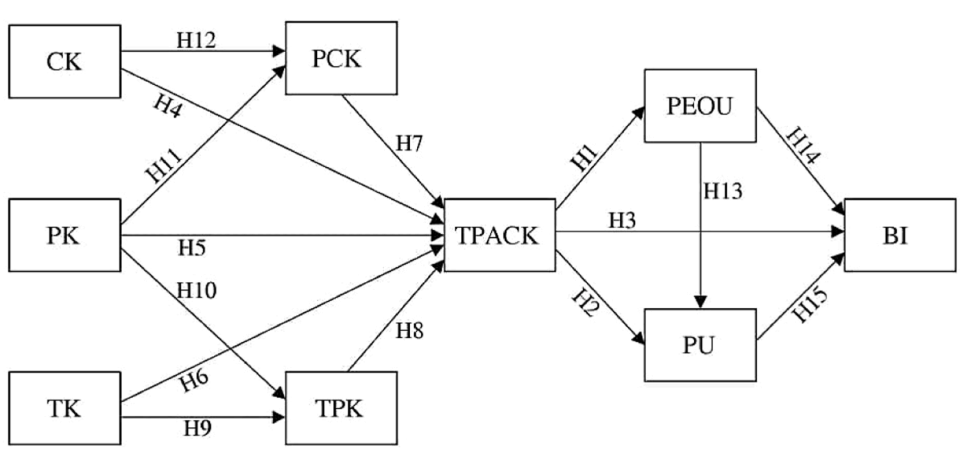

Fig. 2. Proposed baseline research model (Drawn by the authors).

al [39] found TK's direct effect on TPACK to be limited, emphasising the role of contextual integration and teaching design. In addition, Jang and Tsai [40] reported that CK and PK had a greater influence than TK in shaping science teachers' TPACK. Meta-analyses have attributed such inconsistencies to cultural, contextual, and methodological variations [41,42]. Recent studies continue to reflect these contradictions. For example, Shamim et al. [43] found that TK directly influenced TPACK, whereas CK's role was less prominent. In contrast, Huang et al [44] reported that CK is a strong predictor of TCK, which indirectly influences TPACK. These inconsistent findings suggest that TPACK is not purely additive but a dynamic, context-sensitive construct. Accordingly, we propose the following hypotheses:

H4. CK positively influences TPACK.

H5. PK positively influences TPACK.

H6. TK positively influences TPACK.

Third, the impact of intermediary knowledge domains, TPK, TCK, and PCK, on TPACK remains inconclusive. While some studies highlight their foundational role, others reveal context-dependent or inconsistent effects. Jang and Tsai [40] found PCK to be a stronger predictor of TPACK than TPK or TCK, indicating the centrality of pedagogical and content integration. In contrast, Koh et al [37] reported that TPK had the most substantial influence, especially among pre-service teachers, emphasising pedagogical strategies involving technology. Recent findings further complicate the picture: Shamim et al. [43] showed that TCK, influenced by CK, significantly contributes to TPACK. Additionally, Petko et al [17] proposed expanding the model to include Contextual Knowledge (XK), which interacts with intermediary domains to shape TPACK in practice. These findings suggest that the influence of TPK, TCK, and PCK varies across different educational settings, depending on the teacher's background, subject matter, and institutional factors. Consequently, we propose the following hypotheses:

H7. PCK positively influences TPACK.

H8. TPK positively influences TPACK.

Fourth, the relationships among TK, PK, CK, and the intermediary constructs TPK, TCK, and PCK remain inconsistent in the literature. Chai et al [39] found that TK and PK influenced TPK, while CK had no effect on TCK or PCK. Conversely, Koh et al [37] reported significant relationships among all components. More recent studies continue to reflect this lack of consensus. For example, Hsu and Chen (2022) observed strong pathways from TK and CK to their respective combinations (TPK and TCK) yet found weaker links from PK to PCK. Similarly, Lin et al. (2023) highlighted variations in these relationships depending on contextual factors such as teaching experience and subject domain. Accordingly, we propose the following hypotheses to examine the structural relationships in the TPACK framework.

H9. TK positively influences TPK.

H10. PK positively influences TPK.

H11. PK positively influences PCK.

H12. CK positively influences PCK.

Since pre-service teachers often have general experience with mobile devices but limited exposure to m-learning tools for pedagogical purposes, their PEOU may shape their beliefs about the PU, ultimately influencing their willingness to adopt them [45,46]. As such, examining the relationship between PU, PEOU, and BI is essential for understanding the factors that drive m-learning adoption among pre-service teachers. As such, we propose the following hypothesis:

H13. PEOU positively influences PU of m-learning.

H14. PEOU positively influences BI of m-learning.

H15. PU positively influences BI to use m-learning.

To recap, we summarised the study's hypotheses in Table 1 to enhance clarity for the reader.

Table 1
Hypotheses summary.

Hypothesis	Path	Hypothesis	Path
H1	TPACK PEOU	H9	TK TPK
H2	TPACK PU	H10	PK TPK
H3	TPACK BI	H11	PK PCK
H4	CK TPACK	H12	CK PCK
H5	PK TPACK	H13	PEOU PU
H6	TK TPACK	H14	PEOU BI
H7	PCK TPACK	H15	PU BI
H8	TPK TPACK		

5. Methodology

5.1. Research design

This study employed a quantitative, non-experimental, cross-sectional survey design, with data analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. The choice of PLS-SEM in this study was deliberate and aligned with both the nature of our research and the characteristics of our dataset. While covariance-based SEM (CB-SEM, such as the Analysis of Moment Structures - AMOS) emphasises model fit and theory confirmation, PLS-SEM is a variance-based, prediction-oriented approach that is particularly suited to exploratory research aimed at uncovering complex relationships and mediating mechanisms (Hair et al., 2022). This orientation aligns with recent empirical work in educational technology acceptance. For example, SEM has been applied to examine how behavioural predictors influence pre-service teachers' adoption of AI chatbots, thereby illustrating its value for modelling complex technology-acceptance relationships [8]. Our investigation centres on how pre-service teachers' TPACK competencies relate to their perceptions and intentions to adopt m-learning. Survey data in such technology research often show non-normality and heterogeneity, making PLS-SEM appropriate as it does not require multivariate normality [47–49]. Moreover, PLS-SEM also accommodates small to moderate sample sizes, as in our study, and enables the simultaneous assessment of the measurement and structural models [50]. Importantly, PLS-SEM enabled us to rigorously evaluate the proposed pathways by assessing both the quality of our constructs and the strength and significance of the hypothesised paths within a single integrated framework.

5.2. Participants and data collection

Data were collected from 328 s-year Bachelor of Education pre-service teachers through a voluntary online questionnaire at a university in South Africa. After data screening, 292 usable cases were retained, exceeding minimum sample size recommendations based on the *10-times rule* and *a priori* power analysis [48]. The sample included 179 female participants (63.1%) and 113 male participants (38.7%), with a mean age of 21.6 years.

5.3. Instrumentation

A structured questionnaire was adapted from validated measurement scales in prior studies. TAM-related constructs (PU, PEOU, BI) were drawn from Davis [45] and Venkatesh and Davis [51], while TPACK constructs (TPACK, TPK, PCK, CK, PK, TK) were adapted from Schmidt et al [38]. All 49 Likert-scale items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), as recommended by Revilla et al [52], who caution against fewer than five or more than seven points. A neutral option was included to reduce response bias, in line with the guidance of Kankaraš and Capecchi [53]. To ensure clarity, questions were specific and avoided abstract or unfamiliar terminology. Additionally, no research hypotheses or intentions were disclosed in the questionnaire to prevent bias. The instrument underwent expert review to assess content relevance, clarity, and appropriateness. Minor revisions were made based on the experts' feedback to enhance the precision and comprehensibility of the items.

5.4. Ethical considerations

The University of the Free State Research Ethics Committee granted ethical clearance. Participation was voluntary, and informed consent was obtained prior to data collection. Respondents were assured of anonymity and confidentiality, and the data were managed in accordance with institutional and national ethical guidelines for research.

6. Data analysis

The analysis followed a two-stage procedure suggested by Hair et al [48]. First, the measurement (outer) model was evaluated to ensure construct quality. This included assessing indicator reliability, internal consistency, convergent validity, and discriminant validity [48]. Second, the structural (inner) model was assessed by estimating path coefficients and testing their significance through bootstrapping procedures. The model's explanatory power was evaluated using coefficients of determination, while effect sizes were examined to determine the relative contribution of exogenous constructs, and predictive relevance was assessed to evaluate out-of-sample predictive capability (Hair et al., 2022; [54]).

6.1. Measurement model evaluation

6.1.1. Descriptive statistics

Descriptive statistics indicated that skewness values ranged from −0.82 to 0.94, and kurtosis values ranged from −0.97 to 0.88, all within the acceptable ±1 threshold [47,55]. Given that in PLS-SEM, assessment of multivariate normality is not a prerequisite for model estimation [47], skewness and kurtosis of the indicators were examined for descriptive purposes. The evaluation focused instead on indicator reliability, construct reliability and validity. Outer loadings, Cronbach's alpha, composite reliability, AVE, Fornell-Larcker criterion, and HTMT ratios were used to confirm measurement model adequacy before testing structural relationships.

6.1.2. Reliability and convergent validity

Indicator reliability was examined using standardised factor loadings; values of 0.70 or higher indicated acceptable reliability [50]. All indicators, except one (PEOU3, 0.679), exceeded the recommended 0.70 threshold (Fig. 3, Table 2), confirming satisfactory item reliability [49, 56]. The PEOU_3 item, with a loading of 0.679, below 0.70 but above 0.40, was retained because removing it would have reduced content coverage of the PEOU construct, and the construct's overall reliability and convergent validity remained adequate (CR = 0.807; AVE = 0.619). Following Hair et al. (2022), items with loadings between 0.40 and 0.70 may be retained if their removal negatively affects content validity and the construct meets reliability and validity criteria. Internal consistency reliability was further supported as both Cronbach's alpha and composite reliability (CR) values were above 0.70 [57], as shown in Table 3. Among the constructs, PU and TK had the highest reliability coefficients, suggesting strong internal consistency, while PCK exhibited the lowest, though still acceptable, reliability coefficient. Convergent validity was also achieved, with all average variance extracted (AVE) values exceeding 0.50 [58]. This confirms that each construct explained more than half of the variance in its respective indicators.

6.1.3. Discriminant validity

Discriminant validity was assessed using the Fornell-Larcker criterion [58]. According to this criterion, the square root of the AVE for each latent construct should exceed its correlations with other constructs, thereby confirming discriminant validity. As shown in Table 4, the square roots of the AVE values (displayed on the diagonal) were consistently higher than the corresponding inter-construct correlations. This result indicates that each construct accounted for more variance among its indicators than among those of other constructs. Therefore,

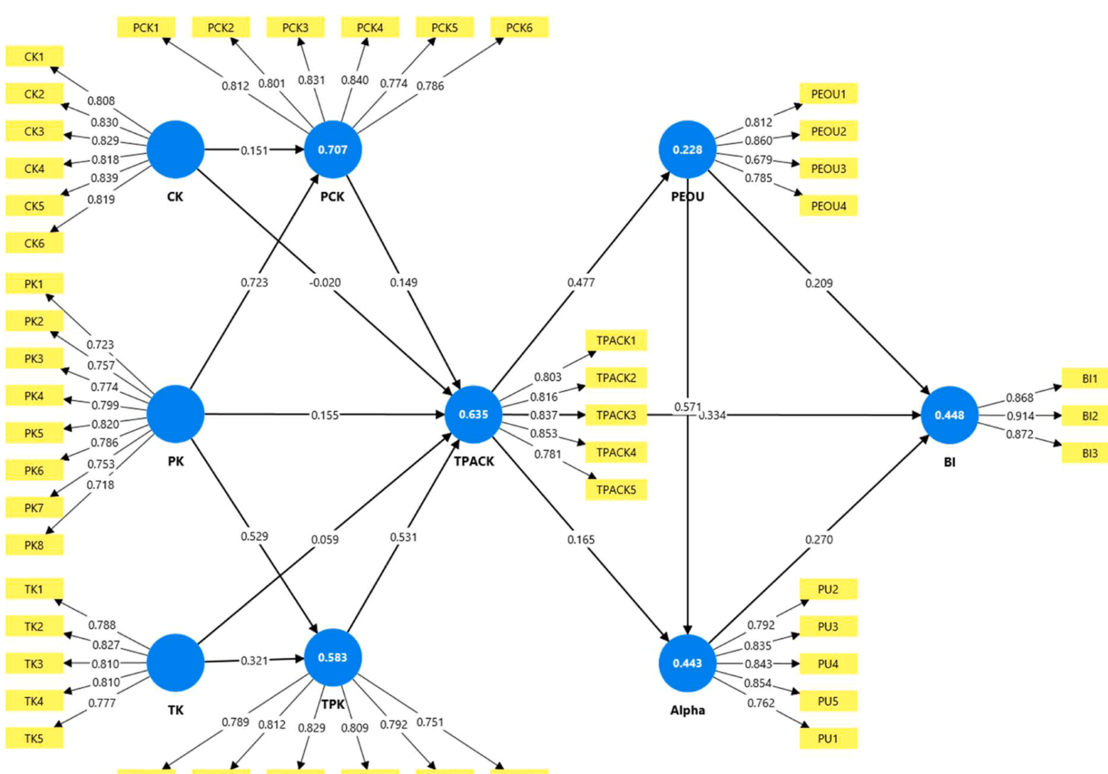

Fig. 3. Measurement model.

Table 2
Outer loadings.

	PU	BI	CK	PCK	PEOU	PK	TK	TPACK	TPK
PU1	0.762								
PU2	0.792								
PU3	0.835								
PU4	0.843								
PU5	0.854								
BI1		0.868							
BI2		0.914							
BI3		0.872							
CK1			0.808						
CK2			0.830						
CK3			0.829						
CK4			0.818						
CK5			0.839						
CK6			0.819						
PCK1				0.812					
PCK2				0.801					
PCK3				0.831					
PCK4				0.840					
PCK5				0.774					
PCK6				0.786					
PEOU1					0.812				
PEOU2					0.860				
PEOU3					0.679				
PEOU4					0.785				
PK1						0.723			
PK2						0.757			
PK3						0.774			
PK4						0.799			
PK5						0.820			
PK6						0.786			
PK7						0.753			
PK8						0.718			
TK1							0.788		
TK2							0.827		
TK3							0.810		
TK4							0.810		
TK5							0.777		
TPACK1								0.803	
TPACK2								0.816	
TPACK3								0.837	
TPACK4								0.853	
TPACK5								0.781	
TPK1									0.789
TPK2									0.812
TPK3									0.829
TPK4									0.809
TPK5									0.792
TPK6									0.751

Table 3
Cronbach's alpha coefficients, Rho_A, Rho_C, and Average Variance Extracted.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
PU	0.876	0.880	0.910	0.669
BI	0.861	0.864	0.915	0.782
CK	0.905	0.907	0.927	0.679
PCK	0.893	0.895	0.918	0.653
PEOU	0.793	0.807	0.866	0.619
PK	0.900	0.901	0.919	0.588
TK	0.861	0.862	0.900	0.644
TPK	0.885	0.885	0.913	0.636
TPACK	0.877	0.879	0.910	0.670

the measurement model demonstrated acceptable discriminant validity, confirming that the latent variables were empirically distinct and measured unique aspects of the underlying theoretical framework.

Consistent with Hair et al [48], who highlight the Heterotrait-Monotrait ratio of correlations (HTMT) as a more reliable approach to assessing discriminant validity than traditional methods, such as cross-loadings or the Fornell-Larcker criterion, we also applied HTMT to examine construct distinctiveness. As presented in Table 5, all HTMT values were below the 0.85 threshold [48] and well under the 0.95 cut-off for conceptually similar constructs [59]. These findings indicate that each latent variable captured unique aspects of its underlying construct, further confirming discriminant validity.

6.2. Structural model evaluation

The structural model was assessed using bootstrapping (5000 resamples) applied to estimate standard errors and generate t-statistics for significance testing [54]. The R^2 values, representing the proportion of variance explained in the endogenous constructs, ranged from 0.228 (PEOU) to 0.707 (PCK) (Table 6). This demonstrates acceptable explanatory power according to Falk and Miller's (1992) criterion of $R^2 > 0.10$. The significance of the hypothesised relationships was confirmed when all standardised path coefficients were positive, and their t-statistics exceeded the 1.64 threshold for one-tailed tests [60]. The blindfolding procedure revealed $Q^2 > 0$ [48] for all endogenous constructs, demonstrating the TPACK-TAM model's strong predictive relevance.

Table 4
Discriminant validity matrix (Fornell-Larcker criterion).

	PU	BI	CK	PCK	PEOU	PK	TK	TPACK	TPK
PU	0.818								
BI	0.553	0.885							
CK	0.378	0.431	0.824						
PCK	0.403	0.455	0.686	0.808					
PEOU	0.650	0.545	0.412	0.468	0.787				
PK	0.457	0.463	0.741	0.834	0.515	0.767			
TK	0.392	0.477	0.564	0.539	0.460	0.589	0.802		
TPACK	0.438	0.553	0.549	0.662	0.477	0.681	0.555	0.818	
TPK	0.523	0.593	0.600	0.688	0.540	0.718	0.632	0.770	0.797

Table 5
Discriminant validity matrix (Heterotrait-monotrait ratio [HTMT]).

	PU	BI	CK	PCK	PEOU	PK	TK	TPACK	TPK
PU									
BI	0.632								
CK	0.426	0.488							
PCK	0.455	0.518	0.758						
PEOU	0.772	0.655	0.486	0.554					
PK	0.512	0.526	0.820	0.926	0.607				
TK	0.450	0.554	0.636	0.614	0.561	0.668			
TPACK	0.496	0.635	0.611	0.747	0.570	0.762	0.637		
TPK	0.593	0.679	0.668	0.774	0.644	0.801	0.723	0.874	

Table 6
Structural model results.

	R^2	Sample mean (M)	Std. Dev. (STDEV)	T statistics (|O/STDEV|)	P values	Q^2
PU	0.443	0.448	0.051	8.678	0.000	0.194
BI	0.448	0.457	0.049	9.233	0.000	0.238
PCK	0.706	0.709	0.038	18.479	0.000	0.701
PEOU	0.228	0.234	0.049	4.689	0.000	0.249
TPACK	0.635	0.646	0.047	13.427	0.000	0.477
TPK	0.583	0.588	0.047	12.287	0.000	0.566

7. Results and discussion

Structural equation modelling (SEM) was employed to examine how pre-service teachers' technological pedagogical content knowledge (TPACK) shapes their acceptance of m-learning in teacher education. The proposed structural model integrates core constructs from the TPACK and Technology Acceptance Model (TAM) frameworks to capture both teacher knowledge and mobile adoption belief dimensions specific to m-learning use. Rather than addressing digital technologies in general, the model explicitly focuses on how teachers' knowledge structures support the pedagogical integration of mobile devices for teaching and learning. The results indicate that the model demonstrated strong explanatory power for TPACK, accounting for 63.5% of its variance ($R^2 = 0.635$). This level of explained variance exceeds that commonly reported in prior TPACK studies, suggesting that the model captures key determinants of pre-service teachers' capacity to integrate mobile technologies pedagogically with minimal unexplained variance. Of the 15 hypothesised relationships, 12 were statistically supported, with most paths exhibiting positive, significant effects (Fig. 4, Table 7).

7.1. Predictors of TPACK

The structural results indicate that PK was the strongest predictor of TPACK for m-learning adoption ($\beta = 0.724$, $p < 0.001$). Empirically, this finding underscores that pre-service teachers' ability to plan, manage, and evaluate m-learning is the primary foundation for integrating mobile devices into teaching. In m-learning contexts, where teaching and learning are characterised by mobility, device heterogeneity, and spontaneous learning interactions [12,14], pedagogical decision-making becomes especially critical. The dominance of PK in predicting m-learning adoption represents a significant contribution to scholarship on teacher technology acceptance. While prior studies (e.g., Hsu & Chen, 2022; Shamim et al., [43]) identified CK as the primary driver of TPACK or technology adoption, our findings demonstrate that pedagogical intent, rather than content mastery, is the decisive factor in pre-service teachers' m-learning acceptance. This shifts the theoretical emphasis in TPACK research toward understanding how pedagogical decision-making shapes technology integration.

Notably, both TPK ($\beta = 0.530$, $p < 0.001$) and TK ($\beta = 0.529$, $p < 0.001$) also significantly predicted TPACK. Empirically, this confirms that pre-service teachers must understand both how mobile technologies function and how they can be pedagogically orchestrated to support learning. Theoretically, the near-equivalent strength of these paths as shown in Table 7 suggests that while mobile device familiarity (e.g., operating apps, managing connectivity) is necessary, its pedagogical value emerges only when teachers can align mobile affordances, such as portability, immediacy, and personalisation, with pedagogical goals. This observation challenges Chai et al [39] and Cheng et al [36], who founthat TK's direct effect on TPACK was limited. Thus, our finding suggests that mobile TPACK development appears to be design-oriented rather than tool-oriented.

Contrary to our expectations, results in Table 7 show that PCK did not significantly predict TPACK ($\beta = 0.151$, $p = 0.065$). Empirically, this non-significant relationship diverges from traditional TPACK assumptions that discipline-specific pedagogy naturally extends into digital integration and m-learning [11,33,43]. Theoretically, this finding challenges linear knowledge-transfer models and suggests a more modular pathway for teacher knowledge development. In m-learning contexts, which often rely on generic platforms (e.g., messaging apps, learning management systems, multimedia tools) rather than subject-specialised mobile applications, content-bound pedagogical routines may have limited transferability. This finding is important as it suggests that m-learning competence may develop independently of disciplinary teaching traditions.

At the same time, CK significantly predicted PCK ($\beta = 0.149$, $p = 0.004$), confirming the expected hierarchical knowledge structure among pre-service teachers [44]. This finding contrasts with that of Shamim et al. [43], who found that TK exerts a stronger direct influence

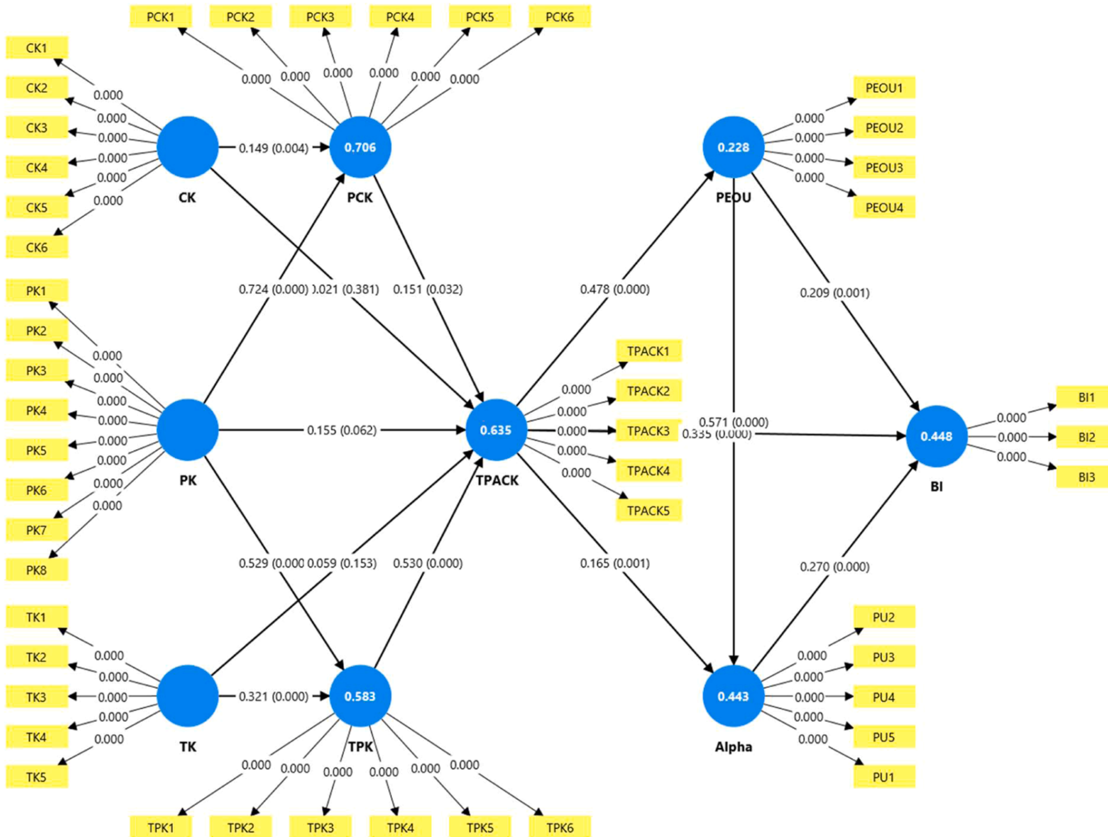

Fig. 4. Structural model.

Table 7
Structural model results. Path significance using percentile bootstrap 95% confidence interval ($n = 5000$ subsamples).

Hyp	Decision	Influence	Sample mean (M)	Std. Dev. (STDEV)	T statistics (|O/ STDEV|)	P values
H1	Supported	TPACK -> BI	0.336	0.065	5.127	0.000
H2	Supported	TPACK -> PEOU	0.482	0.051	9.405	0.000
H3	Supported	TPACK -> PU	0.165	0.054	3.035	0.001
H4	Supported	PEOU -> PU	0.571	0.054	10.659	0.000
H5	Supported	PEOU -> BI	0.211	0.069	3.052	0.001
H6	Supported	PU -> BI	0.267	0.067	4.013	0.000
H7	Supported	PCK -> TPACK	0.150	0.082	1.847	0.032
H8	Supported	CK -> PCK	0.149	0.057	2.636	0.004
H9	Not Supported	CK -> TPACK	−0.020	0.070	0.304	0.384
H10	Supported	PK -> PCK	0.725	0.049	14.676	0.000
H11	Supported	PK -> TPK	0.527	0.064	8.311	0.000
H12	Not Supported	PK -> TPACK	0.154	0.100	1.539	0.062
H13	Not Supported	TK -> TPACK	0.060	0.058	1.023	0.153
H14	Supported	TK -> TPK	0.324	0.064	4.985	0.000
H15	Supported	TPK -> TPACK	0.532	0.062	8.504	0.000

on TPACK, with CK playing a lesser role. The difference likely reflects contextual emphasis. In our study, subject mastery and its pedagogical translation underpin effective m-learning acceptance, making CK a critical precursor to PCK. These findings indicate that the impact of TPACK domains on m-learning adoption is context-dependent, highlighting the central role of pedagogically informed content knowledge. However, the absence of a PCK → TPACK effect indicates that mastery of subject-specific pedagogy does not automatically translate into competence for m-learning adoption. Instead, pre-service teachers may acquire m-learning competence through exposure to cross-disciplinary mobile practices that prioritise flexibility, communication, and learner engagement over content-specific pedagogical strategies.

7.2. TPACK and m-learning acceptance

To examine how teacher knowledge shapes m-learning acceptance, TPACK was integrated with TAM to assess its influence on pre-service teachers' beliefs and behavioural intentions regarding m-learning use. The finding that TPACK significantly predicts both PEOU ($\beta = 0.482, p < 0.001$) and PU ($\beta = 0.165, p = 0.001$) is significant because it empirically links pre-service teachers' integrated knowledge of technology, pedagogy, and content to core determinants of m-learning acceptance. This result demonstrates that TPACK does not merely represent an abstract construct but has tangible implications for how pre-service teachers evaluate and adopt m-learning [1]. The finding that higher TPACK translates into stronger perceptions of usability and value advances scholarship by positioning TPACK as a critical cognitive antecedent in technology acceptance models.

Empirically, the stronger effect on PEOU indicates that pedagogical-technological competence reduces the cognitive, logistical, and teaching effort associated with using mobile devices for teaching. Given that m-learning, with its recurrent concerns about device management, connectivity, and classroom control, particularly in sub-Saharan Africa, our findings suggest that competence is a primary source of perceived ease. From a theoretical perspective, this finding reframes PEOU in m-learning as a competence-mediated belief, implying that pre-service teachers experience mobile technologies as easier to use when they possess the pedagogical strategies to manage mobility, distraction, and learner autonomy. PU, while still significant, appears to be shaped secondarily, once ease-related barriers have been addressed. Consistent with prior TAM studies [30,61–63], both PU ($\beta = 0.267$, $p < 0.001$) and PEOU ($\beta = 0.211$, $p = 0.001$) significantly predicted BI to use m-learning, with PU exerting the more potent effect. This suggests that pre-service teachers are more inclined to adopt m-learning when it demonstrably enhances pedagogical effectiveness, such as supporting engagement, flexibility, and timely feedback, rather than merely simplifying teaching tasks.

Crucially, TPACK exerted a strong direct effect on BI ($\beta = 0.336$, $p < 0.001$), exceeding the effects of both PU and PEOU. Empirically, this indicates that m-learning adoption among pre-service teachers is driven less by favourable perceptions and more by their competence in implementing m-learning pedagogically. This finding advances a crucial theoretical contribution which supports a competence-dominant model of m-learning adoption, in which BI emerges from pre-service teachers' proficiency and readiness to leverage m-learning activities meaningfully in teaching contexts. This pathway underscores the critical role of teacher readiness and competence in translating technology into meaningful learning experiences. For instance, Tang et al [7] showed that micro-lectures significantly enhanced junior high students' mathematics achievement and learning satisfaction, highlighting the potential of pedagogically-informed technology to improve student outcomes. While their study focuses on student performance, our research examines the antecedent mechanisms among pre-service teachers that enable such effective technology integration. These studies illustrate a complementary relationship: teachers' professional knowledge and acceptance of technology form the foundation for learning interventions that positively impact student outcomes. Recent evidence further supports these findings. Systematic reviews indicate that mobile m-learning tools improve student engagement, flexibility, and critical thinking when teachers are equipped to integrate them effectively [64]. This body of research aligns with our TPACK-TAM model: strengthening pre-service teachers' integrated knowledge not only promotes their adoption of m-learning (via PU, PEOU, and BI) but also lays the groundwork for improved educational outcomes in the classroom.

8. Conclusions

This study advances three key theoretical contributions. First, TPACK development is pedagogically anchored rather than content-derived. This challenges linear progression models and establishes pedagogy, rather than content expertise, as the central framework for TPACK. Second, m-learning acceptance is competence-led rather than perception-led, indicating that perceptions of ease and usefulness are shaped by teachers' pedagogical capability with technology. Third, technology adoption is epistemic rather than purely psychological, meaning teachers adopt tools when they possess design-ready pedagogical strategies, not simply when tools appear convenient or beneficial. Practically, these insights have implications for teacher professional development. Training models that prioritise tools or subject-specific digital applications risk misalignment with how digital teaching competence develops. Instead, professional learning should foreground pedagogical design for technology integration, positioning digital tools as instructional methods rather than technical add-ons. Additionally, the non-significant PCK → TPACK path suggests that technology training should begin with general pedagogical integration principles before discipline-specific applications. Sustainable technology adoption, therefore, is best achieved not by improving teachers' perceptions of tools, but by strengthening their capacity to teach with them.

9. Implications

9.1. Theoretical contributions

This study contributes to the literature by integrating TPACK and TAM frameworks to explain pre-service teachers' adoption of m-learning, offering a nuanced understanding of how professional knowledge shapes technology acceptance. The findings extend existing models of teacher technology integration and provide evidence for mediating mechanisms between TPACK competencies and adoption intentions through the empirical testing of the 'knowledge → perception → intention' pathways. This contributes to theory development in educational technology adoption, particularly in higher education and Global South contexts, where evidence on the interplay between teacher knowledge and technology acceptance remains limited.

9.2. Practical implications

The findings have practical relevance for multiple stakeholders:

- Teachers and Pre-service Educators: The study highlights which aspects of professional knowledge most strongly influence perceptions and intentions to adopt m-learning, helping educators focus on specific competencies during professional development.
- Teacher Education Programs and Schools: Insights from this study can inform curriculum design, emphasising TPACK-based interventions that enhance technology integration skills and promote positive attitudes toward m-learning.
- Researchers: The integrated TPACK–TAM model validated in this study provides a framework for future research examining technology adoption among educators in diverse contexts, including AI-mediated and mobile learning environments.

Thus, the study bridges theory and practice by demonstrating how teacher knowledge translates into technology acceptance, offering actionable insights for designing interventions, shaping policy, and guiding future research in educational technology.

10. Limitations and future work

This study has certain limitations. First, the use of self-reported data may have introduced common method bias, although this is common in TPACK-TAM research. The application of PLS-SEM helped mitigate this concern by identifying weak indicators and reducing measurement error. Second, the model explained 22.8% of the variance in PEOU, suggesting that additional predictors, such as technological anxiety or institutional support, may further account for teachers' perceptions of ease of use. Third, individual difference factors (e.g., gender, prior m-learning experience) were excluded to avoid participant fatigue, potentially limiting insight into personal influences on m-learning acceptance. Future research should adopt longitudinal or mixed-method designs to capture how TPACK develops over time and how changes in technological-pedagogical competence shape evolving beliefs about mobile learning. Comparative studies across contexts could also clarify whether the competence-driven adoption pathway identified here generalises beyond this sample.

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Data availability statement

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CRediT authorship contribution statement

Brian Shambare: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thuthukile Jita:** Conceptualization, Investigation, Project administration, Resources, Software, Supervision, Writing – review & editing, Methodology, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100373.

Appendix 1. Descriptive data of the constructs

	Mean	Minimum	Maximum	Std. deviation	Kurtosis	Skewness	N
BI1	3.95	1	5	0.92	−0.49	−0.51	292
BI2	4.01	1	5	0.91	0.02	−0.71	292
BI3	4.11	2	5	0.87	−0.49	−0.62	292
CK1	4.07	1	5	0.87	0.00	−0.66	292
CK2	4.14	1	5	0.82	0.65	−0.82	292
CK3	3.96	1	5	0.82	0.17	−0.52	292
CK4	4.15	1	5	0.89	1.39	−1.10	292
CK5	4.02	1	5	0.86	1.18	−0.88	292
CK6	4.07	1	5	0.90	0.68	−0.88	292
PCK1	4.05	1	5	0.81	−0.23	−0.49	292
PCK2	4.07	2	5	0.81	−0.42	−0.50	292
PCK3	3.95	1	5	0.85	−0.13	−0.51	292
PCK4	4.09	1	5	0.79	0.11	−0.58	292
PCK5	4.16	2	5	0.84	−0.18	−0.74	292
PCK6	4.08	1	5	0.86	0.60	−0.82	292
PEOU1	3.92	1	5	0.91	−0.29	−0.52	292
PEOU2	3.93	1	5	0.91	−0.33	−0.50	292
PEOU3	4.21	1	5	0.93	0.60	−1.07	292
PEOU4	4.06	1	5	0.91	−0.13	−0.69	292
PK1	3.92	1	5	0.81	0.11	−0.41	292
PK2	4.10	1	5	0.82	0.64	−0.79	292
PK3	4.21	1	5	0.81	0.79	−0.95	292
PK4	4.07	1	5	0.85	−0.09	−0.64	292
PK5	4.12	1	5	0.87	0.61	−0.86	292
PK6	4.04	1	5	0.87	0.36	−0.73	292
PK7	3.97	1	5	0.92	−0.41	−0.51	292
PK8	4.08	1	5	0.89	0.04	−0.72	292
PU1	3.80	1	5	1.07	−0.16	−0.63	292
PU2	3.97	1	5	0.94	−0.16	−0.63	292
PU3	3.88	1	5	1.05	−0.17	−0.71	292
PU4	4.09	1	5	0.92	0.03	−0.80	292
PU5	3.89	1	5	0.95	−0.32	−0.52	292
TK1	4.36	1	5	0.88	2.00	−1.46	292
TK2	4.11	1	5	0.96	0.27	−0.92	292
TK3	3.88	1	5	1.02	−0.19	−0.61	292
TK4	4.02	1	5	0.96	0.46	−0.87	292
TK5	4.29	1	5	0.82	1.23	−1.15	292
TPACK1	3.87	1	5	0.91	0.22	−0.65	292
TPACK2	3.97	1	5	0.94	0.59	−0.83	292
TPACK3	3.99	1	5	0.88	−0.08	−0.58	292
TPACK4	4.02	1	5	0.85	−0.26	−0.53	292
TPACK5	4.03	1	5	0.89	0.18	−0.70	292
TPK1	4.19	2	5	0.80	−0.13	−0.71	292
TPK2	4.01	1	5	0.86	0.23	−0.67	292
TPK3	3.99	1	5	0.89	−0.22	−0.53	292
TPK4	4.02	1	5	0.87	−0.04	−0.60	292
TPK5	4.01	1	5	0.90	0.23	−0.72	292
TPK6	4.12	1	5	0.87	1.45	−1.05	292

Appendix 2. Questionnaire TECHNOLOGICAL PEDAGOGICAL CONTENT KNOWLEDGE Please rate the extent to which you agree with each statement below (Please check √ only one answer.]

1=Strongly Disagree 2=Disagree 3=Neutral 4=Agree 5=Strongly Agree					
TECHNOLOGICAL KNOWLEDGE (TK)					
TK1: I know how to use mobile devices (e.g., smartphones, tablets) for different personal and professional purposes.	1	2	3	4	5
TK2: I can install, navigate, and manage educational mobile applications.	1	2	3	4	5
TK3: I can solve common technical problems when using mobile learning tools.	1	2	3	4	5
TK4: I can stay updated with new mobile technologies that support mobile learning.	1	2	3	4	5
TK5: I can use mobile technologies to communicate and collaborate effectively.	1	2	3	4	5
TK6: I can evaluate the usability of mobile devices for various tasks.	1	2	3	4	5
CONTENT KNOWLEDGE (CK)					
CK1: I have deep knowledge of the subject content I will teach.	1	2	3	4	5
CK2: I understand the structure and key ideas of my subject.	1	2	3	4	5
CK3: I can identify common misconceptions in my subject.	1	2	3	4	5
CK4: I can apply subject knowledge to real-world situations.	1	2	3	4	5
CK5: I can explain subject content clearly and accurately.	1	2	3	4	5
CK6: I am confident in my ability to answer content-related questions from students.	1	2	3	4	5
PEDAGOGICAL KNOWLEDGE (PK)					
PK1: I know how to assess learners' performance in, including knowledge of different cognitive levels, degrees of question difficulty and the concept of a 'reasonable learner'.	1	2	3	4	5
PK2: I can adapt my teaching depending on what learners understand or do not understand.	1	2	3	4	5
PK3: I can adapt my teaching style to different learners.	1	2	3	4	5
PK4: I know how to assess learning in multiple ways.	1	2	3	4	5
PK5: I can use a variety of teaching strategies in my class.	1	2	3	4	5
PK6: I am familiar with common learners' understandings and misconceptions	1	2	3	4	5
PK7: I know how to organise and maintain class management and control.	1	2	3	4	5
PK8: I am familiar with the prescribed textbooks and other learning resources used in most South African classrooms.	1	2	3	4	5
PEDAGOGICAL CONTENT KNOWLEDGE (PCK)					
PCK1: I can select teaching strategies that best fit specific content areas.	1	2	3	4	5
PCK2: I can explain complex content ideas in ways that make them understandable.	1	2	3	4	5
PCK3: I can anticipate learners' difficulties with content.	1	2	3	4	5
PCK4: I can assess learners' understanding of specific content.	1	2	3	4	5
PCK5: I can use representations (e.g., examples, analogies) to explain content.	1	2	3	4	5
PCK6: I can adapt my instruction based on how learners respond to content.	1	2	3	4	5
TECHNOLOGICAL PEDAGOGICAL KNOWLEDGE (TPK)					
TPK1: I can use mobile technologies to enhance my teaching strategies.	1	2	3	4	5
TPK2: I can manage mobile learning activities that involve mobile technologies.	1	2	3	4	5
TPK3: I can use mobile apps to promote active mobile learning.	1	2	3	4	5
TPK4: I can select mobile tools that support different pedagogical goals.	1	2	3	4	5
TPK5: I can foster collaboration using mobile learning platforms.	1	2	3	4	5
TPK6: I understand how mobile technologies influence learner engagement.	1	2	3	4	5
TECHNOLOGICAL PEDAGOGICAL CONTENT KNOWLEDGE (TPACK)					
TPACK1: I can integrate mobile technologies effectively in my subject teaching.	1	2	3	4	5
TPACK2: I can plan lessons that use mobile tools to support learning.	1	2	3	4	5
TPACK3: I can use mobile learning strategies to teach complex content.	1	2	3	4	5
TPACK4: I can create learning experiences that combine subject content, pedagogy, and mobile devices.	1	2	3	4	5
TPACK5: I can critically evaluate the effectiveness of mobile learning in my teaching.	1	2	3	4	5
PERCEIVED USEFULNESS (PU) (Al-Adwan et al., 2018)					
PU1: Using mobile learning in class will improve my work efficiency in my studies	1	2	3	4	5
PU2: Using mobile learning will improve my performance in my studies	1	2	3	4	5
PU3: Using mobile learning would make it easier for me to study	1	2	3	4	5
PU4: I would find mobile learning useful in my studies	1	2	3	4	5
PU5: Using mobile learning would enhance my effectiveness in my studies	1	2	3	4	5
PERCEIVED EASES OF USE (PEOU) (Alrajawy et al., 2018)					
PEOU1: It will be easy to learn how to use mobile learning in my studies	1	2	3	4	5
PEOU2: I will find it easy to use mobile learning in my studies	1	2	3	4	5
PEOU3: I would find mobile learning to be flexible to interact with my lectures.	1	2	3	4	5
PEOU4: It will be easy for me to become skilful in using mobile learning	1	2	3	4	5
BEHAVIOUR INTENTION (BI)					
BI1: Assuming I have access to mobile learning, I intend to use it for my learning	1	2	3	4	5
BI2: I am planning to use mobile learning in my learning	1	2	3	4	5
BI3: I would like to use many different mobile applications for learning in the future	1	2	3	4	5

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