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PAPER

Mobile Learning and Competency-Based Education in TVET: A Bibliometric Synthesis

Wagino Wagino[1] (✉), Volodymyr Tymofiiv[2], Ken Polin[3], Nuzul Hidayat[1], Muslim Muslim[1], Rahmat Desman Koto[1]

[1]Universitas Negeri Padang, Padang, Indonesia

[2]Technical University of Košice, Košice, Slovakia

[3]Queensland University of Technology, Brisbane, Australia

wagino@ft.unp.ac.id

ABSTRACT

Mobile learning has emerged as a transformative approach in education, yet a comprehensive synthesis of its application in Technical and Vocational Education and Training (TVET) remains limited. This study maps the research landscape, identifies key themes, evaluates theoretical frameworks, and uncovers research gaps in mobile learning for TVET from 2020 to 2026. A Bibliometric-Systematic Literature Review (B-SLR) was conducted following PRISMA 2020 guidelines using the Scopus database (N = 600 records). Bibliometric analysis employed VOSviewer and the Bibliometrix R package; quality assessment used MMAT 2018. Systematic review of 58 included studies revealed that technology-enhanced pedagogical approaches generally improved learning outcomes in TVET, although effect sizes varied by intervention type and context. VR/AR interventions showed moderate to large effect sizes (d = 0.40–0.84) with some studies reporting null findings, while gamification and LMS-based approaches demonstrated positive but design-dependent results. Nine thematic clusters were identified, with AI and smart technology among the fastest-growing. TAM and UTAUT dominated theoretical frameworks (43.1%), revealing a critical gap in learning-quality-oriented theories. A sub-analysis comparing medical-CBME studies (n = 14) with traditional TVET studies (n = 44) revealed divergent theoretical orientations and assessment challenges. Southeast Asia emerged as the dominant research region, though this concentration warrants caution in generalizing findings. Infrastructure and digital divide constituted the most frequently reported barrier, while psychomotor skills assessment frameworks represented the most TVET-distinctive unaddressed challenge. This study recommends prioritizing longitudinal research, AI integration, the development of psychomotor assessment tools, cross-cultural validation, and cost-effectiveness analysis.

KEYWORDS

quality education, competency-based learning, educational technology, workforce development, learning outcomes

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1 INTRODUCTION

Technical and Vocational Education and Training (TVET) plays a critical role in global workforce development, equipping learners with the practical competencies demanded by a rapidly evolving labour market [1]. In the context of Industry 4.0, TVET institutions face growing imperatives to integrate innovative technologies into their pedagogical processes [2]. Mobile learning, defined as learning across multiple contexts through social and content interactions using personal electronic devices, has emerged as a particularly promising approach for vocational education, facilitating authentic workplace-based learning, just-in-time skill support, and flexible access for diverse learner populations [3], [4], [5].

The COVID-19 pandemic (2020 to 2022) dramatically accelerated mobile learning adoption across educational sectors, yet simultaneously disrupted TVET institutions where laboratory practicals, workshops, and work placements constitute the curriculum core. The post-pandemic period (2023 to 2026) witnessed the maturation of these approaches, with artificial intelligence (AI), augmented reality (AR), and gamification increasingly integrated into mobile platforms in vocational education contexts. Despite this rapid expansion, no bibliometric-systematic review has specifically synthesised mobile learning integration in TVET during the educational transformation phase accelerated by COVID-19 from 2020 to 2026. Prior reviews addressed mobile learning in general higher education or ICT in TVET broadly, without comprehensively examining the specific intersection of innovative mobile learning and the TVET context during this transformative period [6], [7], [8], [9].

The exponential growth of mobile learning publications since 2020 necessitates both bibliometric mapping for landscape understanding and systematic review for analytical depth. Guo et al. [10] documented a remarkable increase in research output, peaking in 2021, with vocational-specific growth reaching 12.93% per year. This study therefore adopts the Bibliometric-Systematic Literature Review (B-SLR) framework [11], guided by five research questions:

RQ1: What are the publication trends, geographic distribution, and most influential contributors in mobile learning research for TVET (2020 to 2026)?
RQ2: What are the dominant research themes and how have they evolved?
RQ3: What theoretical frameworks and methodologies are employed?
RQ4: What mobile technologies, pedagogical approaches, and learning outcomes are reported?
RQ5: What are the main barriers, research gaps, and future directions?

2 RESEARCH METHODS

2.1 Research design

This study adopted the bibliometric-systematic literature review (B-SLR) framework developed by Marzi et al. [11] to integrate quantitative mapping of the research landscape with in-depth qualitative synthesis. This approach was selected because it enables the identification of the field's intellectual structure at a macro level through bibliometric analysis, while simultaneously systematically evaluating methodological quality and empirical findings [12]. Thus, B-SLR provides advantages over purely bibliometric reviews that only map without probing content, as well as conventional systematic reviews that are limited to evaluating individual studies without the broader scientific landscape context. The framework follows ten steps: topic selection, research question formulation, inclusion/exclusion criteria, search string development, database selection, data cleaning with inter-rater reliability, bibliometric analysis (performance analysis and science mapping), cluster identification, systematic review within identified clusters, and theory development and research agenda. Phase 1 provides the quantitative bibliometric landscape; Phase 2 provides systematic depth through PRISMA 2020-compliant selection and MMAT 2018 quality assessment [13].

2.2 Database and search strategy

Scopus was selected as the primary database due to its extensive coverage of social sciences and engineering journals and standardized metadata exports compatible with VOSviewer and Bibliometrix. Keywords were organized into three conceptual groups as presented in Table 1, yielding 600 records.

Table 1. Search keyword groups

Conceptual Group	Search Terms (Boolean OR)
Group A: Mobile Learning	"mobile learn*" OR "m-learn*" OR "mobile-assisted learn*" OR "mobile technolog*" OR "mobile device*" OR "mobile app*" OR "smartphone*" OR "ubiquitous learn*"
Group B: Vocational/ TVET	"vocational educat*" OR "vocational train*" OR "technical educat*" OR "TVET" OR "VET" OR "polytechnic" OR "community college" OR "competency-based" OR "apprenticeship"
Group C: Innovation	"innovat*" OR "technology-enhanced" OR "digital learn*" OR "blended learn*" OR "e-learn*" OR "gamif*" OR "augmented reality" OR "virtual reality" OR "artificial intelligence"

The combination of all three keyword groups using the Boolean AND operator enabled literature retrieval that simultaneously encompassed mobile learning, the TVET context, and technological innovation.

2.3 Inclusion and exclusion criteria

Inclusion and exclusion criteria were formulated to ensure conceptual consistency between mobile learning and the TVET context while maintaining the methodological quality of the analysed studies. Detailed criteria are presented in Table 2.

Table 2. Inclusion and exclusion criteria

Code	Inclusion Criteria	Exclusion Criteria
IC1/EC1	Published between 2020 and 2026	Duplicates, editorials, opinion pieces
IC2/EC2	English language	Not focused on TVET/vocational education
IC3/EC3	Peer-reviewed journal articles or conference papers	No educational outcomes
IC4/EC4	Focused on mobile learning in TVET	Inadequate methodological details
IC5	Full text accessible	–

These criteria were applied in stages following the PRISMA 2020 selection flow, enabling transparent and replicable screening.

2.4 PRISMA 2020 selection process

Selection followed the PRISMA 2020 guidelines by Page et al. [13] and was screened by two independent reviewers ($\kappa \geq 0.80$). A summary of the selection stages is presented in Figure 1.

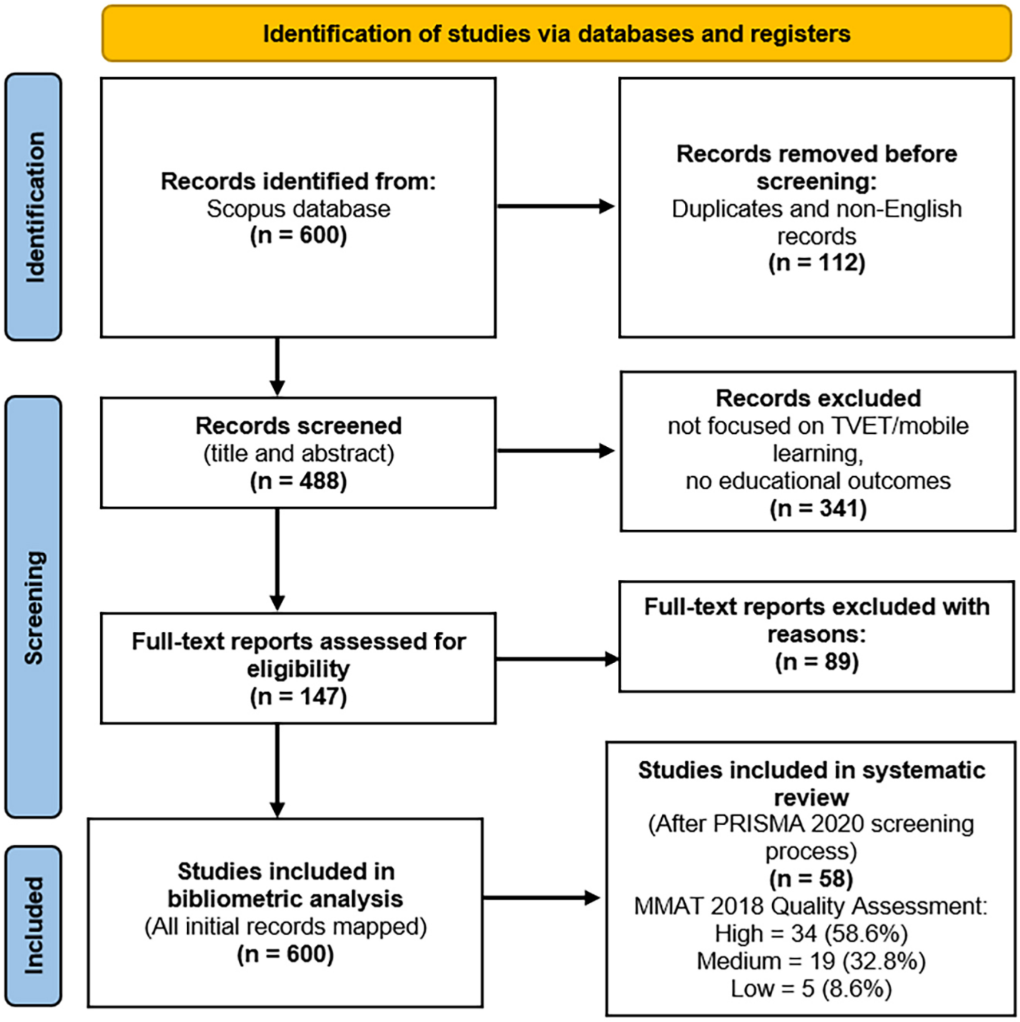

Fig. 1. PRISMA 2020 selection summary

A bibliometric analysis was conducted on all 600 initial records to map the scientific landscape at the macro level. At the same time, a systematic review of 58 studies meeting the inclusion criteria was conducted following the staged screening process. The 9.7% inclusion rate is consistent with systematic reviews in educational technology that generally report inclusion rates below 15% [14].

2.5 Quality assessment

MMAT 2018 [15] was employed: 34 studies (58.6%) rated High quality, 19 (32.8%) Medium, and 5 (8.6%) Low. Low-quality studies were not eliminated but were considered cautiously in thematic synthesis to avoid interpretive bias.

2.6 Bibliometric analysis tools

VOSviewer v1.6.20 [16] and the Bibliometrix R package [17] were used for science mapping, keyword co-occurrence, citation analysis, and co-citation analysis. The minimum occurrence threshold was set at 5 for keyword co-occurrence analysis to ensure network stability.

2.7 Data extraction and synthesis

Data extraction encompassed: authors, year, journal, country, design, sample, technology, theoretical framework, pedagogical approach, TVET domain, learning outcomes, key findings, and MMAT rating. Extraction was conducted independently by two researchers and cross-verified to enhance reliability. The coding process was performed iteratively through open coding, axial coding, and theme refinement stages. Thematic synthesis followed Braun and Clarke [18].

2.8 Ethical considerations

This research is a bibliometric and systematic literature review that focused only on journal articles and conference papers that had already been published and were publicly accessible in the Scopus database. At no point in this study did we acquire any primary data from people. The research did not include surveys, interviews, experiments, or other direct or indirect interactions with human participants. As a result, this evaluation did not need ethical clearance from an institutional review board or research ethics committee. Before being included in this synthesis, all of the papers that were analysed had previously been reviewed by their journals' independent peer reviewers and ethical reviewers. Data extraction was limited to public texts, tables, and figures. No personally identifying information was accessed or processed. The authors affirm that this review adheres to the ethical norms pertinent to secondary research synthesis, in alignment with the PRISMA 2020 principles [11] and the B-SLR framework [10].

3 RESULTS AND DISCUSSION

3.1 Bibliometric analysis results

Publication trends (RQ1). The distribution of publications by year and document type from 600 Scopus records is presented in Table 3.

Table 3. Publication distribution by year and type (N = 600)

Type	2020	2021	2022	2023	2024	2025	Total
Article	191	109	43	33	15	2	393 (65.5%)
Review	71	40	13	10	2	1	137 (22.8%)
Conf. Paper	18	14	5	1	0	0	38 (6.3%)
Book/Chapter	5	4	1	1	0	0	11 (1.8%)
Other	6	8	3	5	0	0	21 (3.5%)
Total	291	175	65	50	17	2	600

Table 3 reveals a clear surge in publications during the early phase of the COVID-19 pandemic (2020, 48.5%), followed by a gradual decline, indicating that the field has entered a post-pandemic phase of scientific consolidation. This finding is consistent with Guo et al. [10], who documented a global peak in mobile learning research in 2021, with vocational-specific growth reaching 12.93% per year.

Geographic distribution (RQ1). The top five contributing countries in mobile learning research for TVET are presented in Table 4.

Table 4. Geographic distribution of contributing countries

Rank	Country	Research Strength	Key Findings
1	Indonesia	Dominant in ML TVET	Most productive ASEAN contributor; strong PBL-elearning research
2	Malaysia	Strong TVET research tradition	Strongest collaboration with Indonesia; UTAUT validation studies
3	China	General ML leader	TVET-specific studies emerging; vocational reform research
4	USA	Global ML leader	Strong theoretical frameworks; limited TVET focus
5	Saudi Arabia	Rapidly developing trajectory	Middle East TVET digital transformation research

A notable finding from Table 4 is the very strong research concentration in Southeast Asia, as confirmed by Abd Majid et al. [19] in an analysis of 7,512 articles. This concentration warrants caution in generalizing the findings, particularly given that Africa and Latin America remain significantly underrepresented.

Leading journals (RQ1). The distribution of leading journals serving as publication venues for mobile learning research in the TVET context is presented in Table 5.

Table 5. Leading journals in ML and TVET research

Journal	Quartile	Focus	TVET Relevance
Computers & Education	Q1 (IF: 8.5)	EdTech	High-impact ML studies
Education & Info. Technologies	Q1	EdTech/ICT	Highest ML content
iJIM	Q2	Mobile learning	Primary specialized venue
J. Technical Ed. & Training	Q2	TVET	Most popular TVET venue
TEM Journal	Q2	Technology & Education	Vocational educational technology
J. of Educators Online	Q2	Online education	E-learning in VET context

As shown in Table 5, this field of study has gained recognition from the academic community across various journal quality tiers, from high-impact Q1 journals to specialized Q2 venues that consistently publish research at the intersection of mobile learning and TVET.

Keyword co-occurrence thematic clusters (RQ2). Keyword co-occurrence analysis using VOSviewer across 600 documents identified nine thematic clusters. The network visualization of these clusters is presented in Figure 2.

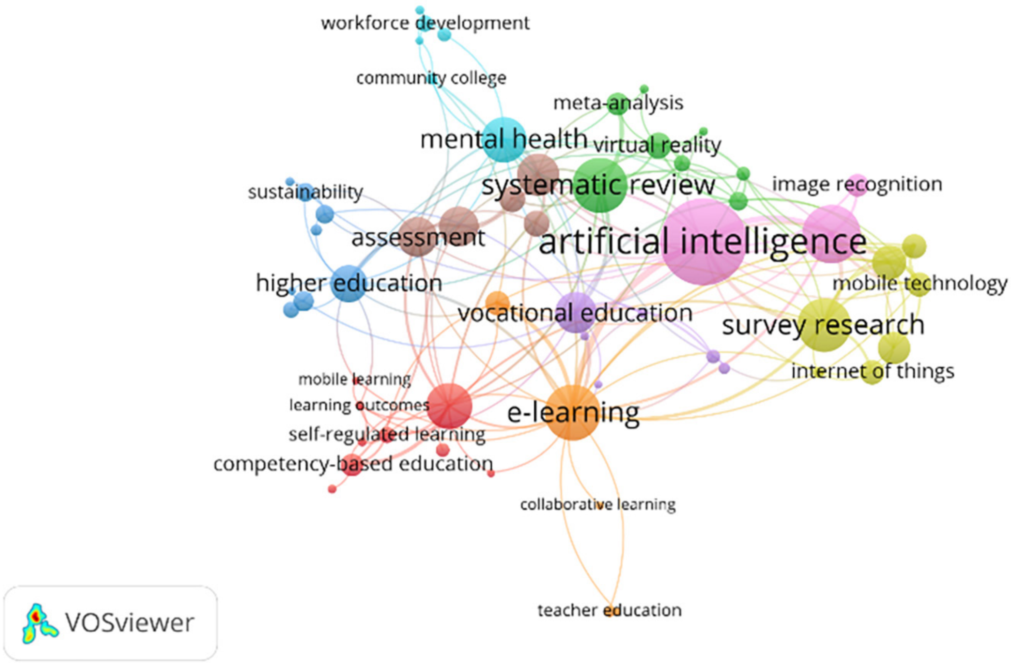

Fig. 2. VOSViewer network analysis

The detailed composition of each thematic cluster, including key terms and research directions, is summarized in Table 6.

Table 6. Thematic clusters from keyword co-occurrence analysis

No.	Cluster	Key Terms	Research Direction
1	AI & Smart Technology (Red/Pink)	artificial intelligence, image recognition, internet of things	Largest node; dominant and fastest-growing theme across the corpus
2	E-learning & Delivery Modalities (Orange)	e-learning, collaborative learning, teacher education	Major delivery platform connecting vocational and pedagogical clusters
3	Research Methodology (Green)	systematic review, meta-analysis, bibliometric	Reflects methodological maturity of the field
4	Vocational Education Context (Yellow-Orange)	vocational education, competency-based education	Institutional context anchoring TVET-specific research
5	Mobile Learning & Outcomes (Red-Pink)	mobile learning, learning outcomes, self-regulated learning	Connecting node linking pedagogy with technology
6	Higher Education & Assessment (Blue)	higher education, assessment, sustainability	Evaluative and institutional quality dimensions
7	Health & Well-being (Brown/Cyan)	mental health, virtual reality	Emerging intersection of immersive tech and learner well-being
8	Survey & Mobile Technology (Yellow-Green)	survey research, mobile technology	Methodological and technological instrumentation cluster
9	Workforce Development (Cyan/Light Blue)	workforce development, community college	Vocational pathway and workforce readiness focus

Table 6 reveals that the "AI & Smart Technology" cluster occupies the most prominent position with "artificial intelligence" as the largest node in the network, reflecting the accelerating integration of AI across mobile learning and TVET research domains. The "E-learning & Delivery Modalities" cluster serves as a major hub connecting vocational education contexts with pedagogical approaches [20]. Notably, the "Mobile Learning & Outcomes" cluster functions as a bridging node linking learning outcomes and self-regulated learning with technology-related clusters, demonstrating the field's growing emphasis on evidence-based integration. The presence of the "Research Methodology" cluster (systematic review, meta-analysis, and bibliometric) indicates the methodological maturation of the field. The "Vocational Education Context" and "Workforce Development" clusters confirm the institutional anchoring of research within TVET-specific settings. The emergence of the "Health & Well-being" cluster, connecting mental health with virtual reality, signals a new research trajectory exploring immersive technologies for learner well-being.

3.2 Systematic review results

Overview of 58 included studies. The distribution of 58 studies by research design, MMAT quality rating, and primary domain is presented in Table 7.

Table 7. Studies by research design (N = 58)

Research Design	Count (%)	MMAT High	Primary Domain
Experimental/quasi-experimental	18 (31.0%)	14	Engineering, automotive, health, IT
Survey/correlational	15 (25.9%)	9	General TVET, business, agriculture
Mixed methods	10 (17.2%)	6	Engineering, tourism, nursing
SLR/meta-analysis	4 (6.9%)	2	Cross-domain synthesis
R&D/design-based	6 (10.3%)	3	LMS development, app design
Qualitative/conceptual	5 (8.6%)	3	TVET policy, teacher perspectives

Table 7 shows the dominance of quantitative designs (56.9%), with the majority of studies rated as high quality (58.6%), providing a sufficiently robust evidence base for findings synthesis. Engineering/automotive and health were the two most researched TVET sectors.

A comprehensive synthesis of all 58 included studies is presented in two complementary tables. Table 8 summarizes the methodological profile of each study, encompassing research design, sample characteristics, context, and technology employed. Table 9 presents the key empirical findings from each study and the MMAT 2018 quality rating for each study. Together, these two tables provide a complete overview of the evidence base while maintaining readability. The Journal column has been omitted as full publication details are available in the References section. Study codes (S1–S58) are used consistently throughout both tables and the manuscript narrative to facilitate cross-referencing.

Table 8. Study identity and methodology of 58 included studies

No.	Author	Design	Sample/Context	Technology
S1	Wagino et al. [21]	R&D + PLS-SEM	n = 50, Heavy Equip., Indonesia	PBL + E-Learning
S2	Maksum et al. [22]	Experimental	n = 44, Automotive, Indonesia	PBL + E-Learning
S3	Wagino et al. [23]	CB-SEM	n = 80, Automotive, Indonesia	PBL + E-Learning
S4	Dahalan et al. [24]	SLR	k = 17, TVET gamification	Gamification (Moodle, H5P)
S5	Chiang et al. [25]	SLR	AR in vocational training	Augmented Reality
S6	Syauqi et al. [26]	Survey	Vocational stud., Indonesia	Online Learning (LMS)
S7	Jayalath and Esichaikul [27]	Mixed	TVET students, blended	Gamification + Blended
S8	Portelli et al. [28]	Meta-analysis	VR vs apprenticeship, surgery	VR Training
S9	Sangsawang [29]	Design-based	Vocational ed., Thailand	Online + SRL
S10	Rabiman et al. [30]	R&D	Vocational ed., Indonesia	LMS (Moodle)
S11	Zheng et al. [31]	Cross-sectional	Medical stud., comp-based	Flipped Learning
S12	Lavrentieva et al. [32]	Review + case	Welders' training, Ukraine	VR/AR Simulation
S13	Antonietti et al. [33]	Survey + SEM	n = 369, Voc. teachers, Italy	Digital Comp. + TAM
S14	Cattaneo et al. [34]	Large survey	n = 6775, Voc. teachers, Swiss	Digital Competence
S15	Beer et al. [35]	Qual. review	TVET systems, Europe	Tech-driven Changes
S16	George et al. [36]	Mixed	Nigerian TVET institutions	Industry 4.0 Tech.
S17	Chatterjee et al. [37]	Quant. survey	n = 387, Voc. stud., India	UTAUT
S18	Ye et al. [38]	Survey	n = 1012, Chinese voc. stud.	Short Video/Digital
S19	Radianti et al. [39]	SLR	k = 38, VR in higher ed.	Immersive VR
S20	Baticulon et al. [40]	Cross-sectional	n = 3670, Med. stud., Philippines	Online Barriers
S21	Mao et al. [41]	SLR	k = 34, VR surgical training	Immersive VR
S22	Alamri et al. [42]	SLR	Blended learning models	Blended Learning
S23	Leong et al. [43]	Review	Microlearning trends	Microlearning
S24	De Ponti et al. [44]	Survey	n = 184, Med. stud., Italy	VR Medical Training
S25	El-Sofany et al. [45]	Experimental	Higher ed., Saudi Arabia	Mobile Learning
S26	Pedram et al. [46]	SEM	n = 238, Mine rescuers, Australia	Immersive VR Safety
S27	Silic et al. [47]	Experimental	n = 2294, Security training	Gamification
S28	Zheng et al. [48]	Quasi-exper.	Medical stud., flipped class	Flipped + SRL
S29	Abdul Bujang [49]	Case study	Malaysian ed. institutions	Digital Learning (E4.0)
S30	Dias et al. [50]	Predictive	LMS log data, COVID-19	DeepLMS (AI)
S31	Ho et al. [51]	Survey + SEM	n = 587, Vietnamese univ.	E-learning Adoption

(Continued)

Table 8. Study identity and methodology of 58 included studies *(Continued)*

No.	Author	Design	Sample/Context	Technology
S32	Egielewa et al. [52]	Mixed	Nigerian higher ed.	Online Learning
S33	Bird et al. [53]	Quasi-exper.	n > 100K, Comm. college, USA	Online vs In-Person
S34	Venkatesh et al. [54]	Survey	n = 378, Med. stud., blended	Blended E-Learning
S35	Zhang & West [55]	Design-based	Professional development	Microlearning
S36	Abbasi et al. [56]	Survey	n = 382, Med. stud., Pakistan	E-learning (COVID)
S37	Lerner et al. [57]	Usability	Emergency simulation	Multi-user VR
S38	Goulart et al. [58]	Lit. review	Digital transformation	Digital Skills/I4.0
S39	Mutohhari et al. [59]	Survey	Vocational ed., Indonesia	21st Century Skills
S40	Indrawati et al. [60]	Policy analysis	Indonesian voc. & higher ed.	TVET Policy
S41	Ana et al. [61]	Content analysis	Vocational ed., Indonesia	Expert Sys./Practicum
S42	McGrath et al. [62]	Lit. review	TVET in Africa	VET Systems
S43	Li et al. [63]	Lit. review	International TVET transfer	VET Transfer
S44	McGrath & Powell [64]	Review	Skills development	Skills/Emerging
S45	Hall et al. [65]	Review	CBME, COVID-19	Online Training
S46	Hall et al. [66]	Evaluation	CBME programs	Competency Assess.
S47	Branfield Day [67]	Focus groups	Medical residents	Assessment & Feedback
S48	Richardson et al. [68]	Conceptual	CBME	Growth Mindset
S49	Downing et al. [69]	Survey	n = 2111, Comm. college	Active Learning
S50	Lewis et al. [70]	Practice update	Nursing ed., comp-based	CBME
S51	Stevens et al. [71]	Quasi-exper.	California comm. colleges	Career Tech. Ed.
S52	Ling et al. [72]	Mixed	Chinese voc. higher ed.	Management Reform
S53	Gill et al. [73]	Review	ChatGPT in education	Generative AI
S54	Francis et al. [74]	Review	Gen AI in higher ed.	AI in Education
S55	Wiguna et al. [75]	R&D	Vocational ed., Indonesia	Raspberry Pi Offline
S56	Pedraja-Rejas et al. [14]	SLR (PRISMA)	k = 20, ML in VET	Mobile Learn. in VET
S57	Li [76]	Quasi-exper.	Voc. certification students	Gamified Chatbot
S58	Baharin et al. [77]	Survey + SEM	n = 200, Malaysian TVET	AI Adoption (UTAUT)

Notes: SLR = Systematic Literature Review. SEM = Structural Equation Modeling. PLS-SEM = Partial Least Squares SEM. CB-SEM = Covariance-Based SEM. R&D = Research and Development.

Based on Table 8, several notable patterns were identified. LMS/e-learning platforms were the most commonly used technology (n = 16), followed by VR/immersive technologies (n = 10) and gamification (n = 6). Geographic distribution confirms the bibliometric findings, with Indonesia as the most represented country (n = 12, 20.7%). The prominence of health/medical education in the corpus (n = 14) reflects a strong competency-based education tradition in medical training, which shares pedagogical principles with TVET more broadly.

Table 9. Key findings of 58 included studies

No.	Author	Key Findings	MMAT
S1	Wagino et al. [21]	EE → LO $p = 0.050$; PBL → LO $p = 0.046$; Self-reflection mediation $p=0.003$; 70% C4+	High
S2	Maksum et al. [22]	Cohen's $d = 1.21$; Significant gains; Enhanced satisfaction & teamwork	High
S3	Wagino et al. [23]	$\beta = 0.82$(exp → qual); $\beta = 0.76$(exp → val); $\beta = 0.79$(val → sat); RMSEA = 0.041, CFI = 0.993	High
S4	Dahalan et al. [24]	Engineering & healthcare primary; Growing Asian interest since 2020	High
S5	Chiang et al. [25]	AR enhances understanding & psychomotor skills; Cost barriers persist	High
S6	Syauqi et al. [26]	Positive perceptions but connectivity issues; Practical skills gap online	Mod
S7	Jayalath and Esichaikul [27]	Gamification enhances motivation & engagement; Performance improved	High
S8	Portelli et al. [28]	VR comparable to apprenticeship; Reduced operating time	High
S9	Sangsawang [29]	Self-regulated learning framework improves vocational outcomes	Mod
S10	Rabiman et al. [30]	LMS effective; User-friendly design critical for adoption	Mod
S11	Zheng et al. [31]	Deep strategies correlated with higher achievement in CBME	High
S12	Lavrentieva et al. [32]	VR/AR effective for welding; Reduce material costs & safety risks	Mod
S13	Antonietti et al. [33]	Digital competence influences tech acceptance; Self-efficacy mediates	High
S14	Cattaneo et al. [34]	Moderate digital competence; Age & subject predict levels	High
S15	Beer et al. [35]	Continuous VET must adapt; Lifelong learning imperative	High
S16	George et al. [36]	Low I4.0 utilization; Infrastructure & training deficits	Mod
S17	Chatterjee et al. [37]	Peer influence & govt support predict technology adoption in VET	High
S18	Ye et al. [38]	Short video addiction negatively affects motivation & well-being	High
S19	Radianti et al. [39]	Design elements identified; HMD most effective	High
S20	Baticulon et al. [40]	Barriers: tech, faculty, connectivity; Digital divide critical	High
S21	Mao et al. [41]	VR effective for skill acquisition; Reduces early training risk	High
S22	Alamri et al. [42]	Personalization improves blended learning; Adaptive paths key	High
S23	Leong et al. [43]	Short-form mobile content improves knowledge retention	Mod
S24	De Ponti et al. [44]	VR maintains training during COVID; Positive perceptions	Mod
S25	El-Sofany et al. [45]	Mobile learning significantly improves outcomes; Flexibility valued	High
S26	Pedram et al. [46]	Presence → engagement → learning; SEM validated	High
S27	Silic et al. [47]	Gamification improves compliance 25%; Design-science effective	High
S28	Zheng et al. [48]	SRL mediates positive effects of flipped classroom	High
S29	Abdul Bujang [49]	High demand; Infrastructure readiness varies across institutions	Mod
S30	Dias et al. [50]	Deep learning predicts performance from LMS data; $R^2 > 0.80$	High
S31	Ho et al. [51]	Self-efficacy & facilitating conditions drive adoption	High
S32	Egielewa et al. [52]	Infrastructure gaps; Students prefer hybrid post-pandemic	Mod
S33	Bird et al. [53]	–11% completion in online shift; Equity gaps widened	High
S34	Venkatesh et al. [54]	Satisfaction: content quality, interaction, perceived usefulness	Mod
S35	Zhang & West [55]	Competency-based microlearning effective; 5-min modules optimal	Mod

(Continued)

Table 9. Key findings of 58 included studies *(Continued)*

No.	Author	Key Findings	MMAT
S36	Abbasi et al. [56]	77% negative perceptions; Prefer F2F; Infrastructure challenges	Mod
S37	Lerner et al. [57]	Multi-user VR improves teamwork training; SUS > 80	Mod
S38	Goulart et al. [58]	Skills balancing needed; Curricula adaptation required	High
S39	Mutohhari et al. [59]	Difficulties implementing 21C skills; Tech integration challenges	Mod
S40	Indrawati et al. [60]	2045 vision requires modernization; Regional digital readiness varies	High
S41	Ana et al. [61]	Digital alternatives needed for vocational practicum	Mod
S42	McGrath et al. [62]	African TVET needs digital infra; Cultural contextualization essential	High
S43	Li et al. [63]	International transfer requires context adaptation	High
S44	McGrath & Powell [64]	Digital competence as emerging priority in VET	High
S45	Hall et al. [65]	Practical tips for CBME during pandemic; Assessment adaptations	Mod
S46	Hall et al. [66]	Rapid CBME evaluation; Long-term measurement needed	Mod
S47	Branfield Day [67]	Inconsistency in CBME assessment; Standardized tools needed	Mod
S48	Richardson et al. [68]	Growth mindset aligns with competency-based education	Mod
S49	Downing et al. [69]	Fear of negative evaluation decreases with active learning	High
S50	Lewis et al. [70]	CBME updated with technology integration recommendations	Mod
S51	Stevens et al. [71]	CTE improves earnings 14%; Flexible delivery aids completion	High
S52	Ling et al. [72]	Personality-based reform improves vocational education quality	Mod
S53	Gill et al. [73]	Transformative AI effects; TVET implications emerging	High
S54	Francis et al. [74]	AI: balance innovation & integrity; Assessment reform needed	High
S55	Wiguna et al. [75]	Offline LMS addresses connectivity; Positive outcomes	Mod
S56	Pedraja-Rejas et al. [14]	Most studies experimental; Asia & Europe lead; ML improves outcomes	High
S57	Li [76]	Chatbot≈teacher-led; Outperforms non-gamified; Higher engagement	High
S58	Baharin et al. [77]	Perf. expectancy strongest; Facilitating conditions critical	High

Notes: MMAT = Mixed Methods Appraisal Tool 2018 quality rating (High/Mod/Low). Mod = Moderate. Effect sizes and statistical values are reported as stated in the original studies. d = Cohen's d; β = standardized path coefficient; R^2 = coefficient of determination; SUS = System Usability Scale.

Based on Tables 8 and 9, several notable patterns were identified across the 58-study corpus. In terms of methodology, quantitative designs predominated (56.9%), with experimental/quasi-experimental studies (31.0%) providing the strongest causal evidence, complemented by survey/correlational (25.9%) and mixed methods (17.2%) approaches. The majority of studies were rated as High quality on MMAT 2018 (34 studies, 58.6%), with 19 (32.8%) rated Medium and 5 (8.6%) rated Low, providing a sufficiently robust evidence base for thematic synthesis. LMS/e-learning platforms were the most commonly used technology (n = 16), followed by VR/immersive technologies (n = 10) and gamification (n = 6). Geographic distribution confirms the bibliometric findings, with Indonesia as the most represented country (n = 12, 20.7%). The prominence of health/medical education in the corpus (n = 14, 24.1%) reflects a strong competency-based education tradition in medical training, which shares pedagogical principles with TVET; a detailed sub-analysis comparing medical-CBME and traditional TVET studies is presented in Section "Sub-Analysis: Medical-CBME Studies vs. Traditional TVET Studies" Engineering/automotive and health were the two most researched TVET sectors, while domains such as agriculture, tourism, and creative industries remain significantly underrepresented.

Theoretical frameworks (RQ3). The distribution of theoretical frameworks employed in mobile learning TVET research, along with their frequency, relevance, and gaps, is presented in Table 10.

Table 10. Theoretical frameworks in ML TVET research

Framework	Frequency	TVET Relevance	Gap	Representative Studies
UTAUT/UTAUT2	High (n = 14)	Strong	Does not explain learning quality	S17,S58; Xue [78]
TAM	Medium (n = 11)	Strong	Needs TVET extension	S13; Muktiarni [79]
TPACK	Medium (n = 8)	Very strong	Limited TVET validation	Tunjera & Chigona [80]
Constructivism	Medium (n = 9)	Very strong	Difficult to quantify	S1,S2,S3
SAMR	Low-Medium (n = 5)	Evaluation tool	No pedagogical guidance	Caceres-Nakiche [81]
Connectivism	Emerging (n = 3)	Suits digital TVET	Lacks instruments	Chen & Chan [82]
SDT	Very low (n = 1)	High potential	Severely under-researched	–
CoI	Very low (n = 1)	Medium potential	Nearly absent in TVET	–

The critical finding from Table 10 is the dominance of technology adoption-based frameworks (TAM and UTAUT), comprising 43.1% of studies, while frameworks that directly explain learning quality, such as SDT and CoI, are nearly absent. This gap indicates that the field has been answering the question "why is technology accepted" rather than "how does technology improve learning."

Technologies and learning outcomes (RQ4). A summary of the technologies reported across the 58-study corpus, along with their effect sizes, is presented in Table 11.

Table 11. Technologies, effect sizes, and representative studies

Technology	Effect Size	N	Representative Studies
Immersive VR/AR	d = 0.40 to 0.84	k = 53	S5, S8, S12, S19, S21, S24, S26, S37
PBL + E-Learning	d = 1.21; β = 0.76 to 0.82	3	S1, S2, S3
Gamification/Chatbot	Reported significant in several studies	6	S4, S7, S27, S57
Flipped + Microlearning	d = 0.48	5	S11, S23, S28, S35
LMS (Moodle)	Consistently positive	16	S6, S9, S10, S29 to S31
AI/Adaptive	$R^2 = 0.68$	5	S30, S53, S54, S57, S58
Mobile Offline	Initial results show improvement	1	S55

Table 11 shows that immersive VR/AR and PBL + E-Learning integration yielded the strongest effect sizes, although the d = 1.21 value for PBL + E-Learning requires cautious interpretation given the limited sample size (n = 44). Another notable finding is that gamified chatbots achieved results comparable to those of face-to-face instruction (S57), opening up scalability opportunities in the TVET context.

Barriers and gaps (RQ5). Ten major barrier categories identified from the 58-study corpus, along with their supporting studies, are presented in Table 12.

Table 12. Barrier framework with supporting studies

No.	Barrier	Description	Supporting Studies
1	Infrastructure/digital divide	Poor ICT, limited connectivity	S6, S16, S20, S29, S32, S36, S55
2	Teacher readiness/TPACK	Low competence, resistance	S13, S14, S39; Criollo-C [83]
3	Cost & sustainability	High implementation costs	S5, S16; Maatuk [84]
4	Cultural barriers	Resistance to digital change	S42, S43
5	Policy gaps	Inadequate regulatory frameworks	S40, S44
6	Pedagogical assessment	Practical skills online	S6, S9, S24, S45
7	Connectivity	Rural/remote TVET	S20, S32, S36, S55
8	Technology resistance	Student/teacher reluctance	S17, S18
9	Workload	Additional preparation time	S14, S15
10	Psychomotor evaluation	No mobile assessment framework	S5, S8, S12 (critical gap)

Two critical findings emerge from Table 12. First, infrastructure and the digital divide are the most frequently reported barriers, which is ironic given that the region with the highest research productivity (Southeast Asia) faces them most acutely. Second, psychomotor evaluation (Barrier 10) is the most TVET-distinctive challenge, as none of the 58 studies identified an adequate mobile assessment framework for hands-on skills.

Sub-Analysis: Medical-CBME Studies vs. Traditional TVET Studies. Given that 14 of 58 included studies (24.1%) originate from medical/health education contexts employing competency-based medical education (CBME) approaches, a sub-analysis was conducted to examine whether findings differ systematically between medical-CBME studies and traditional TVET studies. This distinction is important because, although both domains share competency-based pedagogical principles, their institutional contexts, assessment traditions, and infrastructure conditions differ substantially. No published study has directly compared technology-enhanced learning outcomes between CBME and traditional TVET, making this sub-analysis a novel contribution.

The 58 studies were classified into two sub-groups: (a) Medical-CBME studies (n = 14: S8, S11, S20–S28, S33–S37, S45–S50), encompassing surgical training, nursing education, and clinical competency assessment; and (b) Traditional TVET studies (n = 44: all remaining studies), encompassing engineering, automotive, IT, agriculture, tourism, and general vocational education contexts. The comparative results are presented in Table 13.

Table 13. Comparative sub-analysis: Medical-CBME vs. Traditional TVET studies

Dimension	Medical-CBME (n = 14)	Traditional TVET (n = 44)
Dominant Design	Quasi-experimental (42.9%); SLR/meta-analysis (28.6%)	Survey/correlational (29.5%); Experimental (27.3%); Mixed methods (20.5%)
MMAT Quality	High: 71.4%; Medium: 28.6%; Low: 0%	High: 54.5%; Medium: 34.1%; Low: 11.4%
Primary Technology	VR/simulation (57.1%); Flipped learning (21.4%); Online/LMS (21.4%)	LMS/e-learning (34.1%); Gamification (13.6%); VR/AR (11.4%); AI (11.4%)
Effect Sizes	VR: d = 0.40–0.84 (S8, S19, S21); Flipped: d = 0.48 (S11, S28)	PBL-E: d = 1.21 (S2; note: small sample); Gamification: significant (S4, S7, S27, S57); VR: d = 0.40–0.84 (S5, S12, S26)
Theoretical Framework	CBME/milestones (64.3%); Constructivism (14.3%); SRL (14.3%)	TAM/UTAUT (52.3%); Constructivism (15.9%); TPACK (13.6%)
Primary Barrier	Assessment standardization; Faculty development; Rapid curriculum change	Infrastructure/digital divide; Teacher readiness; Cost sustainability
Psychomotor Assessment	EPA and milestone frameworks available but digital adaptation limited (S45–S47)	No adequate mobile assessment framework identified (critical gap)
Geographic Concentration	North America (42.9%); Europe (28.6%); Asia (28.6%)	Southeast Asia (47.7%); Europe (20.5%); Middle East (13.6%)

Table 13 reveals several important distinctions between the two sub-groups. First, medical-CBME studies demonstrate higher overall methodological quality (71.4% rated High on MMAT vs. 54.5% for traditional TVET), likely reflecting the longer tradition of evidence-based research in medical education. This finding is consistent with Imanipour et al. [85], who documented the robust evidence base for competency-based approaches in health education. Second, the technological focus differs markedly: medical-CBME studies predominantly employ VR/simulation for procedural skill training. In contrast, traditional TVET studies show greater technological diversity, with LMS/e-learning platforms being the most common technology. Bödding et al. [86], in their meta-analysis of mixed reality in VET (k = 53), confirmed that effect sizes for VR/AR are comparable across medical and technical vocational contexts (behavioural d = 0.40; cognitive d = 0.84), suggesting that the technology's effectiveness may transfer across domains.

Third, and most critically, the theoretical frameworks diverge substantially. Traditional TVET studies are dominated by technology adoption models (TAM/UTAUT, 52.3%), which explain acceptance but not learning quality. In contrast, medical-CBME studies employ competency-based and learning-focused frameworks (CBME/milestones, 64.3%), providing richer explanatory power for pedagogical outcomes. This pattern suggests that traditional TVET research could benefit from adopting more learning-oriented theoretical approaches, as advocated by Naveed et al. [87].

Fourth, barriers differ in nature: medical-CBME studies primarily face challenges with assessment standardization within well-resourced institutions, while traditional TVET studies confront infrastructure and digital divide barriers in resource-constrained contexts. Kablitz et al. [88] demonstrated that even in well-resourced German vocational schools, VR implementation faces challenges, including motion sickness and comparable (but not superior) knowledge gains versus conventional instruction, indicating that technology adoption barriers extend beyond infrastructure alone.

The psychomotor assessment gap represents the most critical divergence: medical education has established frameworks (EPAs, milestones) that, while imperfect, provide a foundation for digital adaptation, whereas traditional TVET lacks any equivalent mobile assessment framework for hands-on skills. This finding reinforces the urgent need to develop a psychomotor assessment framework, identified in Section "Barriers and gaps (RQ5)" as a priority research agenda.

These sub-analysis findings should be interpreted cautiously, given that the medical-CBME studies were included based on shared competency-based pedagogical principles rather than the traditional TVET definition. Nevertheless, the cross-domain comparison provides valuable insights for TVET researchers, particularly regarding the potential transfer of competency-based assessment frameworks and learning-oriented theoretical models from medical education to vocational training contexts.

4 DISCUSSION

4.1 Key findings

The B-SLR of 600 records, filtered to 58 selected studies, demonstrates consistent evidence patterns indicating that technology-enhanced pedagogical approaches can improve learning outcomes in the TVET context. However, effect sizes exhibit significant variability across intervention types, research contexts, and methodological designs. This discovery builds on what Crompton and Burke [6] found in general higher education, where they saw comparable favourable trends.

The most compelling and resilient evidence foundation arises from immersive VR/AR therapies. The effect sizes reported in meta-analyses that included multiple studies in the corpus (S5, S8, S19, S21) ranged from $d = 0.40$ to 0.84 across different learning outcome characteristics. Bödding et al. [86] conducted an independent meta-analysis of 53 VR/AR studies in VET and found results consistent with these findings. They found that the impacts on behaviour ($d = 0.40$), cognition ($d = 0.84$), and affect ($d = 0.65$) were all significant. Nevertheless, the results are not consistently favourable. Kablitz et al. [88] found that immersive VR training in German vocational schools yielded knowledge gains equivalent to, though not better than, those achieved via traditional instruction, while also noting motion sickness as a significant adverse effect. Kim et al. [89] also found that VR made practical gardening instruction more engaging, although they noted increased cognitive load. These mixed findings suggest that VR effectiveness is contingent upon implementation design, subject domain, and learner characteristics.

Gamification strategies were identified as relevant in many studies (S4, S7, S27, S57). Weng et al. [90] found that gamification using augmented reality (AR) significantly enhanced psychomotor learning outcomes among Taiwanese vocational electronics students. However, there were no significant effects in cognitive or emotional domains. Hosseini et al. [91] found that gamified chatbots performed as well as face-to-face training (S57), suggesting they may be used on a larger scale. Nonetheless, Silic and Lowry [47] observed that the impact of gamification can depend on its design, leading to a 25% increase in compliance training when certain design-science concepts are applied (S27). Overall, these results show that gamification may be engaging and motivating, but its effectiveness is contingent upon implementation design and the specific vocational domain in which it is applied.

Several studies (S1, S2, S3) showed that combining PBL with e-learning in vocational education was effective, with high path coefficients ($\beta = 0.76$-0.82) and substantial learning gains. Given the small sample size (n = 44), the effect size of d = 1.21 reported in S2 warrants cautious interpretation, as small samples are known to inflate effect size estimates. Tan et al. [92], discovered that project-based blended learning utilising an LMS platform greatly enhanced Chinese vocational students' (n = 90) digital marketing skills and team spirit. This finding partially corroborates the PBL-E evidence base. The convergent data from PBL-E research are encouraging, but they need to be replicated with larger samples and across a wider range of TVET fields to demonstrate their generalizability. Liu and Pasztor's meta-analytic evidence that SMD = 0.640 for PBL's impact on critical thinking is consistent with the direction of these results [93].

Flipped learning with microlearning had a d = 0.48 (S11, S28), which is in line with Zhou [94], who found that it helped vocational learners. Zhang and West [55] showed that competency-based microlearning, delivered in 5-minute courses, helped people grow professionally (S35). These approaches appear most effective for the theoretical components of TVET curricula; however, their applicability to practical and psychomotor skill instruction remains insufficiently investigated.

The most frequent type of technology used was LMS-based techniques (n = 16), which consistently yielded good results (S6, S9, S10, S29–S31). Govender [95] stressed that user-friendly design is critical for adoption in work settings (S10). Dias et al. [50] showed that deep learning algorithms can accurately estimate how well students would do based on LMS log data with $R^2 > 0.80$ (S30). Egielewa et al. [52] and Abbasi et al. [56] found that in certain situations, students preferred hybrid or face-to-face training over entirely online delivery (S32, S36). This indicates that LMS effectiveness is context-dependent.

Only five studies (S30, S53, S54, S57, S58) examine AI-integrated mobile learning, yet this is the fastest-growing group in the bibliometric analysis. Baharin et al. [77] examined UTAUT for AI adoption in Malaysian TVET (S58), while Gill et al. [73] discussed how generative AI may affect education in the future (S53). Empirical evidence for AI integration in TVET remains limited, standing in sharp contrast to the rapid growth identified in the keyword co-occurrence analysis. This disparity underscores the urgency of targeted empirical research in this area.

This evidence covers a wide range of research methods across all technological categories, such as experimental (S2, S25, S27, S28, S33, S51), structural equation modelling (S1, S3, S13, S17, S26, S31), meta-analytic synthesis (S4, S5, S8, S19, S21, S22), and systematic review (S56). Donthu et al. [96] argue that this variety of methods strengthens the results by triangulating evidence. However, it also creates problems with heterogeneity, which are addressed in Section 4.6.

The surge in publications from 2020 to 2021 is consistent with findings by Guo et al. [10] and Kaisara and Bwalya [97], who documented a worldwide acceleration of mobile learning research during the pandemic. The sub-analysis presented in Section 3.2.5 reveals substantial divergences between medical-CBME and conventional TVET research, particularly with respect to theoretical frameworks and assessment methods. These divergences carry direct implications for how findings from the two sub-domains should be synthesised and applied.

4.2 Theoretical implications

The predominance of TAM/UTAUT (43.1%) engenders a deficiency in assessing learning quality. This result is in line with Naveed et al.'s [87] systematic review, which found a similar trend in mobile learning research in general. It is also supported by Xue et al.'s [78] study, which found that UTAUT was the most commonly used method in higher education, but did not detail its effectiveness as a teaching tool. These adoption-based frameworks elucidate the factors that affect technology acceptance; however, they fail to illuminate how technology significantly improves learning processes and outcomes adequately. Valencia-Arias et al. [98] in their PRISMA 2020 review also confirmed that research on the adoption of mobile learning must go beyond models of technological acceptability and examine more closely how it affects teaching.

The constructivist foundation employed in selected studies (S1, S2, and S3) offers a more learner-centred theoretical alternative, placing cognitive engagement and knowledge construction at the forefront of analysis. Tunjera and Chigona [80] support the TPACK method, which clearly combines technical, pedagogical, and content knowledge. This makes it particularly useful in the TVET setting, as these three areas interact in complex ways. Caceres-Nakiche et al. [81] also address the SAMR model, which provides a useful framework for evaluating the level of technology integration in instructional settings, yet offers insufficient pedagogical guidance for translating integration levels into improved learning outcomes. There is an urgent need for an integrated framework that combines adoption models (UTAUT), learning theories (constructivism, TPACK), and motivational theories (SDT) to provide a complete model that explains both usage and effectiveness. Chen and Chan [82] illustrated the promise of connectivism as an alternative paradigm appropriate for the digital TVET setting, while its measuring tools require further refinement.

4.3 Practical implications

The synthesis of 58 studies yields several evidence-based practical recommendations for TVET practitioners and policymakers. LMS integration combined with PBL emerges as the most robustly supported pedagogical approach across the corpus (S1, S2, S3, S6, S9, S10). VR/AR interventions demonstrate particularly high effectiveness for cognitive skill development, with effect sizes reaching d = 0.84 (S8, S19, S21, S26), though their deployment requires adequate institutional infrastructure. Gamification-based approaches offer scalable engagement potential across diverse TVET domains (S4, S7, S27, S57). Teacher professional development warrants treatment as a prerequisite rather than an optional component of technology integration programmes (S13, S14, S39), a position reinforced by Criollo-C et al. [83], who identified instructor readiness as a primary determinant of successful mobile technology adoption. For institutions operating under constrained infrastructure conditions, offline-capable solutions represent a viable alternative pathway (S55). Muktiarni et al. [79] further noted that technology readiness among vocational learners varies considerably across individual profiles, suggesting that implementation strategies should be calibrated to user readiness rather than applied uniformly.

Bibliometric findings indicate that the Southeast Asian region leads in research productivity, as confirmed by Fam et al. [99] in a Scopus bibliometric analysis of vocational education research in the region. However, paradoxically, this region also faces the most severe implementation barriers, including digital infrastructure gaps [84]. This condition demands translational work bridging research productivity and practical implementation in the field, particularly given that Hassan et al. [8] had already identified similar gaps in their systematic review of ICT for TVET.

While these recommendations are grounded primarily in Southeast Asian evidence, several pathways for transferability to European and other international TVET contexts can be identified. The VR/AR effectiveness findings, corroborated by Bödding et al. [86], whose meta-analysis drew heavily on European and North American studies, suggest that immersive technology benefits are likely to generalize across TVET systems when basic infrastructure conditions are met. For European dual-system TVET providers, the evidence on gamification (S4, S7, S27) and microlearning (S23, S35) is particularly relevant, as these approaches are well-suited to the structured apprenticeship model where theoretical and practical training components are clearly delineated. The barrier profile differs, however: whereas Southeast Asian institutions primarily face infrastructure and connectivity barriers, European institutions are more likely to encounter pedagogical resistance, data privacy regulatory constraints (e.g., GDPR implications for LMS data collection), and the challenge of integrating mobile learning within highly regulated competency-certification frameworks. Policymakers and practitioners in European TVET systems are therefore encouraged to adapt the practical recommendations from this review to their specific governance context, rather than adopting them wholesale. Collaborative action research between Southeast Asian and European TVET institutions could serve as a productive model for cross-cultural validation of mobile learning interventions, building the international evidence base that the field currently lacks.

4.4 Research agenda

A gap analysis of the 58 studies found five research needs. First, longitudinal studies are critically necessary, since practically all existing data is cross-sectional or short-term, rendering them incapable of elucidating long-term impacts; this constraint was also acknowledged by Samala et al. [7] in their bibliometric evaluation of mobile learning in higher education. Second, only five papers (S30, S53, S54, S57, S58) provide the first empirical evidence for AI-integrated mobile learning in TVET, even though our bibliometric analysis shows that the AI/Smart Learning cluster has grown the fastest since 2023. Third, the current research does not address the most TVET-specific challenge: frameworks for assessing psychomotor abilities. Fourth, given the strong geographic concentration documented by Abd Majid et al. [19] and Kaisara and Bwalya [97], cross-cultural comparative studies are needed to determine the generalizability of findings from Southeast Asian contexts to the broader global TVET landscape. Fifth, cost-effectiveness analysis is entirely absent from the evaluated literature, despite cost representing a critical constraint for TVET institutions in lower-income countries [84].

4.5 Limitations

This study has several limitations that should be considered when interpreting findings. First, using Scopus as a single database may exclude studies indexed in other databases, such as Web of Science or ERIC. However, Scopus is recognized as the most comprehensive database for the social sciences and engineering [96]. Second, English-language restrictions may introduce bias against studies from non-anglophone contexts, a limitation also acknowledged by Valencia-Arias et al. [98] in a similar review. Third, inherent biases in bibliometric analysis must be acknowledged, including citation tendencies and journal coverage. Fourth, subjectivity in thematic synthesis was minimized through inter-researcher cross-verification, but cannot be eliminated, as recommended by Marzi et al. [11] in their B-SLR guidelines. Fifth, the inclusion of health/CBME studies (S8, S11, S20 to S28, S33 to S37, S45 to S50) was based on shared competency-based pedagogical principles rather than the traditional TVET definition.

Sixth, the large geographic concentration of primary studies in Southeast Asia, especially Indonesia and Malaysia, is a significant problem that warrants further debate on how well they can be applied in other countries. Certain structural conditions make Southeast Asian TVET settings unique. For example, there are many students compared to teachers, the quality of infrastructure varies, per-capita investment in digital resources is relatively low, and the learning culture is mostly collectivist, which affects how teachers choose to teach [17]. These conditions are very different from the institutional environments common in European dual TVET systems, such as those in Germany, Switzerland, and Austria. In these systems, apprenticeship-based training is closely linked to industry, digital infrastructure is well established, and regulatory frameworks clearly govern the use of technology in vocational settings [15].

Similarly, North American community colleges and Australian vocational providers operate under distinct funding mechanisms and quality assurance frameworks that differ substantially from those of Southeast Asian institutions. Findings should therefore be applied with contextual sensitivity, particularly with respect to LMS adoption, mobile-based PBL, and gamification outcomes. Where positive results were observed in Southeast Asian contexts (e.g., S1, S2, S17, S55), the enabling conditions including student smartphone ownership rates, institutional support structures, and instructor digital readiness must be carefully considered before extending conclusions to European or other settings. Cross-cultural validation studies, identified as a top research priority in Section 4.3, are explicitly needed to establish whether intervention effects particularly for VR/AR and AI-integrated approaches hold across different TVET governance models and pedagogical traditions [96].

4.6 Methodological heterogeneity and implications for synthesis strength

The 58 included studies encompass considerable methodological heterogeneity, spanning experimental/quasi-experimental designs (31.0%), survey/correlational studies (25.9%), mixed methods (17.2%), R&D/design-based approaches (10.3%), qualitative/conceptual studies (8.6%), and SLR/meta-analyses (6.9%). This diversity, while enabling comprehensive coverage of the field, introduces important implications for the strength of synthesized conclusions that must be transparently acknowledged.

Chong et al. [100], in their meta-methodological review of 160 systematic literature reviews in higher education, identified that methodological heterogeneity in primary studies poses significant challenges for evidence synthesis. They found that when primary studies employ fundamentally different research paradigms, the resulting synthesis may produce findings that are difficult for education stakeholders to translate into practice. Their framework recommends either an integrated design approach, in which different study types are synthesized with explicit attention to their complementary contributions, or a segregated design approach, in which quantitative and qualitative evidence streams are analysed separately before being combined in a final synthesis stage. The present review adopted an integrated approach, guided by the B-SLR framework [11], which explicitly accommodates mixed-design evidence synthesis through its ten-step methodology.

The implications of this heterogeneity are threefold. First, effect sizes reported in this review originate from different study designs with varying levels of internal validity. Experimental and quasi-experimental studies (S1–S3, S25, S27, S33, S51, S57) provide the strongest causal evidence but account for only 31.0% of the corpus. Survey and correlational studies (S6, S13, S14, S17, S18, S31, S36, S58) identify associations but cannot establish causality, while qualitative and conceptual studies (S15, S40, S42–S44, S48) provide contextual depth without quantifiable outcomes. Consequently, synthesized findings should not be interpreted as having uniform evidential weight. Bond et al. [101], in their meta-systematic review of AI in higher education, documented that only 26% of educational technology evidence syntheses conduct quality assessment of primary studies, highlighting the importance of the MMAT 2018 quality appraisal employed in this review.

Second, the heterogeneity of outcome measures across studies limits direct comparability. Some studies report Cohen's d effect sizes (S2, S8, S11, S19, S21, S28), others report path coefficients from SEM analyses (S1, S3, S13, S17, S26, S31), and still others report significance levels without standardized effect sizes (S6, S7, S9, S25, S55). Sailer et al. [102], in their second-order meta-analysis of technology-enhanced learning, demonstrated that high heterogeneity in TEL research is primarily caused by differences in instructional methods rather than technological features. They recommended applying theoretical classification frameworks to explain and reduce this heterogeneity. In the present review, the thematic cluster analysis (Section "Keyword co-occurrence thematic clusters (RQ2)") serves a similar function by organizing studies into coherent groupings based on shared conceptual foundations.

Third, the inclusion of both primary empirical studies and secondary review studies (S4, S5, S8, S19, S21, S22, S56) creates an additional layer of complexity. The effect sizes reported from meta-analytic studies (e.g., d = 0.40–0.84 from VR/AR meta-analyses) represent aggregated findings from multiple primary studies that may overlap with other studies in the corpus. This potential for double-counting was mitigated by carefully distinguishing between primary evidence and aggregated evidence in the thematic synthesis.

Despite these challenges, the methodological diversity of the corpus can also be viewed as a strength when appropriately managed. The convergence of positive findings for VR/AR effectiveness across experimental studies, survey data, and meta-analytic syntheses provides more robust evidence through triangulation than any single methodological approach could offer [96]. Similarly, identifying barriers through both quantitative surveys and qualitative case studies yields a richer understanding of implementation challenges. Readers should, however, weigh the findings from high-quality experimental studies more heavily than those from lower-quality or correlational designs when making implementation decisions, particularly in contexts where the sub-analysis (Section 3.2.5) reveals important domain-specific differences between medical-CBME and traditional TVET settings.

5 CONCLUSION

The B-SLR of 600 Scopus records, comprising 58 systematically reviewed studies, reveals that mobile learning in TVET is at a critical juncture between the pandemic-accelerated adoption phase and the evidence-based integration demanded by Industry 4.0.

Three key contributions emerge from this study. First, the field's theoretical toolkit is inadequate: TAM and UTAUT (43.1% of studies) explain adoption but not learning quality. At the same time, frameworks such as SDT and CoI remain nearly unexplored in the mobile learning TVET context despite their high relevance. Second, the most promising interventions based on empirical evidence, including VR/AR (d = 0.40 to 0.84), gamified chatbots showing results comparable to teacher instruction, and flipped classrooms enhanced by microlearning (d = 0.48), require infrastructure that many TVET institutions in developing countries lack, creating equity challenges requiring policy attention. Third, five priority research directions were identified: longitudinal studies, AI-integrated mobile learning, psychomotor skills assessment frameworks, cross-cultural validation, and cost-effectiveness analysis.

Findings from several studies on integrating PBL into e-learning confirm that this approach significantly improves both learning outcomes and satisfaction in vocational education. When triangulated against the broader 58-study evidence base, these findings provide support for technology-enhanced PBL-E as a viable pedagogical innovation for TVET institutions.

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7 AUTHORS

Wagino Wagino is with the Department of Automotive Engineering, Faculty of Engineering, Universitas Negeri Padang, Padang, Indonesia (E-mail: wagino@ft.unp.ac.id).

Volodymyr Tymofiiv is with the Faculty of Aeronautics, Technical University of Košice, Košice, Slovakia.

Ken Polin is with the Faculty of Engineering, Queensland University of Technology, Brisbane, Australia.

Nuzul Hidayat is with the Department of Automotive Engineering, Faculty of Engineering, Universitas Negeri Padang, Padang, Indonesia.

Muslim Muslim is with the Department of Automotive Engineering, Faculty of Engineering, Universitas Negeri Padang, Padang, Indonesia.

Rahmat Desman Koto is with the Department of Automotive Engineering, Faculty of Engineering, Universitas Negeri Padang, Padang, Indonesia.