Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 9, 174-189
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i9.13568

Psychological predictors of employee acceptance of mobile learning technologies: A scoping review of global evidence and implications for South African higher education

Mustapha Olanrewaju Aliyu[1*], Betty Portia Maphala[2]
[1,2]Department of Industrial and Organisational Psychology, College of Economic and Management Sciences, University of South Africa; aliyumo@unisa.ac.za (M.O.A.), maphabpm@unisa.ac.za (B.P.M.).

Abstract: Mobile learning technologies (MLTs) have been on the rise in both higher education and organisational settings, but progress in implementing them within organisations has been uneven. While there is evidence base for psychological predictors of acceptance across the globe, primarily through the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, and Theory of Planned Behaviour, these models and theories have limited contextual applicability in South African higher education (SAHE). The review followed PRISMA-ScR guidance. Searches were conducted in Scopus, Web of Science, PubMed, PsycINFO, and ERIC for studies published between 2019 and 2025. The synthesis suggests that acceptance is consistently related to perceived usefulness or performance expectancy, perceived ease of use or effort expectancy, self-efficacy, and social influence. These predictors, however, are more strongly moderated by perceived behavioural control, facilitating conditions, anxiety, and trust in SAHE, reflecting infrastructural constraints, workload pressures, and digital inequality. The review concludes that, although dominant acceptance models remain theoretically sound, they need to be applied in the context of SAHE, with a focus on institutional-level interventions. This implies that MLTs are best used as integrated resources rather than as complete replacements for traditional teaching, and that platforms with lower friction are more acceptable to employees.

Keywords: *Higher education institutions, M-learning technologies, Psychological predictor, Staff acceptance, technology acceptance.*

1. Introduction

Mobile learning technologies (MLTs) are digital tools and platforms that can be accessed on smartphones, tablets, and other portable devices to support teaching, learning, communication, assessment, and professional development. In higher education, these technologies have become increasingly important because they allow staff and students to access learning materials, communicate quickly, and support blended learning beyond the physical classroom. Their use expanded after the COVID-19 pandemic, but institutional adoption has not automatically produced consistent staff acceptance or sustained use [1, 2]. Aside from that, they increase the likelihood of learning and replication and, in certain instances, enhance structural disparities in digital literacy [3, 4].

There is an emphasis on staff acceptance, as this relates to whether MLTs become part of routine university practice. Staff can affect their adoption in daily routines. Although these platforms are available within institutions, staff may be unwilling to use them if they find the systems cumbersome, unreliable, poorly aligned with their work, or inadequately supported by the institution [5]. However, psychological factors such as PU, EOU, SE, SI, PBC, trust, and anxiety continue to play a pivotal role in technology adoption [6, 7]. Most of these factors form part of elaborated models such as TAM [8], UTAUT/UTAUT2 [9], and TPB [8]. However, the validity and suitability of these models in the

History: Received: 12 June 2026; Revised: 18 August 2026; Accepted: 24 August 2026; Published: 7 September 2026
* Correspondence: aliyumo@unisa.ac.za

context of higher education, particularly for analysing the socioeconomic and technological environment, have not been fully explored [9, 10].

The theoretical conception of TAM holds that perceived ease of use (PEOU) and perceived usefulness (PU) are critical for identifying how users will accept new technologies [11]. UTAUT/UTAUT2 builds on these issues by adding social influence, facilitating conditions, and hedonic motivation, among others. In contrast, TPB focuses on attitudes, subjective norms, and PBC as key factors in understanding technology adoption [8, 12, 13]. Indeed, these models have been adopted and have demonstrated an essential role in understanding technology adoption in workplaces and education, providing a strong theoretical basis for the field. The success of these models is well established, and South African universities are increasingly adopting blended learning in response to the COVID-19 pandemic; yet, no robust studies exist on the functioning of psychological predictors in the SAHE sector [5, 14, 15].

The existing literature lacks sufficient information on whether the established models apply to developing environments, where challenges such as socioeconomic inequality, unequal access to technology, low levels of digital literacy, and attitudes towards new technology exist [16, 17]. In addition, the models are incomplete because they do not consider cultural factors and trust in the technology, which play crucial roles in determining model acceptance but have not been included in current models [18, 19]. Moreover, Letjani et al. [9] highlight that South Africa's digital infrastructure and access to technological resources differ from those in the Global North, potentially affecting the relevance of such models and necessitating adaptations to local contextual factors.

When universities decide to implement MLTs as part of their digital transformation, it is necessary to understand the psychological barriers and facilitators to technology adoption. If used without a proper understanding of employees' perceptions and uptake of such technologies, there is a risk of poorly implemented technologies that may widen inequalities and hinder the perceived benefits of mobile learning [20, 21]. The current study is a scoping review aimed at identifying gaps in the literature, summarising the literature, and exploring the implications for SAHE. This study will enable educators, policymakers, and technology developers to understand how well current models and theories apply in South Africa and how they can be applied effectively to enhance the successful implementation of MLTs, resulting in a better digital learning environment. Accordingly, research questions were formulated:

1.1. Research Questions

RQ1: What psychological predictors of MLT acceptance among higher education staff have been reported in the literature?

RQ2: Which theoretical frameworks have been used to explain MLT acceptance?

RQ3: What contextual factors influence staff acceptance of MLTs?

RQ4: What evidence gaps exist regarding MLT acceptance in South African higher education?

2. Theoretical Framing

2.1. Technology Acceptance Model

The TAM is an information systems theory that explains how users are encouraged to accept and utilise new technology, assuming that PEOU and PU are the drivers of technology acceptance [7, 16]. The principal concept is that when employees believe an MLT will enhance their job performance and is user-friendly, they are more inclined to accept and use the technology. For instance, when a firm launches a mobile learning application as a training initiative for employees, PU would be determined by employees' belief that the application enables them to gain pertinent skills and enhance their job performance [22, 23]. PEOU would be based on the app's level of intuitiveness and ease of use [24]. Meanwhile, there has been considerable debate about the weakness of TAM, which uses PU and PEOU as the only predictors of technology acceptance. Tomić et al. [25] argue that additional variables, such as social influence, organisational support, and individual characteristics related to innovation or resistance to change, are predictors that cannot be explicitly modelled by TAM. The role of social influence and enabling conditions in explaining technology acceptance has been emphasised [12]. Research indicates that social influence may be a key factor in determining the acceptance of M-learning in organisations, particularly when top-level leaders or colleagues promote its use [26, 27].

2.2. Unified Theory of Acceptance and Use of Technology

The UTAUT [13] and later UTAUT2 [12] models are more comprehensive and better suited to capturing the complexity of technology acceptance. While UTAUT presents eight (8) constructs, making it a more thorough method, UTAUT2 was built upon the original model in 2012 by introducing additional factors: hedonic motivation, price value, and habit, which are particularly pertinent to consumer technology [12, 13]. Performance expectancy (PE) in an M-learning situation captures employees' beliefs that mobile learning would lead to better learning outcomes [27]. If employees believe M-learning tools can help them acquire new competencies, they are more likely to adopt the technology.

Meanwhile, one of the model's critical arguments concerns the complexity of measuring and applying it in practice. For instance, hedonic motivation (enjoyment of using the technology) is more likely to occur in consumer use of technology but less so in a work context, where it is more closely associated with PE [28, 29]. Similarly, UTAUT2 was built on Western cultural assumptions and may not be directly applicable to non-Western cultures. For instance, social influence might not work equally well across organisational contexts or geographical areas, and price value can pose a hindrance in economically strained settings where mobile devices are not widely available. Venkatesh et al. [12] found that habit and hedonic motivation were significant predictors when consumers were involved, but less so when applied in the workplace. This raises the question of whether all UTAUT2 constructs are equally applicable across various technologies.

2.3. Theory of Planned Behaviour

TPB [8], the choice to behave in a specific way is the most reliable predictor of behaviour and is determined by three major factors: attitude towards the behaviour, subjective norms, and perceived behavioural control [8]. TPB has been widely adopted in studies to understand the psychological factors underlying technology adoption [30]. For instance, if workers are convinced that MLTs are easy to operate, aligned with their work requirements, and supported by the organisation, their intentions to use these technologies will be stronger. TPB has also been criticised for emphasising psychological factors without considering external environmental factors that may influence adoption. For example, employees may have the right attitudes and intentions towards adoption; however, if their mobile devices are outdated or the learning content is poorly designed, adoption will still be slowed [31, 32]. The theory has also been criticised for focusing on behavioural intention (BI) as the next step towards behaviour. Evidence from Alade et al. [33] supports the premise that attitudes and perceived behavioural control are powerful predictors of technology adoption. However, they further posit that external conditions suggest that, although TPB helps in the decision-making process, it may not capture the external factors and obstacles influencing adoption.

3. Materials and Methods

This scoping review followed the PRISMA-ScR reporting guidance and the methodological framework proposed by Arksey and O'malley [34] as refined by Levac et al. [35]. The review was designed to map recent evidence on psychological predictors of employee acceptance of mobile learning technologies and to interpret its implications for South African higher education. A protocol was developed before screening began. It specified the review questions, databases, eligibility criteria, screening procedure, data-charting categories, and synthesis approach. The protocol was not registered, but all screening decisions and extraction records were documented using Covidence. The databases searched were Scopus, Web of Science, PubMed, PsycINFO, and ERIC. Searches covered studies published from January 2020 to December 2025. The search combined terms for mobile learning, acceptance, psychological predictors, and higher education or workplace learning. The search string was adapted to each database's indexing rules [36].

The search entailed identifying relevant keywords, using Boolean operators, and applying inclusion and exclusion criteria to narrow the results, as presented in Table 1. The search terms were carefully chosen to align with the key themes of the review: mobile learning technologies, employee acceptance, and psychological predictors. The main ideas were divided into several keywords and associated terms, designed to be as sensitive as possible in the search. The search terms were: TITLE-ABS-KEY(("mobile learning" OR m-learning OR "mobile learning technology" OR "mobile app" OR smartphone) AND (employee OR staff OR worker OR workforce OR "corporate learner") AND (acceptance OR adoption OR "behavioural intention" OR "behavioral intention" OR "technology acceptance") AND (attitude OR motivation OR "self-efficacy" OR anxiety OR trust OR "perceived usefulness" OR "perceived ease of use" OR "social influence" OR "learning readiness")). Subsequently, the eligibility criteria for this review were carefully considered, ensuring that only relevant studies were included and that the review remained focused on the following constructs:

Table 1.
Inclusion and Exclusion Criteria.

Inclusion Criteria	Exclusion Criteria	Rationale
Peer-reviewed journal manuscripts	Non-peer-reviewed articles, conference papers, theses, and unrelated literature.	Ensures inclusion of high-quality, credible sources with scientific rigour.
Studies published from 2020 to the present.	Studies published before 2020 or those that are outdated do not reflect current trends in MLTs.	Focus on recent research to capture the latest developments and trends in MLTs' acceptance.
Publications written in English.	Publications written in languages other than English.	To maintain consistency and feasibility in data extraction and analysis.
Studies focusing on MLTs, acceptance, and psychological predictors.	Studies unrelated to mobile learning, employee acceptance, or psychological predictors.	Ensures relevance to the research topic, which is centred on the intersection of the constructs.
Studies involving employees or adult learners in professional or higher education.	Studies focused on children or populations outside the context of adult learning.	Focus on adult learners in professional or higher education.

3.1. Selection and Screening Process

The review for this study was conducted in several steps: titles and abstracts were screened, followed by a full-text review, and data were extracted [21, 37]. To reduce bias and ensure the validity of the selection process, two researchers conducted independent reviews, and potential disagreements were addressed by engaging a third reviewer [20, 38]. To further ensure the quality and transparency of the process, the Covidence platform was used to automate study selection, screening, and data extraction [7].

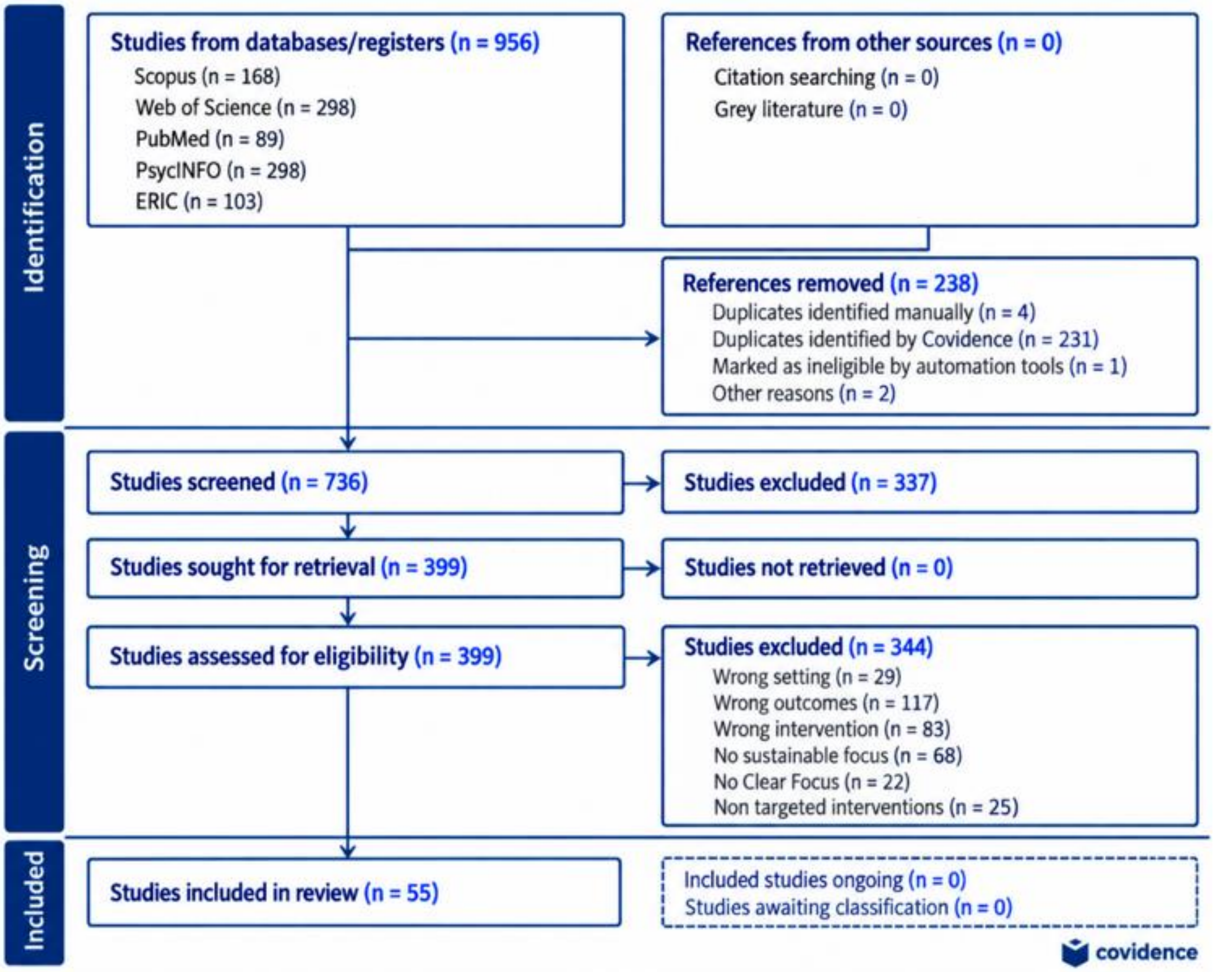

Figure 1.
PRISMA-Covidence extraction of final included studies.

Figure 1 presents the PRISMA report of 966 records identified across four databases: Scopus (n = 168), Web of Science (n = 298), PubMed (n = 89), and PsycINFO (n = 298), plus an additional 103 records from ERIC. No records were identified through other sources. Following the removal of duplicates and other records (n = 238), 736 studies remained for title and abstract screening. Of these, 337 studies were excluded, leaving 399 studies for full-text retrieval and eligibility assessment. All 399 studies were successfully retrieved. Full-text assessment resulted in the exclusion of 344 studies because they had the wrong settings (n = 29), wrong outcomes (n = 117), wrong interventions (n = 83), no sustainable focus (n = 68), no clear focus (n = 22), or non-targeted interventions (n = 25). Consequently, 55 studies were included in the final review. In addition, Cohen's kappa (k) was employed to assess inter-rater consistency during screening and respondent selection [38].

Cohen's k Formula: $\kappa = \frac{P0-Pe}{1-Pe}$

$$P_e = (0.45 \text{ x } 0.44) + (0.55 \text{ x } 0.56) = 0.198 + 0.308 = 0.506$$

$$k = \frac{Po-Pe}{1-Pe} = k = \frac{0.928-0.506}{1-0.506} = k = \frac{0.422}{0.494} = 0.854$$

The inter-rater reliability analysis yielded a Cohen's kappa of 0.854, indicating almost perfect agreement between raters. This suggests that the coding/classification process was highly reliable and that the observed agreement was not attributable to chance [16, 39]. After selecting the studies, data extraction began. Relevant data were extracted from the included studies using the Covidence platform. Study characteristics, psychological predictors, methods, and results were systematically derived and tabulated. The final list of studies was included in the review following full-text screening and the resolution of inconsistencies. The Covidence platform also facilitated tracking of included studies, making the process transparent and reproducible.

The review protocol was developed a priori and guided by the PRISMA-ScR framework [34]. The protocol was not formally registered; however, all procedures were documented on the Covidence Platform prior to study screening. The evidence-mapping process involved four iterative steps: familiarisation with the included studies, initial coding of the extracted data, creation of descriptive categories, and identification of overarching themes [1, 7]. This iterative process ensured that the synthesis remained grounded in evidence and conceptual connections across studies.

Table 2.
Data Charting Process.

Author	**Country**	**Sample Size**	**Population**	**Traits Examined**	**Outcomes Examined**	**Design**	**Bias**
Aboderin and Govender [40]	Nigeria	317	Distance e-learners	Age, ICT skills, motivation, self-regulation	Academic performance	Cross-sectional survey	Moderate self-report bias, good analysis
Abu-AlSondos, et al. [41]	Jordan	412	University students	PU, PEOU, trust, mobility	Acceptance of mobile e-learning	SEM	Strong model fit, validated constructs
Al Ahbabi and Ahmad [42]	UAE	NR	Hospital administrators	Technology readiness, integration	COVID-19 management effectiveness	Case study	Context-specific, limited generalisation
Alade, et al. [33]	Multinational	46	Workplace employees	Just-in-time learning, usability	Knowledge acquisition efficiency	Experimental	Strong design, small sample
Alkhateeb and Abdalla [43]	Middle East	240	University students	System quality, ease of use	Student satisfaction	SEM	Robust LMS evaluation
Antonczak and Burger-Helmchen [3]	Europe	NR	Knowledge workers	Mobility, collaboration	Innovation practices	Conceptual	No empirical validation
Benslimen, et al. [21]	Europe	Simulated	Network systems	Failure prediction accuracy	Network reliability	Modelling/simulation	High internal validity (technical scope)
Bentley, et al. [44]	Global	1025	Farmers	Accessibility, relevance	Knowledge uptake	Online survey	Large sample, self-selection bias
Konyani, et al. [24]	Malawi	326	Nursing students	Digital literacy, infrastructure	E-learning preparedness	Survey	Contextually strong, cross-sectional
Brage, et al. [45]	Global	68 studies	Radiographers	Reporting competence	Diagnostic performance	Systematic review	Rigorous synthesis, secondary data
Cervini, et al. [46]	USA	>30,000 ZIP codes	EV users	Temperature sensitivity	EV adoption	Longitudinal regression	Strong causal inference
Chadwick et al. [2]	India	241	Rural adults	AI-enabled behaviour nudges	Diabetes risk reduction	Quasi-experimental	Pre-post strengthens inference
Edo et al. [47]	Nigeria	215	Bank staff	Perceived risk, usefulness	Fintech adoption	ML-enhanced survey	Innovative, survey bias possible

ISSN: 2576-8484
Vol. 10, No. 9: 174-189, 2026
DOI: 10.55214/2576-8484.v10i9.13568

Emmett, et al. [48]	Global	22 studies	Health professionals	Usability, workflow fit	ECG adoption experiences	Qualitative review	Heterogeneous evidence
Al Fehaidi and Khan [38]	Middle East	180	Employees	System usability	Satisfaction	Survey	Narrow scope, acceptable rigour
Halbert, et al. [49]	Global	NR	Social media users	Exposure, behaviour	CVD risk perception	Narrative review	Non-systematic synthesis
Hmoud and Salah [1]	Middle East	263	University employees	Attitudes, self-efficacy	Mobile learning adoption	SEM	Strong construct validity
Hsiao, et al. [50]	Taiwan	398	Trainees	TAM variables, satisfaction	Continuous use intention	SEM	Continuance modelling robust
Huseynov, et al. [20]	Türkiye	512	Bank customers	App usability traits	Adoption likelihood	ML prediction	High predictive accuracy
Jabbar et al. [51]	Gulf region	201	Academic staff	Communication efficiency	Work performance	Survey	Limited inferential depth
Khan and Gupta [7]	Global	742 papers	Academic literature	Research trends	Knowledge mapping	Bibliometric	Objective mapping, database bias
Kuciapski [32]	Europe	245	Employees	Enjoyment, motivation	M-learning acceptance	SEM	High explanatory power
Kumoji, et al. [52]	Kenya	601	Micro-retailers	Digital capacity	Platform adoption	Latent class analysis	Reduces aggregation bias
Liébana-Cabanillas, et al. [16]	Europe	524	Consumers	Trust, biometrics	Use intention	Multi-analytic SEM	Method triangulation
Marcus-Quinn and Hourigan [53]	Ireland	NR	Secondary teachers	Accessibility awareness	Inclusion quality	Conceptual review	Triangulation strength
Milner and O'Reilly [6]	Multinational	412	University lecturers	Attitudes to smartphones	Classroom management	Comparative survey	Smaller sample
Mwalukasa [54]	Tanzania	284	University students	Access, skills	Academic information use	Mixed methods	Reliable instruments
Vaiopoulou et al. [37]	Greece	412	Parents	Perceptions of apps	Educational value	Instrument validation	Strong psychometrics
Walle [18]	Africa	498	App users	Trust, risk, usefulness	Adoption prediction	SEM-NN hybrid	Advanced predictive modelling

3.2. Evidence Mapping

As shown in Table 2, 55 studies were identified as eligible for evidence mapping. These studies investigated psychological factors influencing technology acceptance, mobile learning adoption, or digital learning behaviours in higher education and workplace learning environments. The included studies spanned 2020 to 2025 and were primarily from the Global North, with the Global South underrepresented. The evidence base was geographically representative, spanning studies in Europe, North America, the Middle East, Asia, and some African countries, including South Africa, Tanzania, Malawi, and Nigeria. The distribution of studies shows that research on mobile learning adoption has increased since the COVID-19 pandemic, pointing to the rapid digitalisation of higher education institutions worldwide. The majority of studies used quantitative survey designs and SEM, with fewer using qualitative, mixed-methods, experimental, or longitudinal designs. This reflects a strong focus on describing BI and acceptance relationships, while comparatively little emphasis is placed on understanding how acceptance develops over time or within specific institutional contexts.

3.3. Mapping of Psychological Predictors

Table 3 presents a synthesis of several psychological constructs frequently mentioned in the reviewed literature. The most commonly cited predictors of M-learning acceptance were performance-related beliefs, which included PU and PE [55]. Employees were more likely to accept MLTs when they believed that MLTs would positively affect their professional performance, teaching effectiveness, learning outcomes, and communication efficiency [40]. Similarly, effort expectancy, a subscale of effort-related beliefs, and PEOU were also identified as relevant predictors [38]. The evidence was consistent with the intuitive, easy-to-use, and work-friendly nature of these technologies, leading to high adoption intentions and long-term use.

Table 3.
Psychological Predictors of MLT Acceptance.

Predictor	Frequency (n)	% of Studies
Perceived Usefulness	41	74.5%
Ease of Use	38	69.1%
Self-Efficacy	33	60.0%
Social Influence	29	52.7%
Facilitating Conditions	27	49.1%
Trust	18	32.7%
Anxiety	15	27.3%
Habit	11	20.0%

Furthermore, self-efficacy was another consistent predictor: for instance, research repeatedly shows that increased self-efficacy in technological skills is linked to higher levels of engagement with mobile learning platforms and lower resistance to learning through media [9, 48]. In the meantime, self-efficacy also seemed to increase ease of use and decrease technology-related anxiety. Social influence and subjective norms were among the secondary predictors reported very often [26]. Regarding employees' perceptions of the legitimacy and acceptance of technology, the evidence indicates that institutional culture, peer endorsement, managerial support, and leadership encouragement are all factors. However, the impact of these effects varied across organisations and cultures. Anxiety and trust in the technology were important affective factors for acceptance. These constructs were less commonly investigated than usefulness or self-efficacy, but they seemed especially relevant in situations of digital inequality.

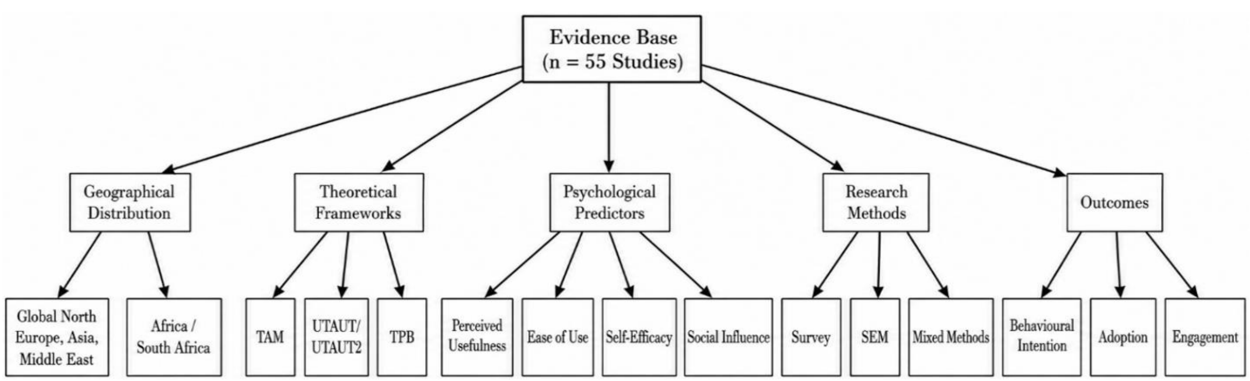

Figure 2.
Evidence Map of Literature on Psychological Predictors of MLT Acceptance.

Figure 2 shows the evidence map of the literature on psychological predictors of employee acceptance of M-learning technologies. It summarises the distribution of evidence across geographic context, theory, key psychological predictors, methods, and accepted outcomes identified in the reviewed studies.

3.4. Mapping of Theoretical Claims

The evidence map in Figure 3 indicates that technology use is still primarily guided by three theories: TAM, UTAUT/UTAUT2, and TPB. Among these frameworks, TAM was the most widely used, particularly in research examining factors influencing the intention to adopt (e.g., PU and PEOU). The most frequently cited models in research on PE, EE, SE, and FC were UTAUT and UTAUT2, whereas attitudes, subjective norms, and PBC were most often examined using TPB [20, 30]. The evidence suggests substantial theoretical convergence across studies. Regardless of the specific framework employed, similar psychological constructs consistently emerged as determinants of acceptance behaviour. This indicates that the differences between models may be less important than the recurring predictors they seek to explain.

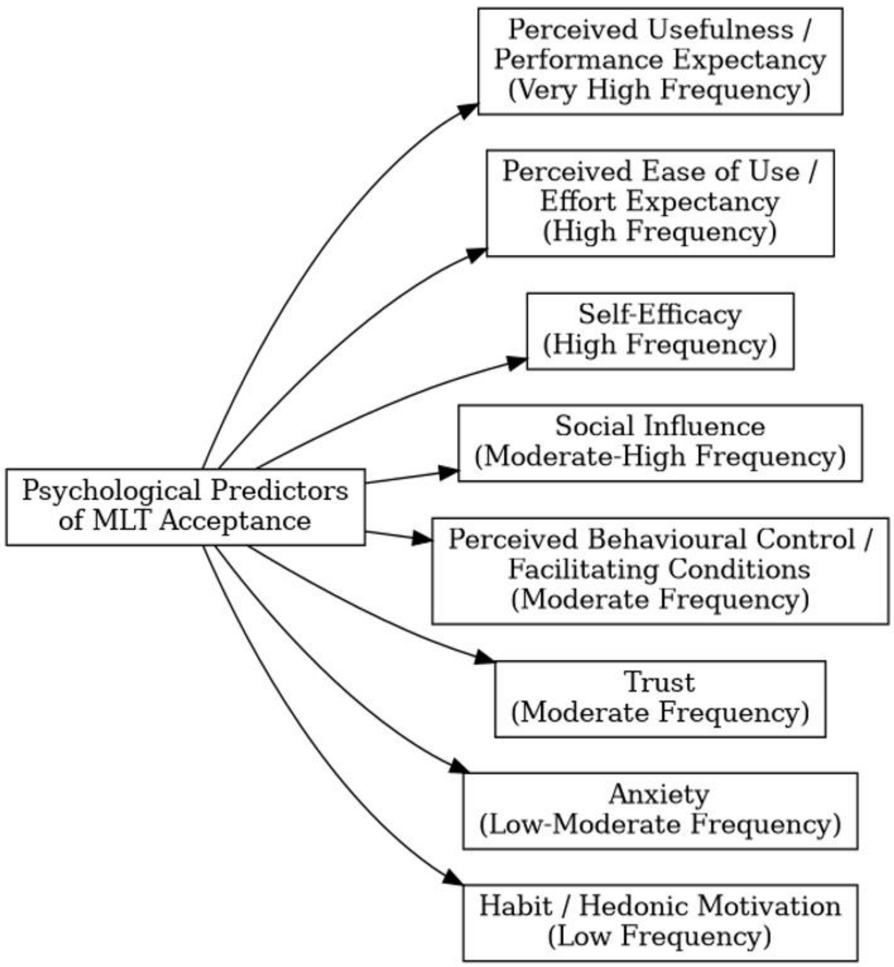

Figure 3.
Evidence Map of Psychological Predictors of MLT Acceptance.

Figure 3 summarises the relative prominence of psychological constructs reported across the reviewed literature. PU/PE, PEOU/EE, and SE emerged as the most frequently reported predictors of MLT acceptance, followed by SI, PBC, FC, trust, anxiety, and habit-related constructs. Meanwhile, the most commonly analysed frameworks for mobile-enabled learning acceptance in the literature are TAM (PU, PEOU, attitude, BI) and UTAUT/UTAUT2 (PE, EE, SI, FC, hedonic motivation, habit) [56-58]. One of the most important South African studies at a historically disadvantaged university employed TAM to explain technology acceptance in teaching and learning, and the application of usefulness/ease-of-use beliefs has remained pertinent in that context. Even though some work in South Africa focuses on students, it still informs the context for employees because of the structural similarity of many acceptance pathways (usefulness–intention; ease-of-use–usefulness; self-efficacy–ease-of-use) across user groups. Meanwhile, research consistently suggests that usefulness/PE, ease of use/effort expectancy, and self-efficacy/enjoyment/anxiety are among the most prevalent predictors of educational technology adoption [32]. Although facilitating conditions are relevant worldwide, they are more structurally relevant in resource-constrained situations and shape perceptions of control and risk. In the case of MLTs, including platforms, data, or assessments, factors such as anxiety (fear of error, lack of confidence) and trust (in the system, privacy, and reliability) can determine acceptance [12, 37].

3.5. Mapping of Outcomes Associated with M-Learning Acceptance

The evidence map revealed that most studies measured behavioural, adoption, and continuance intentions, or actual system use, as primary outcomes. Fewer studies focused on educational outcomes, including teaching effectiveness, employee productivity, learning performance, or organisational performance [6, 53]. The literature, therefore, remains largely acceptance-oriented, and little evidence is provided regarding the long-term educational and organisational gains of MLTs. In other positive studies, acceptance was found to be correlated with increased engagement, communication, learning flexibility, and efficient access to learning materials [59]. However, the evidence also reinforced that positive results were achieved when mobile technology was used alongside and integrated with other instructional approaches.

In addition to individual factors, the evidence also identified several contextual factors that affected MLTs. Examples of facilitating factors included infrastructure reliability, technical support, digital readiness, workload compatibility, and organisational support, which were cited across multiple studies as critical to the success of the adoption process [24, 54]. These factors were assumed to be external variables, but the evidence shows that they indirectly influence acceptance by shaping users' perceptions of control, confidence, and risk [20]. The predictive factors were mostly the same, but studies in resource-poor settings focused significantly more on perceived behavioural control, institutional support, and infrastructure reliability. This indicates that feasibility-related factors can have as much impact on acceptance of SAHE as attitudes towards technology.

4. **Discussion**

Employees' perceptions of M-learning appear theoretically familiar (usefulness/performance expectancy, ease/effort, self-efficacy, attitude, intention) but, in practice, more control-heavy, supportive, and risky. This aligns with broader syntheses of TAMs, in which PU and PEOU are recurring core factors in the adoption of m-learning, while external factors enhance explanatory value [37]. The gap the study suggests is the difference between which predictors matter and when and why they translate into action: in resource-variable environments, PBC is a gatekeeper, such that high PU does not result in uptake if staff expect poor connectivity, inadequate training, or incompatibility with workloads [37]. The latter focus is consistent with reviews of African-context higher education, which find that residual implementation limitations and distributional imbalances in readiness determine what can be done, rather than what should be desired, and that mechanisms of sustained use (habit) and affective responses (technostress) have undergone little testing [57, 58].

The combination of mapping evidence suggests that M-learning is most effective as an augmentation rather than a substitution, and that the most plausible benefits are achieved when adoption minimises friction and increases interaction density in blended designs. This is consistent with evidence suggesting that integrating mobile learning can enhance engagement and learning outcomes in higher education, which are heterogeneous and depend on pedagogy and the quality of implementation rather than on the tool itself [55, 59]. The mapped evidence shows that high-uptake, low-barrier platforms (WhatsApp) are being utilised for rapid communication, microlearning, and continuity to enhance teacher–student interaction and learning support [2, 51]. However, the weakness is also evident: most positive studies continue to focus on perceived engagement rather than objective performance, and they rarely involve strong comparators (mobile versus conventional); instead, they mostly confound mobile learning with general digital supplementation [20, 24].

4.1. Evidence Gaps

One of the most significant gaps identified in the literature is the limited empirical testing of established technology acceptance theories within African higher education institutions. Although TAM, UTAUT/UTAUT2, and TPB dominate the global literature, most empirical validations have originated in North America, Europe, and Asia. Comparatively few studies have examined whether the underlying assumptions, predictor relationships, and explanatory power of these models remain stable in African educational environments. The available African studies tend to adopt these models without critically examining their contextual appropriateness or whether additional constructs are required to explain acceptance behaviour under conditions of technological uncertainty. The evidence mapping also shows that, in studies on the acceptance of M-learning, TPB has been studied significantly less than TAM and UTAUT. PBC proved to be a key factor in resource-poor settings, but few studies have fully examined the synergy among attitudes, subjective norms, and PBC in driving employees' uptake of MLTs [55]. For SAHE, this gap is particularly important because psychological beliefs and practical considerations influence decision-making.

While many studies examine technology acceptance worldwide, few specifically address the South African university context. Consequently, current knowledge is largely derived from extrapolating results from international settings that vary widely in resource availability and infrastructure. This gap is especially worrisome in the context of the current digital transformation in South African universities and the increasing significance of M-learning in enabling flexible, blended learning. This imbalance is problematic because staff are key to the successful implementation and institutionalisation of MLTs. Their acceptance directly impacts pedagogical integration and sustainability.

4.2. Implications for South African Higher Education

Institutions need to move from platform adoption to implementation readiness within the university. Before introducing new mobile learning tools, decision-makers need to evaluate staff workloads, connectivity, device access, digital confidence, technical support, and data affordability [59]. Universities need to go beyond one-time technical training for staff development. Staff development should involve peer mentoring, guided practice, mini-demonstrations, discipline-specific use cases, and ongoing support. The intention should be to build self-efficacy and lower anxiety.

For platform design, institutions should prioritise low-friction tools that are mobile-first, easy to navigate, compatible with existing learning management systems, and accessible under low-bandwidth conditions. For infrastructure, universities should invest in reliable connectivity, device access support, help desk services, and policies that reduce data burdens on staff and students. For pedagogy, mobile learning should be integrated into blended teaching design. It should support communication, microlearning, feedback, assessment reminders, and flexible access, but it should not be presented as a full substitute for structured teaching.

5. Conclusion

This scoping review integrated existing evidence on the acceptance and use of MTs among employees working in South African institutions of higher learning, with a specific focus on psychological predictors, adoption–outcome relationships, interventions grounded in models and theories, and the comparative significance of focused and general strategies. It was discovered that the core drivers of acceptance are theoretically aligned with global evidence, with PU/performance expectancy, PEOU/effort expectancy, self-efficacy, attitude, and behavioural intention at the centre. However, they are expressed more contextually: in South Africa, these psychological predictors are more closely connected to PBC, facilitating conditions, anxiety, and risk. The implication is that acceptance depends not solely on motivation but also on staff members' realistic evaluations of feasibility, given variable infrastructure, workload, and imbalanced institutional support.

It was equally evident that a mobile learning application is most effective as a secondary support in a blended design, rather than as a complete substitute for traditional teaching. Mobile platforms, especially familiar, low-friction tools, continuously enhance interaction and engagement density, whereas improvements in learning and performance are determined by the instructional design's pedagogical alignment and the organisation's capacity to support it. It was also discovered that interventions consistent with TAM, UTAUT/UTAUT2, and TPB are more promising than traditional, skills-only training because of their superior ability to address belief formation, confidence, norms, and perceived control; however, no comparative intervention studies with a high level of rigour in South African higher education were found. The study also supports the idea that staff-specific solutions are more effective than general interventions, as they directly enhance performance beliefs and build self-efficacy in the workplace.

5.1. Policy and Practice Implications

This review identifies several priorities: (i) studies that involve only employees (without including other stakeholders) to distinguish between academic and administrative/professional staff; (ii) longitudinal and quasi-experimental designs to study sustained use, the formation of habits, and intention-use disconnects; (iii) the presence of objective outcomes (indicators of teaching quality, throughput, and assessment performance) in addition to perceptions; and (iv) well-described and theory-consistent interventions that will permit replication and comparison, with a need to know who benefits from mobile learning and under what circumstances. In terms of policy, institutions should shift their focus from platform adoption to implementation preparedness. That is, policies that lower perceived risk and raise perceived control tend to have a greater effect on acceptance. In practice, staff development should focus on confidence-building solutions: show tangible performance improvements, make the technology easy to use, fit it into the workflow, scaffold self-efficacy through peer modelling and continuous guidance, and employ blended strategies that integrate formal systems with a familiar mobile tool.

5.2. Limitations and Future Research Agenda

This review has several limitations that should be acknowledged. First, the review was constrained by database coverage and indexing bias. Much of the SAHE literature on M-learning and technology acceptance is published in regional or institution-based journals, which are not always indexed in major international databases. Consequently, some applicable studies might not have been included, especially locally based ones.

Second, the review was based primarily on peer-reviewed journal articles, whereas institutional reports, policy documents, conference proceedings, and doctoral theses were not included extensively. Since most South African university mobile learning projects are carried out and assessed within their institutions, this likely leads to a lack of practice-based evidence.

The definition and operationalisation of mobile learning were also highly heterogeneous, ranging from informal messaging programmes to mobile-enabled learning management systems, making synthesis and cross-study comparison difficult.

Subsequent studies should therefore focus more on employee-oriented, role-sensitive research that distinguishes between academic, administrative, and professional staff, as they have different responsibilities and incentives for adopting mobile learning.

Longitudinal and experimental or quasi-experimental designs are required that go beyond intention and PU to investigate sustained use, use formation, and habitual use, yielding more measurable outcomes over time.

The evidence base would also be considerably advanced by carrying out direct tests of theory-congruent acceptance interventions (TAM-, UTAUT-, or TPB-informed programmes) against traditional training models. Objective performance measures should also be included in further research: teaching quality measures, assessment results, throughput rates, and completion of professional development, combined with self-reported perceptions. The addition of grey literature and implementation case studies would provide useful information on the institutional policies that determine implementation in practice.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study adhered to all ethical practices throughout the writing process.

Copyright:

References
[1] A. Y. R. Hmoud and O. H. Salah, *Adoption of mobile learning in higher education: An investigation of employees' perspectives. In From Industry 4.0 to Industry 5.0: Mapping the Transitions (Studies in Systems, Decision and Control)*. Cham, Switzerland: Springer, 2023.
[2] J. Chadwick, N. Jaswal, J. Surya, C. Sivamani, V. Ramesan, and N. Saligram, "Artificial intelligence–enabled mobile health intervention (mDiabetes) to reduce diabetes risk behaviors in rural India: Quasi-experimental pre-post study," *Journal of Medical Internet Research*, vol. 27, p. e79283, 2025. https://doi.org/10.2196/79283
[3] L. Antonczak and T. Burger-Helmchen, "Being mobile: A call for collaborative innovation practices?," *Information and Learning Sciences*, vol. 122, no. 5-6, pp. 360-382, 2021. https://doi.org/10.1108/ILS-02-2020-0035
[4] M. O. Aliyu and B. P. Maphala, "Psychological capital as a strategy for enhancing alternative dispute resolution in Nigeria's higher education," *Wukari International Studies Journal*, vol. 9, no. 7, pp. 455–471, 2025. https://doi.org/10.64633/wissj.v9i7.33
[5] F. Anciano and M. Lombard, "Hybridising governance for resilience in a time of crisis: Learning from community-based organisations in Cape Town and Cali," *International Development Planning Review*, vol. 47, no. 1, pp. 41-63, 2025. https://doi.org/10.3828/idpr.2024.15
[6] J. Milner and S. L. O'Reilly, "Beyond distraction: A cross-cultural look at instructors' perspectives on smartphone use in university classrooms," *Innovations in Education and Teaching International*, vol. 62, no. 3, pp. 767-780, 2025. https://doi.org/10.1080/14703297.2024.2382416
[7] F. M. Khan and Y. Gupta, "A bibliometric analysis of mobile learning in the education sector," *Interactive Technology and Smart Education*, vol. 19, no. 3, pp. 338-359, 2022. https://doi.org/10.1108/ITSE-03-2021-0048
[8] I. Ajzen, "The theory of planned behavior," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179–211, 1991. https://doi.org/10.1016/0749-5978(91)90020-T
[9] K. P. Letjani, K. Kurniawan, and S. Muthaiyah, "Adoption of chatgpt in educational institutions in Botswana: A customer perspective," *Asia Pacific Management Review*, vol. 30, no. 1, p. 100346, 2025. https://doi.org/10.1016/j.apmrv.2024.100346
[10] P. Muneesawang, K. Yawised, D. Apasrawirote, and M. Chatrangsan, "Extending UTAUT-2 toward acceptance of mobile application platform provide by government for local travelers," *Journal of Industrial Integration and Management*, pp. 1-31, 2025. https://doi.org/10.1142/S2424862225500101
[11] F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems: Theory and results," Doctoral Dissertation. Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA, USA, 1986.
[12] V. Venkatesh, J. Y. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1," *MIS Quarterly*, vol. 36, no. 1, pp. 157-178, 2012. https://doi.org/10.2307/41410412
[13] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view1," *MIS Quarterly*, vol. 27, no. 3, pp. 425-478, 2003. https://doi.org/10.2307/30036540
[14] T. Sethibe and E. Naidoo, "The adoption of robotics in the auditing profession," *South African Journal of Information Management*, vol. 24, no. 1, p. 1441, 2022. https://hdl.handle.net/10520/ejc-info_v24_i1_a1441
[15] D. K. Maduku, "Antecedents of mobile marketing adoption by SMEs: Does industry variance matter?," *Journal of Organizational Computing and Electronic Commerce*, vol. 31, no. 3, pp. 222-249, 2021. https://doi.org/10.1080/10919392.2021.1956847

[16] F. Liébana-Cabanillas, Z. Kalinic, F. Muñoz-Leiva, and E. Higueras-Castillo, "Biometric m-payment systems: A multi-analytical approach to determining use intention," *Information & Management*, vol. 61, no. 2, p. 103907, 2024. https://doi.org/10.1016/j.im.2023.103907

[17] L. Liu, L. Cai, L. Ma, and G. Qiao, "Channel state information prediction for adaptive underwater acoustic downlink OFDMA system: Deep neural networks based approach," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 9063-9076, 2021. https://doi.org/10.1109/TVT.2021.3099797

[18] Y. M. Walle, "Deep learning-based hybrid SEM-neural network approach for predicting mobile application adoption in whistleblowing services," *International Journal of Disclosure and Governance*, vol. 22, pp. 896-909, 2025. https://doi.org/10.1057/s41310-025-00295-2

[19] A. Sukkasem and N. Punpugdee, "The determinants of employee acceptance of mobile learning at a Thai state-owned enterprise," in *Proceedings of the 2nd International Conference on E-Society, E-Education and E-Technology*, 2018.

[20] F. Huseynov, Y. S. Balcıoğlu, and C. Ç. Çerasi, "Application of machine learning techniques to predict perceived usability of mobile banking apps in Türkiye," *İşletme Araştırmaları Dergisi*, vol. 16, no. 2, pp. 1001-1011, 2024. https://doi.org/10.20491/isarder.2024.1838

[21] Y. Benslimen, H. Sedjelmaci, and A.-C. Manenti, "Attacks and failures prediction framework for a collaborative 5G mobile network: Y. Benslimen et al," *Computing*, vol. 103, pp. 1165-1181, 2021. https://doi.org/10.1007/s00607-020-00893-8

[22] S. Zucchi, S. K. Füchter, G. Salazar, and K. Alexander, "Combining immersion and interaction in XR training with 360-degree video and 3D virtual objects," presented at the 2020 23rd International Symposium on Measurement and Control in Robotics (ISMCR) (pp. 1–5). Budapest, Hungary: Institute of Electrical and Electronics Engineers (IEEE), 2020.

[23] M. O. Aliyu and B. P. Maphala, "Psychological capital and digital learning behaviour: A meta-analysis of global antecedents and implications for South African higher education," *Journal of Information Systems Engineering and Management*, vol. 13, no. 3s, pp. 1270–1284, 2026.

[24] B. Konyani, P. Katanga, F. Chiundira, C. Mulenga, and P. Mapulanga, "E-learning preparedness of nursing students at Kamuzu University of Health Sciences in Malawi," *Education and Information Technologies*, vol. 30, pp. 3095-3114, 2025. https://doi.org/10.1007/s10639-024-12930-6

[25] N. Tomić, Z. Kalinić, and V. Todorović, "Using the UTAUT model to analyze user intention to accept electronic payment systems in Serbia," *Portuguese Economic Journal*, vol. 22, pp. 251-270, 2023. https://doi.org/10.1007/s10258-022-00210-5

[26] C. B. Singh, "Acceptance and use of digital technology: Re-validating Venkatesh's model on school teachers," *Abhigyan*, vol. 41, no. 1, pp. 3-12, 2023. https://doi.org/10.56401/Abhigyan_41.1.2023.3-12

[27] C. Neves, T. Oliveira, F. Cruz-Jesus, and V. Venkatesh, "Extending the unified theory of acceptance and use of technology for sustainable technologies context," *International Journal of Information Management*, vol. 80, p. 102838, 2025. https://doi.org/10.1016/j.ijinfomgt.2024.102838

[28] M. Blut, A. Y. L. Chong, Z. Tsigna, and V. Venkatesh, "Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean," *Journal of the Association for Information Systems*, vol. 23, no. 1, pp. 13-95, 2022. https://doi.org/10.17705/1jais.00719

[29] R. Raman, R. Aljafari, V. Venkatesh, and V. Richardson, "Mixed-methods research in the age of analytics, an exemplar leveraging sentiments from news articles to predict firm performance," *International Journal of Information Management*, vol. 64, p. 102451, 2022. https://doi.org/10.1016/j.ijinfomgt.2021.102451

[30] M. O. Aliyu, *Behavioural impediments in realising decent academic citizenship: Evidence from Nigeria's higher education sector. In C. G. Iwu (Ed.), Academic citizenship in African higher education: Towards a socioeconomic development agenda.* US: Palgrave Macmillan, 2024.

[31] S. Gupta *et al.*, "Integration of pool scrubbing research to enhance Source-Term calculations (IPRESCA) project–Overview and first results," *Nuclear Engineering and Design*, vol. 404, p. 112189, 2023. https://doi.org/10.1016/j.nucengdes.2023.112189

[32] M. Kuciapski, "Interaction enjoyment perspective in explaining technology acceptance: A study of employees' acceptance of M-learning," in *AMCIS 2020 Proceedings (pp. 1749–1759). Association for Information Systems*, 2020.

[33] T. Alade, R. Welch, A. Robinson, and L. Nichol, "Mobile learning for just-in-time knowledge acquisition in a workplace environment," in *2020 3rd International Conference on Information and Computer Technologies (ICICT) (pp. 198-204). IEEE*, 2020.

[34] H. Arksey and L. O'malley, "Scoping studies: Towards a methodological framework," *International Journal of Social Research Methodology*, vol. 8, no. 1, pp. 19-32, 2005. https://doi.org/10.1080/1364557032000119616

[35] D. Levac, H. Colquhoun, and K. K. O'brien, "Scoping studies: Advancing the methodology," *Implementation Science*, vol. 5, p. 69, 2010. https://doi.org/10.1186/1748-5908-5-69

[36] M. O. Aliyu, B. P. Maphala, and C. G. Iwu, "Mapping the models of employee satisfaction: A bibliometric analysis of organisational climate and interactive demographics," *Administrative Sciences*, vol. 16, no. 5, p. 217, 2026. https://doi.org/10.3390/admsci16050217

[37] J. Vaiopoulou, S. Papadakis, E. Sifaki, D. Stamovlasis, and M. Kalogiannakis, "Parents' perceptions of educational apps use for kindergarten children: Development and validation of a new instrument (PEAU-p) and exploration of parents' profiles," *Behavioral Sciences*, vol. 11, no. 6, p. 82, 2021. https://doi.org/10.3390/bs11060082

[38] B. A. Al Fehaidi and M. A. Khan, "Towards employee perceived satisfaction in using Citrix workspace technology," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 4, pp. 194-201, 2022. https://doi.org/10.14569/IJACSA.2022.0130423

[39] M. O. Aliyu and B. P. Maphala, "Understanding the mind of the modern workers through the short Dark Tetrad and Light Triad traits: The good, the bad and the situational," *Social Sciences & Humanities Open*, vol. 13, p. 102816, 2026. https://doi.org/10.1016/j.ssaho.2026.102816

[40] O. S. Aboderin and D. W. Govender, "Predictors of academic performance of distance e-learners in a Nigerian University," *International Journal of Research in Business and Social Science (2147-4478)*, vol. 12, no. 1, pp. 296-307, 2023. https://doi.org/10.20525/ijrbs.v12i1.2296

[41] I. A. Abu-AlSondos, A. A. Salameh, A. F. Alkhwaldi, A. S. Mushtaha, M. Shehadeh, and A. a. Al-Junaidi, "Evaluating mobile e-learning systems acceptance: An integrated model," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 16, pp. 30-47, 2023. https://doi.org/10.3991/ijim.v17i16.42679

[42] J. M. Al Ahbabi and S. Z. Ahmad, "Using health-care technology to manage COVID-19 pandemic: A case of Al-Ain city hospital, UAE," *Emerald Emerging Markets Case Studies*, pp. 1-18, 2021. https://doi.org/10.1108/EEMCS-10-2020-0356

[43] M. A. Alkhateeb and R. A. Abdalla, "Factors influencing student satisfaction towards using learning management system moodle," *International Journal of Information and Communication Technology Education*, vol. 17, no. 1, p. 16, 2021. https://doi.org/10.4018/IJICTE.2021010109

[44] T. A. Bentley *et al.*, "Psychosocial influences on psychological distress and turnover intentions in the workplace," *Safety Science*, vol. 137, p. 105200, 2021. https://doi.org/10.1016/j.ssci.2021.105200

[45] K. Brage *et al.*, "Reporting radiographers in CT and MRI: A literature review with a systematic approach," *Radiography*, vol. 31, no. 2, p. 102901, 2025. https://doi.org/10.1016/j.radi.2025.102901

[46] G. Cervini, J. Jung, and K. Gkritza, "Temperature and electric vehicle adoption: A ZIP code-level analysis in the US," *Transportation Research Part D: Transport and Environment*, vol. 136, p. 104435, 2024. https://doi.org/10.1016/j.trd.2024.104435

[47] O. C. Edo *et al.*, "Fintech adoption dynamics in a pandemic: An experience from some financial institutions in Nigeria during COVID-19 using machine learning approach," *Cogent Business & Management*, vol. 10, no. 2, p. 2242985, 2023. https://doi.org/10.1080/23311975.2023.2242985

[48] A. Emmett, B. Kent, A. James, and J. March-McDonald, "Experiences of health professionals towards using mobile electrocardiogram (ECG) technology: A qualitative systematic review," *Journal of Clinical Nursing*, vol. 32, no. 13-14, pp. 3205-3218, 2023. https://doi.org/10.1111/jocn.16434

[49] J. Halbert *et al.*, "Social media and cardiovascular disease," *Journal of Organizational Psychology*, vol. 23, no. 2, pp. 17-26, 2023. https://doi.org/10.33423/jop.v23i2.6160

[50] H.-S. Hsiao, S.-Y. Lu, T.-L. Chang, and C.-S. Lee, "Using mobile technology acceptance model to explore the satisfaction and continuous use of live streaming for training," *Interactive Learning Environments*, vol. 33, no. 2, pp. 1298-1321, 2025. https://doi.org/10.1080/10494820.2024.2369875

[51] J. Jabbar, S. I. Malik, G. AlFarsi, and R. M. Tawafak, *The impact of WhatsApp on employees in higher education. In Recent Advances in Intelligent Systems and Smart Applications*. Cham: Springer International Publishing, 2020.

[52] E. Kumoji, O. Oyenubi, A. Rhoades, J. Cassaniti, F. Rariewa, and S. Ohkubo, "Understanding the audience for a digital capacity-building platform for micro-retailers in Nairobi, Kenya: A latent class segmentation analysis," *Social Marketing Quarterly*, vol. 28, no. 2, pp. 147-168, 2022. https://doi.org/10.1177/15245004221097715

[53] A. Marcus-Quinn and T. Hourigan, "Digital inclusion and accessibility considerations in digital teaching and learning materials for the second-level classroom," *Irish Educational Studies*, vol. 41, no. 1, pp. 161-169, 2022. https://doi.org/10.1080/03323315.2021.2022519

[54] N. Mwalukasa, "Factors influencing mobile phone use for accessing academic information in Tanzania," *Qualitative and Quantitative Methods in Libraries*, vol. 11, no. 2, pp. 229-248, 2022.

[55] M. Aliyu and B. Maphala, "Post-COVID technostress in remote and hybrid work: A bibliometric analysis (2020–2025)," *International Journal of Management, Accounting and Economics*, vol. 13, no. 7, pp. 890-911, 2026. https://doi.org/10.22034/ijmae.2026.573378.1945

[56] D. Aghimien, C. O. Aigbavboa, D. W. Chan, and E. I. Aghimien, "Determinants of cloud computing deployment in South African construction organisations using structural equation modelling and machine learning technique," *Engineering, Construction and Architectural Management*, vol. 31, no. 3, pp. 1037-1060, 2024. https://doi.org/10.1108/ECAM-05-2022-0464

[57] H. M. Combrink, V. Marivate, and B. Masikisiki, "Technology-enhanced learning, data sharing, and machine learning challenges in South African education," *Education Sciences*, vol. 13, no. 5, p. 438, 2023. https://doi.org/10.3390/educsci13050438

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 9: 174-189, 2026
DOI: 10.55214/2576-8484.v10i9.13568

[58] M. C. Teffo, K. Sigama, and F. Kanobe, "A contextualised model of the use of agile technique in South African software development team," *South African Journal of Information Management*, vol. 25, no. 1, p. 1617, 2023. https://hdl.handle.net/10520/ejc-info_v25_n1_a1617

[59] M. Aliyu and B. Maphala, "Realising decent academic citizenship behaviour in Nigeria's higher education sector: The role of servant leadership and psychological ownership," *Acta Universitatis Danubius. Œconomica*, vol. 21, no. 6, pp. 133-149, 2025.