

A Learning-Centred Conceptual Framework of Technology Acceptance in Vocational Education: A Systematic Review

Lanxin Li^{1,2*}

¹Sichuan Aerospace Vocational College, Chengdu 610100, China, ²School of Distance Education, Universiti Sains Malaysia, Penang, Malaysia
Corresponding Author Email: lilanxin202011@outlook.com

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Abstract

Digital transformation has reshaped technical and vocational education and training (TVET), accelerating the adoption of learning management systems, mobile learning, immersive technologies, and AI-enabled instructional tools. Although technology acceptance has been widely studied, existing research remains theoretically fragmented and insufficiently synthesised within vocational contexts characterised by practice-oriented, skill-based, and industry-aligned learning. This study presents a systematic review of approximately 100 empirical and review studies published between 1989 and 2025, guided by PRISMA 2020 guidelines. Integrating perspectives from the Technology Acceptance Model, UTAUT/UTAUT2, Social Cognitive Theory, the Stimulus–Organism–Response framework, and learning sciences, the review identifies four overarching categories of factors influencing technology acceptance in TVET: technical, psychological, environmental and institutional, and cognitive–affective mechanisms. The findings demonstrate that technology acceptance in vocational education is a multi-level, learning-centred process shaped by learners’ cognitive processing, emotional experience, motivation, and engagement. Building on this synthesis, the study proposes an integrated conceptual framework that embeds technology acceptance within the pedagogical and institutional context of TVET, highlighting procedural learning, authenticity, industry alignment, and cultural context.

Keywords: Technology Acceptance, Vocational Education and Training, Distance Education and Online Learning, Cognitive and Affective Mechanisms, Technology-Enhanced Learning

Introduction

The rapid digital transformation of education has fundamentally reshaped how learners access knowledge, engage with instructional resources, and develop professional competencies. This transformation is particularly significant in vocational education, where learners must acquire both theoretical understanding and authentic, industry-relevant practical skills using digital technologies such as learning management systems, mobile platforms, VR/AR simulations, and AI-enabled tools (Radianti et al., 2020; Thomann et al., 2024).

Research on technology acceptance has been shaped by foundational behavioural models, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). These models emphasise perceived usefulness, perceived ease of use, performance expectancy, and social influence as key determinants of behavioural intention. Complementary frameworks such as Social Cognitive Theory (SCT) and the Stimulus–Organism–Response (S-O-R) model foreground self-efficacy, emotional responses, and cognitive processing as critical influences on technology use (Bandura, 1997; Mehrabian & Russell, 1974).

Despite substantial contributions from these models, existing research often treats acceptance as a purely behavioural construct, overlooking the central role of cognitive load, attention, emotional experience, motivation, and engagement in technology-mediated learning. Learning sciences research demonstrates that cognitive processing is influenced by instructional design, interface complexity, and scaffolding, while emotional states shape persistence and willingness to use digital tools (Mayer, 2014; Leppink et al., 2013; Fredrickson, 2001).

Vocational education presents a distinctive context for studying technology acceptance due to its skill-based, practice-oriented curriculum, heterogeneous learner profiles, and strong alignment with industry practices. Cultural context also moderates learners' acceptance processes, with collectivist cultures exhibiting stronger effects of social influence and institutional expectations (Xu & Chen, 2016; Nistor & Hernández-García, 2012).

However, existing literature remains fragmented across theories, technologies, and cultural contexts. Few systematic reviews integrate behavioural, cognitive, affective, and contextual mechanisms specifically within vocational education (Granić, 2022; Sánchez-Prieto et al., 2017).

This study addresses these gaps by conducting a systematic review of approximately 100 studies (extended period to include foundational and recent works), guided by PRISMA guidelines. The review aims to identify key factors influencing technology acceptance, analyse interactions among psychological, technological, and contextual mechanisms, and propose a comprehensive conceptual framework for vocational education.

Building on the identified theoretical fragmentation in prior research, this study advances the literature on technology acceptance in education in several important ways. Specifically, it integrates multiple theoretical perspectives to provide a coherent synthesis of factors influencing learners' technology acceptance, reconceptualises acceptance as a learning-centred process rather than a purely behavioural outcome, and positions vocational education as a distinct domain that requires context-sensitive theoretical approaches. In addition, the study highlights the role of cultural context in shaping acceptance mechanisms through pedagogical practices, institutional norms, and learning experiences. Accordingly, this study conducts a systematic review of learners' technology acceptance in technical and vocational education and training (TVET) and develops an integrated, learning-centred conceptual framework to synthesise key behavioural, cognitive, affective, and contextual mechanisms underpinning technology acceptance in vocational learning environments.

Literature Review

Technology Acceptance Research in Education

Research on technology acceptance has historically been shaped by behavioural intention models, most notably the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). TAM identifies perceived usefulness (PU) and perceived ease of use (PEOU) as central predictors of behavioural intention. Over decades, TAM has been widely applied and validated across educational contexts, demonstrating consistent explanatory power in predicting learners' acceptance and adoption of digital tools (Dakduk et al., 2018; Raman & Don, 2013; Abbad, 2021; Birch & Irvine, 2009; Tiwari, 2020; Antonietti et al., 2022; Kittinger et al., 2025; Putra, 2025; Al-Emran & Teo, 2021; Darsono, 2005).

UTAUT and UTAUT2 expanded this perspective by incorporating additional constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012). These models recognise the social and institutional dimensions of acceptance, making them especially relevant in structured learning environments such as vocational institutions (Chipeva et al., 2018; Hew et al., 2025; Al-Emran et al., 2023; Wu et al., 2024; Ahmad et al., 2024; Al-Zahrani, 2024; Liu & Wang, 2024; Goupil & Veilleux, 2024; Nwajiuba & Onyeneke, 2024; Oyetade et al., 2020; Lai, 2022; Buchanan et al., 2020; Rogers & Singhal, 2017; Al-Emran & Teo, 2024; Liu & Wang, 2024; Thomann et al., 2024; Zhang & Wang, 2024; Chen & Li, 2024; Al-Emran & Teo, 2024; Zhang & Wang, 2023; Al-Emran & Teo, 2023; Nistor & Hernández-García, 2013; Chen & Li, 2024; Al-Emran & Teo, 2024; Zhang & Wang, 2024; Chen & Li, 2024; Thomann et al., 2024; Kim et al., 2013; Pawłowski & Bick, 2015; Smith & Smith, 2014).

However, a substantial limitation in both TAM and UTAUT traditions is their emphasis on behavioural intention without fully accounting for learners' cognitive, emotional, and motivational processes. As educational technologies become more immersive, interactive, and cognitively demanding, intention-based models alone cannot fully explain why learners choose to adopt—or reject—specific technologies (Granić, 2022; Sánchez-Prieto et al., 2017). Recent research increasingly suggests that technology acceptance must be interpreted within a broader learning ecosystem, where cognitive load, emotional responses, self-efficacy, and engagement mediate learners' perceptions and adoption behaviours. This shift highlights the need for deeper theoretical integration beyond classical models (Plass & Kalyuga, 2019; Leppink et al., 2013; Linnenbrink-Garcia et al., 2016).

Psychological and Learning-Related Mechanisms in Technology Acceptance

A growing body of research demonstrates that technology acceptance is deeply intertwined with learners' psychological states, cognitive processes, and affective experiences. Unlike traditional behavioural intention models, which view acceptance as a function of perceived usefulness or usability, contemporary perspectives emphasise that learning with technology is a cognitively and emotionally situated process. This makes motivational, self-regulatory, cognitive, and affective mechanisms essential components of acceptance, especially in technology-mediated vocational learning environments (Bandura, 1997; Bandura, 1977; Bandura, 2006; Dixon, 2015; Ertmer & Ottenbreit-Leftwich, 2013; Linnenbrink-Garcia et al., 2016; Zimmerman & Kitsantas, 2014; Zimmerman & Schunk, 2011; Yavuzalp & Bahçivan,

2020; Ng, 2012; Wang & Wu, 2021; Schreiner & Sjøberg, 2018; Gong et al., 2004; Darsono, 2005; Lent et al., 1994; Lent et al., 2022; Palmer et al., 2020).

Self-efficacy has been consistently identified as one of the strongest predictors of technology acceptance (Bandura, 1997). Learners with higher levels of technological self-efficacy exhibit greater willingness to experiment with digital tools, sustain engagement during complex tasks, and cope more effectively with challenges (Wang & Wu, 2021; Al-Emran & Teo, 2021; Yavuzalp & Bahçivan, 2020; Zimmerman & Kitsantas, 2014; Gong et al., 2004; Darsono, 2005). In vocational education, where many learners come with diverse digital backgrounds, self-efficacy becomes particularly critical. Students with limited prior exposure to digital tools often experience higher levels of anxiety, which in turn reduces their perceived ease of use and overall acceptance (Cattaneo et al., 2022).

Motivational beliefs such as intrinsic motivation, task value, and perceived relevance also play a central role (Davis et al., 1992). Learners are more likely to adopt digital tools when they perceive meaningful value in technology-supported tasks—especially when these tasks connect directly to professional goals, workplace expectations, or tangible skill development (Linnenbrink-Garcia et al., 2016). Motivation is also linked to perseverance and depth of engagement, making it a key mediator between technological design features and behavioural intention (Thomann et al., 2024).

Cognitive load is an additional mechanism influencing acceptance. According to learning sciences research, learners can only process a limited amount of information at one time (Mayer, 2014; Leppink et al., 2013). Poorly designed digital environments—such as systems with cluttered interfaces, excessive multimedia, or unclear navigation pathways—impose extraneous load, leading to cognitive overload. This not only diminishes learning effectiveness but also reduces perceived ease of use and intention to continue using the technology. In contrast, systems that follow principles of multimedia learning, segmentation, signalling, and scaffolding can significantly enhance acceptance (Sirakaya & Kilic-Cakmak, 2018; Plass & Kalyuga, 2019; van der Heijden et al., 2024; Ayres, 2021; Sweller et al., 2011).

Affective experience—including emotions such as enjoyment, curiosity, frustration, and anxiety—has emerged as a critical predictor of technology acceptance (Fredrickson, 2001). Positive emotions broaden learners' cognitive and behavioural repertoires, promoting deeper exploration and sustained use of digital tools. Negative emotions, conversely, can undermine confidence, suppress exploratory behaviour, and weaken intention. Studies grounded in the Stimulus–Organism–Response (S-O-R) framework demonstrate that emotional responses often mediate the relationship between system characteristics (stimulus) and learners' behavioural intentions (response) (Mehrabian & Russell, 1974; Pekrun et al., 2002; Linnenbrink-Garcia et al., 2016; Skulmowski & Xu, 2022; Fröhlich et al., 2022).

Engagement—behavioural, cognitive, and emotional—has been shown to mediate acceptance and learning outcomes. Higher engagement levels correlate with stronger perceived usefulness, deeper processing, and improved task performance (Dixon, 2015). In vocational education, where students must master procedural and applied skills, engagement is especially important because technology serves as both a learning tool and a simulated practice environment (Thomann et al., 2024; Garzón et al., 2021).

Learning outcomes, including knowledge acquisition, skill development, and performance improvement, also influence acceptance. Learners who experience measurable gains are more willing to continue using technology. This reciprocal relationship—acceptance influencing outcomes and outcomes reinforcing acceptance—highlights the need to conceptualise technology acceptance not as a static decision but as an iterative learning process (Radianti et al., 2020; Muskhir et al., 2024).

Vocational Education as a Distinct Domain for Technology Acceptance

Vocational education (TVET) differs fundamentally from general higher education in its pedagogical orientation, learner characteristics, curricular structure, and institutional priorities. These differences create a unique set of conditions that shape how learners perceive, evaluate, and ultimately accept digital technologies. As a result, technology acceptance in TVET cannot be fully understood through models developed for academic higher education alone (Kleinert, 2014; Moodie, 2016; Yang, 2024; Zhang, 2024; Li, 2023; Sichuan Provincial People's Government, 2023; State Council of the People's Republic of China, 2021; Ministry of Education of the People's Republic of China, 2015-2024).

A central distinguishing feature of vocational education is its strong emphasis on procedural, practical, and industry-aligned competencies. Unlike university programs that often prioritise conceptual knowledge, vocational curricula focus on applied skills requiring hands-on practice, operational accuracy, and real-world task execution (Kim & Lee, 2024; Thomann et al., 2024; Garzón et al., 2021; Radianti et al., 2020; Muskhir et al., 2024; Liu et al., 2023; Sirakaya & Kilic-Cakmak, 2018; Antonietti et al., 2022).

Digital tools—such as VR/AR simulations, virtual workshops, interactive machinery models, and competency-based training systems—enable learners to practise these skills in safe, controlled, and repeatable environments. Because these technologies simulate authentic workplace tasks, perceived usefulness is intimately linked to skill relevance, employability outcomes, and alignment with industry standards (Lau et al., 2020; Marin et al., 2021; Smith et al., 2023; Chen & Li, 2024; Zhang & Wang, 2023; Garzón et al., 2024).

Another distinctive aspect of the TVET population is learner diversity. Vocational learners vary widely in age, academic background, prior learning experiences, and digital readiness. Many enter TVET programs with lower levels of academic self-efficacy or fragmented prior schooling, which affects their willingness and confidence in adopting complex technologies. Digital literacy, in particular, emerges as a critical moderating factor: learners with stronger digital skills perceive greater ease of use, experience less cognitive overload, and display higher intention to use technology-enhanced learning systems. Conversely, learners with limited digital experience face higher barriers, making usability, scaffolding, and institutional support more influential than in traditional higher education (Ng, 2012; Al-Emran et al., 2023).

Recent empirical studies conducted in vocational education contexts have further demonstrated that learners' engagement and academic outcomes are shaped by both individual characteristics and perceived instructional support. For example, empirical evidence from vocational education in China indicates that personality-related factors and teacher support jointly influence students' engagement and learning performance,

highlighting the importance of psychosocial and instructional conditions in vocational learning environments (Li & Rahim, 2025; Schreiner & Sjøberg, 2018; Wang & Wu, 2021).

Authenticity also plays a uniquely influential role in shaping technology acceptance within vocational contexts. When learners perceive that technologies closely mirror real workplace procedures—such as automotive repair simulations, nursing practice modules, or manufacturing process models—their motivation, engagement, and perceived usefulness increase significantly. Authenticity strengthens the perceived value of learning activities and reinforces learners' belief that digital tools can enhance their professional competence. This authenticity-driven mechanism is far less pronounced in general academic settings, where learning tasks may be more abstract (Ertmer & Ottenbreit-Leftwich, 2013; Garzón et al., 2021).

Industry alignment is another crucial contextual factor. Vocational education operates under the influence of industry partners, accreditation bodies, and national qualification frameworks that define the competencies learners must acquire. Technologies endorsed by industry or integrated into apprenticeship programs tend to gain stronger acceptance because they are viewed as legitimate, professionally relevant, and directly connected to workplace expectations. Learners are more willing to adopt tools that they believe will enhance their employability and align with employer requirements (Zhang, 2021; Zhang, 2024).

The institutional environment in TVET also contributes to the distinctiveness of technology acceptance. Many vocational institutions face constraints such as limited funding, outdated infrastructure, or uneven access to high-quality support services. These structural factors influence learners' perceptions of the reliability and usability of technology systems. Stable infrastructure and timely technical support become essential for sustaining learners' trust and willingness to engage with digital platforms (Abumalloh et al., 2021; Al-Adwan et al., 2013).

Finally, vocational education operates within diverse international systems—ranging from dual-training models in Germany, competency-based frameworks in Australia, rapidly expanding TVET sectors in China, and flexible modular training structures in Southeast Asia. These global variations create significant contextual differences in technology implementation and learner expectations. Cross-country comparisons suggest that institutional culture, national policy priorities, and the maturity of digital ecosystems shape acceptance mechanisms in ways not captured by generic educational technology models (Nistor & Hernández-García, 2012; Gupta, 2016).

In summary, vocational education constitutes a distinct domain for studying technology acceptance because of its skills-oriented learning tasks, heterogeneous learner profiles, authenticity-driven pedagogies, strong industry alignment, structural constraints, and diverse global systems. These contextual features highlight the need for acceptance frameworks that reflect the realities of practice-based learning environments rather than relying solely on intention-based models developed for academic education (Kleinert, 2014; Moodie, 2016).

Cultural Context and Technology Acceptance

Cultural context plays a decisive role in shaping learners' perceptions, motivations, and behaviours toward technology use. In technology acceptance research, cultural influences extend beyond surface-level differences, shaping deeper cognitive, affective, and social mechanisms that guide learners' decisions. This makes cultural context especially important in vocational education (VET), where institutional norms, social expectations, and classroom power structures vary widely across countries (Gupta, 2016; Hassan et al., 2020; Xu & Chen, 2016; Zhao et al., 2020; Nistor & Hernández-García, 2012; Srite & Karahanna, 2006; Taylor, 2011; Chen & Li, 2024; Smith & Johnson, 2024; Thomann et al., 2024).

In collectivist cultures—such as China, Korea, and parts of Southeast Asia—technology acceptance is strongly influenced by social and relational factors. Learners tend to value guidance from teachers, approval from peers, and alignment with institutional norms. Social influence, therefore, emerges as a powerful determinant of behavioural intention. When respected instructors adopt or endorse a digital tool, learners are significantly more likely to follow. Institutional expectations also reinforce acceptance by framing technology use as a collective obligation rather than an individual choice (Zhao et al., 2020; Xu & Chen, 2016).

Teacher authority plays an especially prominent role in East Asian VET contexts, where educators are perceived not only as instructors but as moral and professional guides. This strengthens the effect of teacher modelling: when teachers demonstrate confidence in digital tools or integrate them seamlessly into instruction, learners interpret this as a sign that the technology is trustworthy, useful, and professionally relevant (Hassan et al., 2020).

In contrast, Western contexts—such as Europe, North America, and Australia—tend to emphasise autonomy, self-direction, and intrinsic motivation. Learners in these settings are more likely to adopt technologies when they perceive them as personally beneficial, engaging, or aligned with their preferred learning styles. Social influence still matters but typically plays a smaller role compared to self-efficacy, intrinsic motivation, and perceived relevance (Nistor & Hernández-García, 2012; Srite & Karahanna, 2006).

Another important cultural dimension concerns attitudes toward uncertainty and failure. Learners from cultures with low tolerance for uncertainty may hesitate to experiment with complex technologies, particularly those involving simulation, problem-solving, or open-ended tasks. Conversely, students from cultures with higher tolerance for experimentation may be more willing to learn through trial and error, even if this involves making mistakes (Gupta, 2016).

Despite the clear importance of cultural influences, cross-cultural research in VET technology acceptance remains limited. Very few empirical studies directly compare acceptance patterns across countries, leaving major gaps in the global understanding of how cultural norms shape learning behaviours. This “cultural blind spot” highlights the need for acceptance models that integrate sociocultural moderators and recognise that behavioural predictors may not function uniformly across contexts (Nistor & Hernández-García, 2013; Chen & Li, 2024; Smith & Johnson, 2024).

Understanding cultural influences is essential for designing technology-supported vocational learning environments that are equitable, inclusive, and locally relevant. It also underscores the importance of adapting theoretical frameworks to cultural realities rather than assuming universality (Taylor, 2011).

Synthesis and Conceptual Gaps

The reviewed literature demonstrates that technology acceptance in vocational education is a complex, multi-layered phenomenon that cannot be sufficiently explained by any single theoretical lens. Behavioural intention models such as TAM and UTAUT provide valuable predictive foundations, yet they fall short in accounting for the cognitive, motivational, emotional, and contextual mechanisms that strongly influence how vocational learners interact with technology. Psychological mechanisms—including self-efficacy, intrinsic motivation, and perceived task relevance—play a more substantial role than previously assumed, particularly for learners with diverse digital readiness profiles (Bandura, 1997; Davis, 1989; Venkatesh et al., 2003).

At the same time, cognitive and affective processes highlighted by learning sciences and the S-O-R framework remain underexplored in acceptance research. Cognitive load, interface design, attentional demands, and emotional responses significantly shape learners' willingness to adopt and sustain use of digital tools, yet most empirical studies continue to prioritise intention-based predictors over learning-centred factors. This results in a narrow conceptualisation of acceptance that fails to reflect the full complexity of technology-enhanced vocational learning (Mayer, 2014; Leppink et al., 2013; Fredrickson, 2001; Pekrun et al., 2002).

The vocational education context itself introduces unique acceptance mechanisms that differ meaningfully from those in general higher education. Authenticity, workplace relevance, procedural skill development, and industry alignment amplify the importance of perceived usefulness and reshape learners' motivational and engagement patterns. However, despite the growing digitalisation of VET systems globally, theoretical models have not yet been adequately adapted to this specialised context. Most existing frameworks implicitly assume generic learning environments and overlook the practical, hands-on, and competency-based nature of VET (Thomann et al., 2024; Garzón et al., 2021).

Cultural context further complicates the landscape. Cross-cultural differences in social influence, autonomy, attitudes toward uncertainty, and expectations of teacher authority lead to significant variation in acceptance mechanisms across countries. Despite this, cross-cultural comparative research remains sparse, and many models continue to assume universal applicability without empirical support. This cultural blind spot undermines the generalisability of widely used acceptance models (Xu & Chen, 2016; Nistor & Hernández-García, 2012).

Taken together, these gaps highlight the need for a systematic synthesis that integrates behavioural, cognitive, motivational, affective, contextual, and cultural perspectives to explain technology acceptance in vocational learning environments. The present review responds to this need by analysing approximately 100 studies. By synthesising multi-theoretical insights, identifying context-specific acceptance mechanisms, and revealing

critical gaps in current research, this review lays the groundwork for a more comprehensive and learning-centred understanding of vocational technology acceptance. It also provides the conceptual foundation for the methodological approach and thematic results presented in the following chapters.

Conceptual Framework of Technology Acceptance in TVET

Building on the synthesis of prior research and the identified conceptual gaps, this study proposes a learning-centered conceptual framework to explain technology acceptance in technical and vocational education and training (TVET). Rather than treating technology acceptance as a purely behavioural or attitudinal outcome, the framework conceptualises acceptance as a dynamic process embedded within vocational learning activities and shaped by multiple interacting mechanisms (see Figure 1).

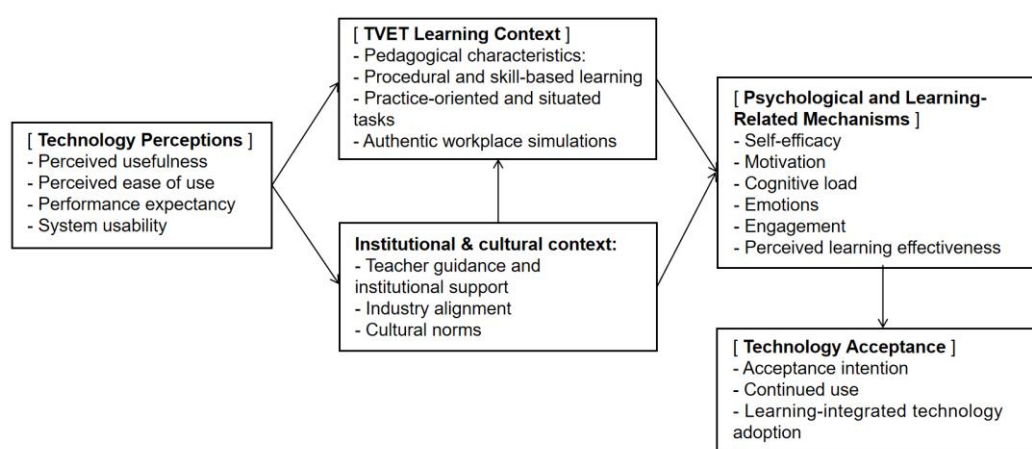


Figure 1 Conceptual Framework of Technology Acceptance in TVET

At the entry level, technology-related perceptions—such as perceived usefulness, perceived ease of use, performance expectancy, and system usability—serve as initial stimuli influencing learners’ engagement with educational technologies. Consistent with established acceptance models, these perceptions remain important predictors; however, the framework emphasises that their effects are not direct or universal. Instead, they are filtered through the distinctive learning context of TVET.

The TVET learning context constitutes the central integrative layer of the framework. Vocational education is characterised by procedural, practice-oriented, and situated learning tasks that emphasise skill acquisition, operational accuracy, and workplace relevance. Technologies in TVET are therefore evaluated not only in terms of general usefulness or usability, but also according to their authenticity, alignment with industry practices, and capacity to support hands-on learning. In addition, institutional and cultural conditions—such as teacher guidance, institutional support, industry expectations, and culturally embedded norms—shape how technologies are introduced, interpreted, and legitimised within vocational learning environments.

Within this contextualised learning setting, learners’ psychological and learning-related mechanisms mediate the relationship between technology perceptions and acceptance

outcomes. Self-efficacy influences learners' confidence in managing digital tools and coping with task complexity; motivation determines the perceived value and persistence of technology-supported learning activities; cognitive load reflects the mental demands imposed by system design and instructional structure; emotional experiences shape learners' willingness to explore and sustain technology use; and engagement represents the behavioural, cognitive, and affective investment in learning processes. Together, these mechanisms explain why similar technologies may generate different acceptance patterns across learners and contexts.

Technology acceptance is therefore conceptualised as learning-integrated adoption, encompassing not only intention to use, but also continued use and meaningful integration of technology into vocational learning activities. Positive learning experiences and perceived learning effectiveness reinforce acceptance over time, highlighting the reciprocal relationship between acceptance and learning outcomes.

By integrating behavioural, cognitive, affective, and contextual perspectives, this framework advances a comprehensive understanding of technology acceptance in TVET. It provides a theoretically grounded structure for interpreting existing research findings and offers a foundation for future empirical studies that seek to examine acceptance as a learning-centred and context-sensitive process.

Methodology

This study employed a systematic literature review approach to synthesise empirical research on factors influencing learners' technology acceptance in vocational education. The review adhered to the PRISMA guidelines to ensure methodological transparency, replicability, and rigour. The SPIDER framework guided the formulation of inclusion and exclusion criteria, acknowledging the diversity of empirical research designs within educational technology.

Search Strategy

A comprehensive search was conducted across major international and Chinese academic databases, including Web of Science, Scopus, ERIC, CNKI, Wanfang, and VIP. Search strings incorporated keywords related to technology acceptance (eg., "technology acceptance," "technology adoption," TAM, UTAUT), vocational education (eg., "TVET," "technical and vocational training"), and learning processes (eg., "engagement," "learning outcomes"). Searches covered an extended period from 1989 to 2025 to capture foundational and emerging research.

Inclusion and Exclusion Criteria

The SPIDER framework (Sample, Phenomenon of Interest, Design, Evaluation, Research Type) was used to guide screening. Studies were included if they involved vocational learners, examined technology acceptance or learning-related outcomes, used empirical methods, and were published in peer-reviewed journals. Excluded studies were those without empirical data, those focused on teachers instead of learners, non-TVET contexts, dissertations, and conference papers.

Screening Procedure

The initial search yielded thousands of records. After removing duplicates and screening, approximately 100 studies were retained for synthesis. The screening procedure followed PRISMA recommendations, and discrepancies between reviewers were resolved through discussion. The study selection process followed the PRISMA 2020 guidelines, as illustrated in Figure 2.

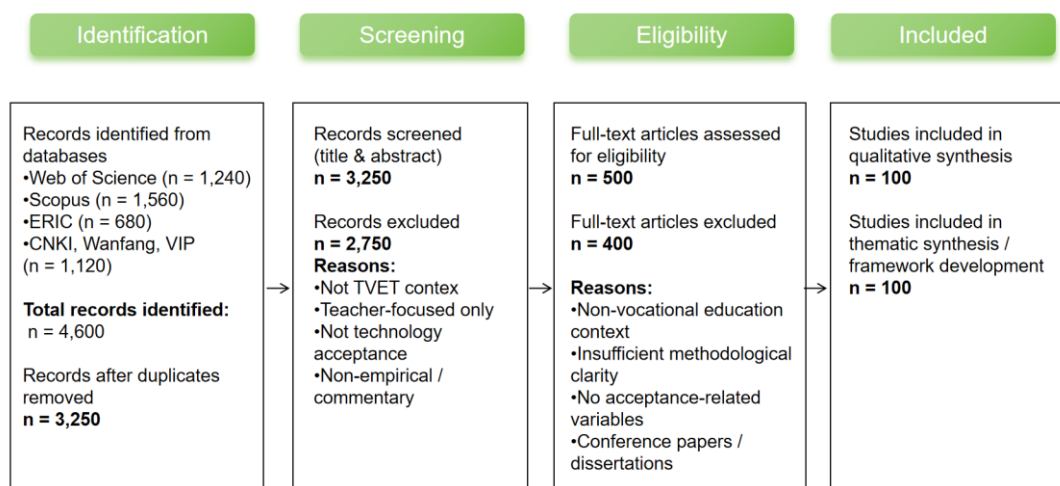


Figure 2 PRISMA 2020 flow diagram of the study selection process

Data Extraction

A structured data extraction form was developed to ensure systematic comparison across studies. Extracted information included publication year, country/region, participant characteristics, type of technology, theoretical framework, methodological design, variables measured, analytical strategy, and key findings. This process enabled consistent cross-study comparisons and supported subsequent thematic analysis.

Quality Appraisal

Quality appraisal assessed clarity of research questions, methodological appropriateness, instrument reliability, transparency of analysis, and overall contribution. A subset of studies (20%) was double-coded to assess inter-rater reliability, yielding Cohen's $\kappa = .81$, indicating substantial agreement. Studies meeting minimum quality thresholds were included in synthesis; lower-quality studies were noted but not excluded unless critically flawed.

Data Coding and Analysis

NVivo 12 was used to organise and analyse extracted data. A hybrid coding approach was adopted:

- Deductive coding based on established theoretical frameworks (TAM, UTAUT, SCT, S-O-R, cognitive load theory).
- Inductive coding to capture emergent themes unique to vocational education, such as authenticity, skill relevance, and institutional expectations.

Thematic synthesis followed Thomas & Harden's (2008) three-stage method: line-by-line coding, generation of descriptive themes, and development of analytical themes. This

approach supported the identification of multilevel acceptance mechanisms that span individual, technical, environmental, cognitive, and affective domains.

Synthesis Approach

A framework synthesis integrated behavioural, motivational, emotional, cognitive, and contextual constructs into a multi-layered conceptual model of technology acceptance in vocational education. This approach facilitated systematic triangulation of findings and provided a coherent structure for interpreting results presented in the next chapter.

Results

This chapter presents findings from the thematic synthesis of approximately 100 studies on learners' technology acceptance in vocational education. The results are organised into descriptive characteristics, theoretical model usage, technology types and learning contexts, and four overarching thematic categories: technical factors, individual psychological factors, environmental/institutional factors, and cognitive–affective mechanisms.

Descriptive Characteristics of Included Studies

Publication trends show a steady increase from earlier foundational works to accelerated growth in recent years, influenced by digital transformation and immersive technologies (Radianti et al., 2020; Thomann et al., 2024; see Figure 3). Most studies used quantitative, cross-sectional designs, with structural equation modelling being the most common analytical approach. Qualitative and mixed-methods studies, while fewer, provided richer insight into learners' lived experiences (see Figure 4).

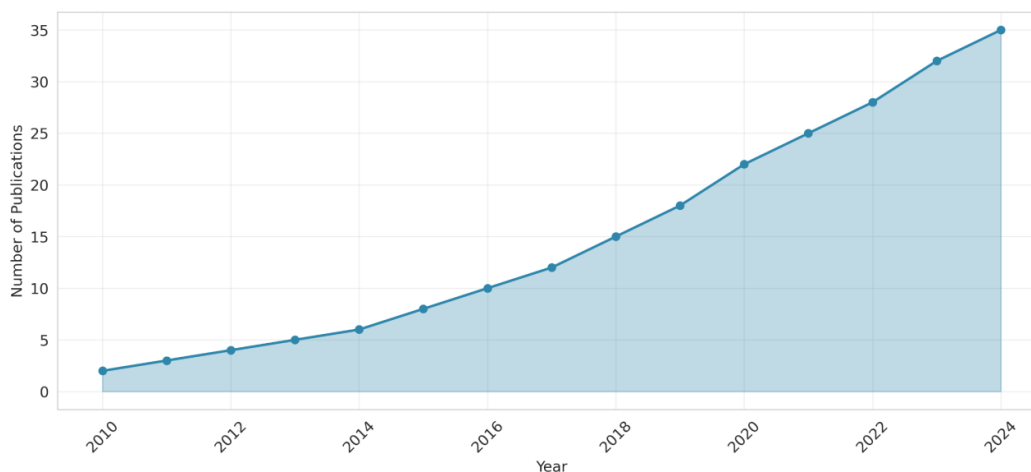


Figure 3 Publication trends in technology acceptance research vocational education (2010–2024)

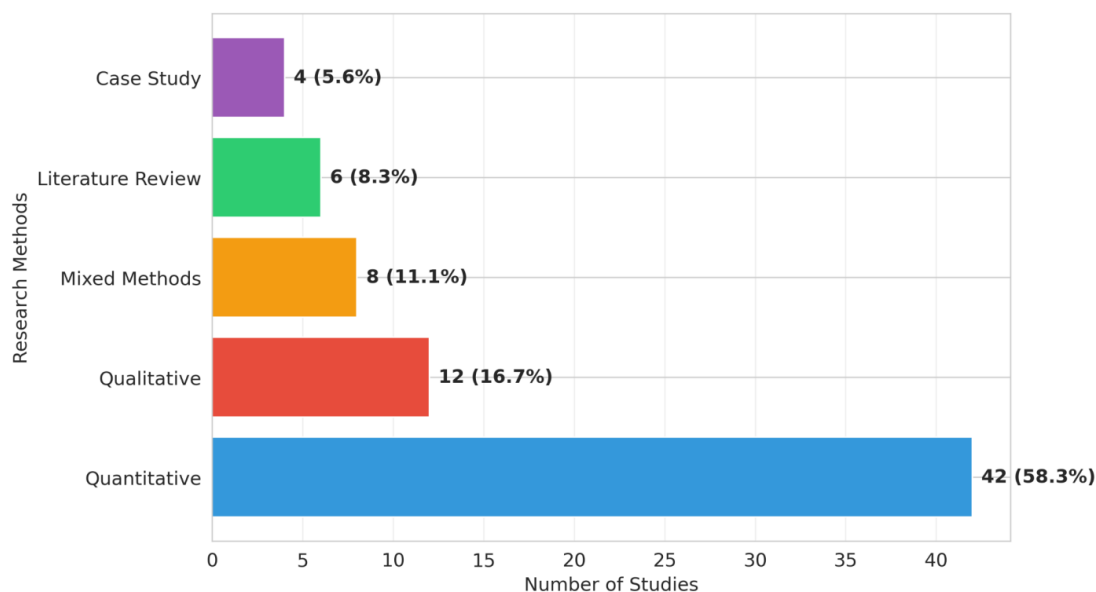


Figure 4 Distribution of research methods across the included technology acceptance studies

Geographically, research was dominated by Western countries, followed by China and East Asia. Cross-cultural studies were limited, restricting global generalisability (Nistor & Hernández-García, 2012; see Figure 5).

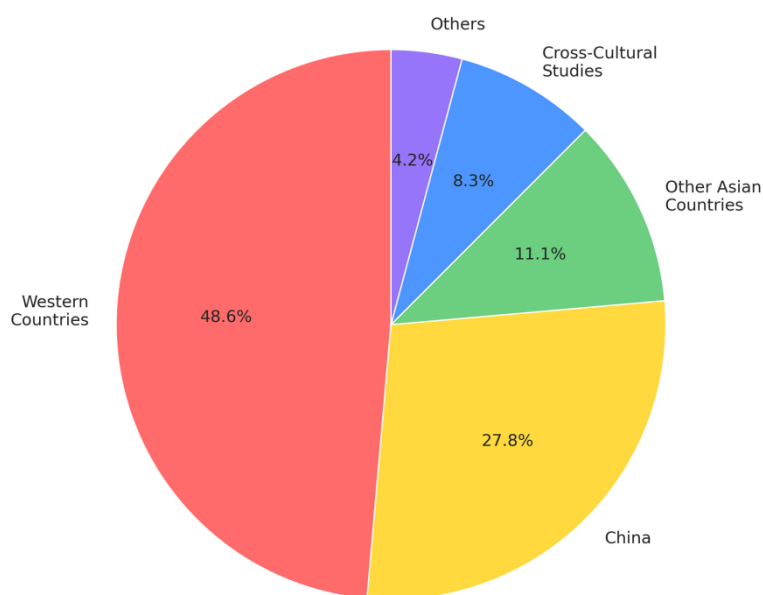


Figure 5. Cultural background distribution of studies included in the systematic review

Theoretical Model Utilisation

TAM and UTAUT(2) were the most frequently adopted frameworks, used to explain perceived usefulness, ease of use, performance expectancy, and social influence (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012; Antonietti et al., 2022; Kittinger et al., 2025; Putra, 2025; Al-Emran & Teo, 2021). Studies incorporating SCT highlighted the significance of self-efficacy and self-regulation (Bandura, 1997), while S-O-R-based studies emphasised

emotional and cognitive reactions (Mehrabian & Russell, 1974). Recent years showed increased multi-theoretical integration, especially in research involving immersive technologies such as VR/AR and AI-supported systems (Thomann et al., 2024; Garzón et al., 2021; see Figure 6).

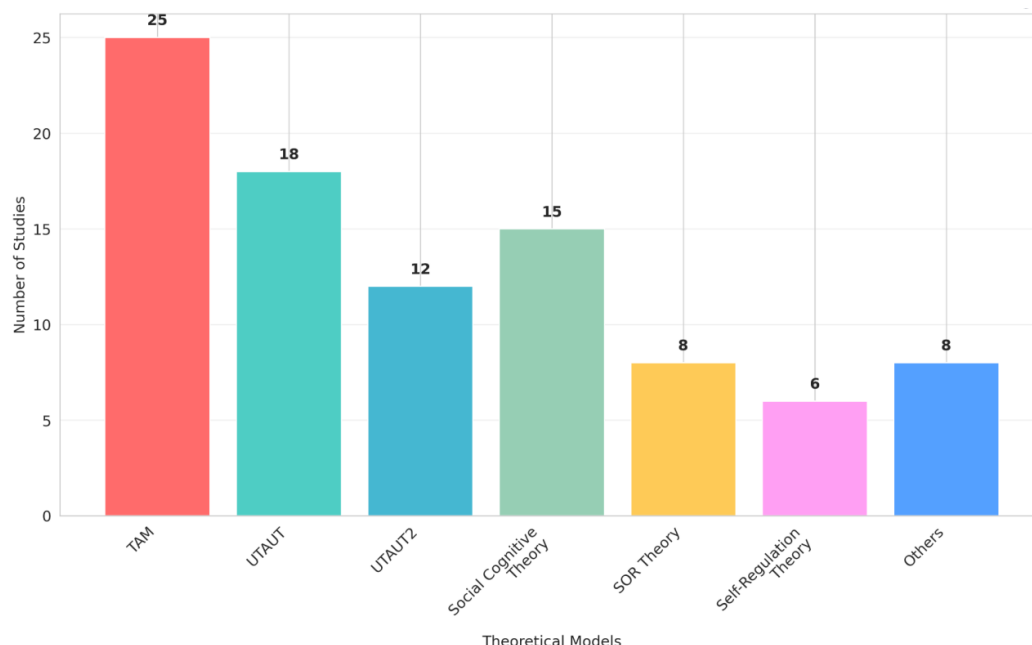


Figure 6 Frequency of theoretical models used in technology acceptance research

Technology Types and Learning Contexts

The technologies examined included LMS platforms, mobile learning tools, VR/AR simulations, and AI-enabled learning systems. LMS and mobile learning dominated early studies, whereas VR/AR systems became more prevalent after 2018 due to advancements in simulation-based vocational training (Garzón et al., 2021; Radianti et al., 2020; Thomann et al., 2024; Muskhir et al., 2024; Liu et al., 2023; Sirakaya & Kilic-Cakmak, 2018; see Figure 7). Learning contexts varied across classroom-based blended learning, online courses, technical workshops, simulation laboratories, and industry-integrated training environments.

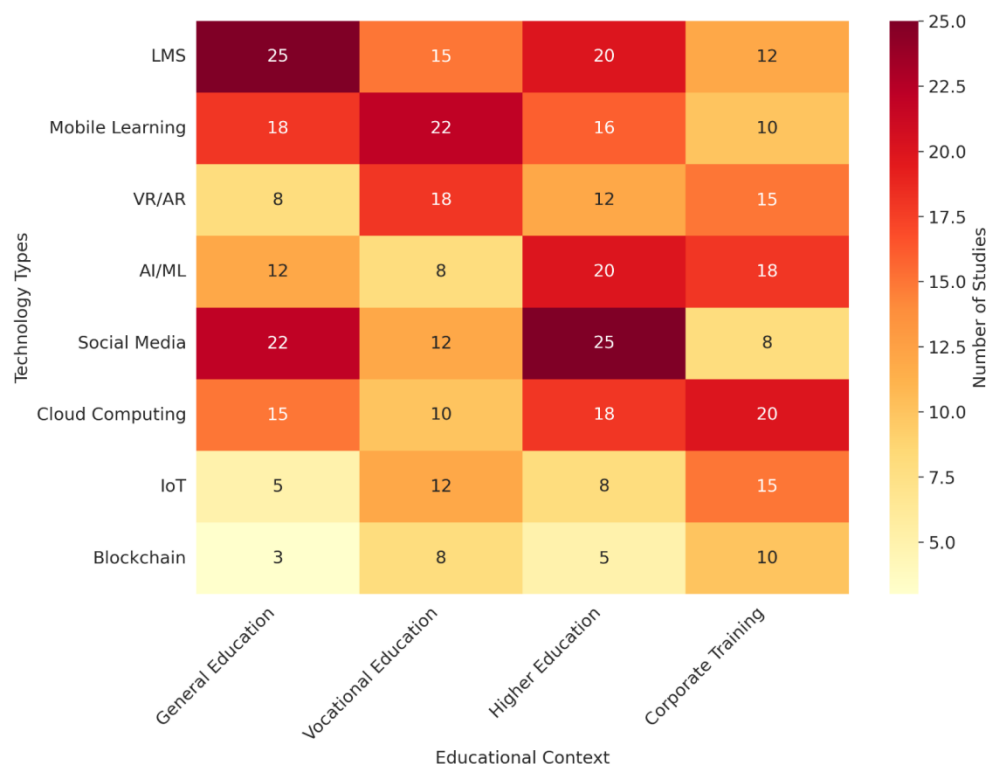


Figure 7 Distribution of technology types across educational contexts in technology acceptance research

Thematic Synthesis of Technology Acceptance Factors

Technical Factors

Across studies, perceived usefulness emerged as the strongest behavioural predictor, particularly when technologies provided authentic, workplace-relevant practice (Garzón et al., 2021; Thomann et al., 2024). Perceived ease of use and usability features such as interface clarity, navigation simplicity, and system stability significantly influenced acceptance, especially among learners with low digital readiness. Technology-specific affordances—immersion in VR/AR, flexibility in mobile learning, and scaffolding in LMS—shaped context-specific acceptance pathways (Radianti et al., 2020; Muskhir et al., 2024). Collectively, these findings indicate that technical factors primarily shape learners' initial evaluations of educational technologies by influencing perceived functionality, usability, and task relevance in vocational learning contexts.

Individual Psychological Factors

Self-efficacy was consistently linked to greater willingness to use technology, reduced anxiety, and deeper engagement (Bandura, 1997; Cattaneo et al., 2022; Wang & Wu, 2021; Schreiner & Sjøberg, 2018; Al-Emran & Teo, 2021; Yavuzalp & Bahçivan, 2020). Motivation—especially intrinsic motivation and perceived relevance—affected intention and persistence (Linnenbrink-Garcia et al., 2016). Character strengths such as curiosity and perseverance were highlighted in several East Asian studies (Peterson & Seligman, 2004; Wright et al., 2017). Learners' digital literacy levels moderated perceived ease of use and behavioural intention (Ng, 2012). Taken together, these studies suggest that individual psychological factors function

as key internal drivers of technology acceptance by shaping learners' confidence, persistence, and willingness to engage with technology-supported learning.

Environmental and Institutional Factors

Teacher support, peer influence, and technical/institutional infrastructure played substantial roles. Social influence was particularly strong in collectivist contexts (Zhao et al., 2020; Hassan et al., 2020). Facilitating conditions, including training, help desks, and system reliability, improved learners' confidence and continued use. Institutional culture and policy environments also shaped acceptance trajectories (Ministry of Education of the People's Republic of China, 2015-2024). Overall, environmental and institutional factors were found to condition technology acceptance by influencing learners' access to support, normative expectations, and the stability of technology use within vocational institutions.

Cognitive and Affective Mechanisms

Cognitive load strongly influenced perceived ease of use, with poorly designed systems increasing mental effort and reducing acceptance (Leppink et al., 2013; Mayer, 2014; Plass & Kalyuga, 2019; van der Heijden et al., 2024; Ayres, 2021). Emotional states—enjoyment, curiosity, frustration—were shown to mediate relationships between system design and behavioural outcomes (Fredrickson, 2001; Pekrun et al., 2002; Linnenbrink-Garcia et al., 2016; Skulmowski & Xu, 2022). Engagement acted as both an outcome of acceptance and a mediator linking perceptions to learning performance (Dixson, 2015). Together, these findings highlight cognitive and affective mechanisms as process-oriented factors that link technology design features to learners' engagement, learning experience, and sustained technology use.

Integrated Thematic Model of Technology Acceptance in TVET

To synthesise the findings across the four thematic categories, an integrated thematic model of factors influencing technology acceptance in technical and vocational education and training (TVET) was developed (see Figure 8). The model illustrates technology acceptance as a multi-level phenomenon shaped by the interaction of technical, psychological, environmental, and cognitive–affective factors, rather than as a single behavioural outcome.

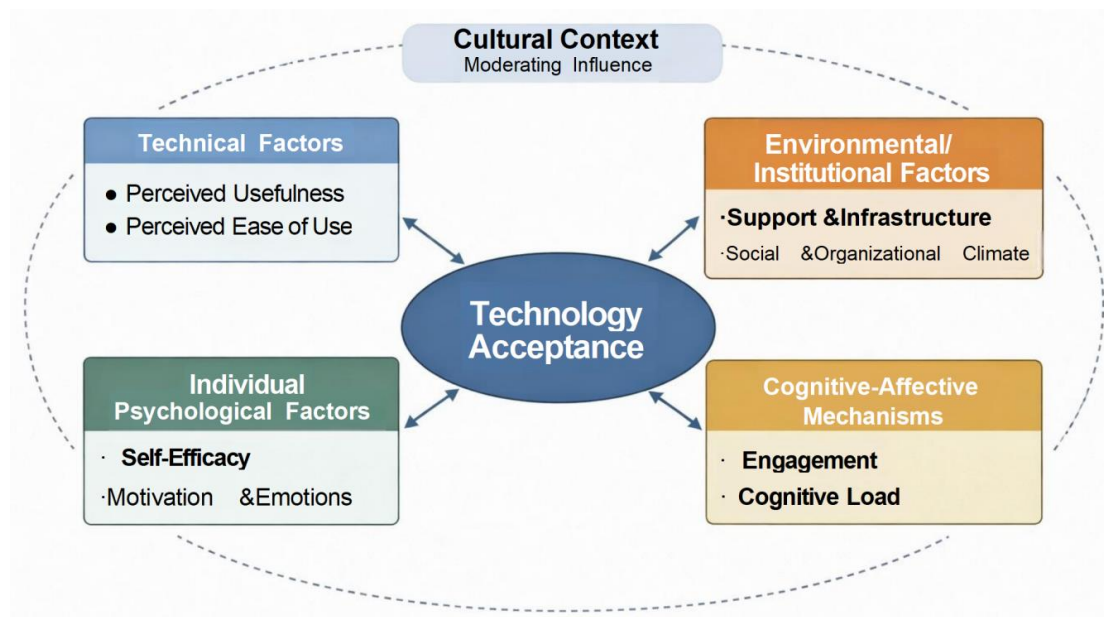


Figure 8 Thematic Model of Factors Influencing Technology Acceptance in TVET

At the technical level, perceived usefulness and perceived ease of use consistently emerged as foundational determinants influencing learners' initial evaluations of educational technologies. These technical perceptions interact closely with environmental and institutional factors, including the availability of support and infrastructure, as well as the broader social and organisational climate within vocational institutions. Institutional conditions shape not only access to technology but also learners' confidence in sustained use. Individual psychological factors—particularly self-efficacy, motivation, and emotional experience—were found to play a central role in mediating learners' engagement with technology. Learners with higher self-efficacy and perceived task relevance were more likely to persist in technology-supported learning activities, even when encountering technical or instructional challenges.

In addition, cognitive–affective mechanisms, including engagement and cognitive load, emerged as critical process-related factors linking technology use to learning experiences. High levels of engagement facilitated deeper interaction with learning tasks, whereas excessive cognitive load undermined both learning effectiveness and continued technology use.

Across these thematic categories, cultural context was identified as a cross-cutting moderating influence that shapes how technical, institutional, and psychological factors are interpreted within vocational learning environments. Cultural norms influence instructional practices, expectations of teacher authority, and the salience of social influence, thereby affecting acceptance patterns indirectly rather than through direct effects.

Overall, Figure 3 provides a consolidated overview of the thematic structure derived from the synthesis and highlights the interconnected and context-sensitive nature of technology acceptance in TVET.

Discussion

Building on the thematic synthesis and integrated model presented in the Results, this discussion interprets the findings in relation to existing research on technology acceptance and vocational education. The Results demonstrate that technology acceptance in technical and vocational education and training (TVET) emerges from a dynamic interplay of technical, psychological, environmental, and cognitive–affective mechanisms, rather than from isolated determinants or behavioural intention alone. This section therefore moves beyond descriptive synthesis to examine how these mechanisms operate together within vocational learning environments, why acceptance patterns differ from those observed in general education contexts, and how a learning-centred perspective advances current understanding of technology acceptance in education.

Advancing a learning-centred understanding of technology acceptance

This study makes several important theoretical contributions to the literature on technology acceptance and vocational education.

First, this review reconceptualises technology acceptance as a learning-centred process rather than a purely behavioural outcome. Existing acceptance models, such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003), predominantly conceptualise acceptance in terms of behavioural intention and usage prediction. While these models have demonstrated strong explanatory power, they tend to treat learning processes as secondary or implicit outcomes. By synthesising evidence from learning sciences, Social Cognitive Theory, and the S-O-R framework, the present study positions psychological and learning-related mechanisms—such as self-efficacy, motivation, cognitive load, emotional experience, and engagement—as central mediators within the acceptance process. This reconceptualisation shifts the focus of acceptance research from “whether learners intend to use technology” to “how learners cognitively and affectively experience technology-supported learning,” thereby advancing a more educationally grounded understanding of technology acceptance (Bandura, 1997; Mehrabian & Russell, 1974; Mayer, 2014; Plass & Kalyuga, 2019; Pekrun et al., 2002).

Second, the study advances acceptance theory by explicitly embedding technology acceptance within the distinctive pedagogical and institutional context of TVET. Prior acceptance research has largely assumed generic educational settings, implicitly treating learning context as a background condition or control variable. In contrast, this review demonstrates that technology acceptance in TVET is fundamentally shaped by procedural, practice-oriented, and situated learning tasks, as well as by authenticity, workplace relevance, and industry alignment. By positioning the TVET learning context as a central integrative layer in the conceptual framework, the study highlights how vocational pedagogical characteristics and institutional conditions fundamentally reshape the meaning of perceived usefulness, ease of use, and engagement. This contribution extends acceptance theory beyond higher education by recognising TVET as a distinct domain with unique acceptance mechanisms that cannot be fully explained by models developed for academic learning environments (Leppink et al., 2013; Linnenbrink-Garcia et al., 2016).

Third, the proposed framework contributes to acceptance research by integrating cultural context as an indirect but structurally embedded influence on learning-centred acceptance

mechanisms. Rather than conceptualising culture as a direct predictor of technology acceptance, this study synthesises evidence showing that cultural norms shape instructional practices, teacher authority, social influence, and learners' interpretive frames within vocational learning environments. By embedding cultural context within the TVET learning layer, the framework explains how cultural influences operate through learning experiences and psychological mechanisms, rather than acting as isolated background variables. This perspective addresses a persistent gap in acceptance research, which often assumes cross-cultural universality, and provides a more nuanced theoretical account of how acceptance processes vary across educational systems and sociocultural settings (Thomann et al., 2024; Garzón et al., 2021; Radianti et al., 2020, Xu & Chen, 2016; Nistor & Hernández-García, 2012; Srite & Karahanna, 2006).

Taken together, these contributions advance technology acceptance research by integrating behavioural, cognitive, affective, and contextual perspectives into a coherent, learning-centred framework tailored to vocational education. Importantly, the purpose of the proposed framework is not to extend or compare individual acceptance models, but to synthesise fragmented findings into an explanatory structure that clarifies how acceptance mechanisms operate within vocational learning environments. The framework not only synthesises fragmented findings across multiple theoretical traditions but also provides a foundation for future empirical studies that seek to examine technology acceptance as a dynamic and context-sensitive learning phenomenon.

Implications for the design and implementation of technology-enhanced vocational learning

Designing Technologies for Cognitive and Emotional Alignment

Educational technologies used in VET must balance cognitive demands with emotional engagement. Overly complex systems increase extraneous cognitive load, reducing acceptance and learning effectiveness. Designers should adopt multimedia learning principles, offer scaffolding, and create emotionally supportive interfaces that promote curiosity, enjoyment, and confidence (Mayer, 2014; Fredrickson, 2001).

Enhancing Institutional and Instructional Support

Teacher modelling, peer influence, and technical support significantly shape learners' acceptance—especially among learners with limited digital readiness. Institutions should invest in digital infrastructure, provide systematic training for teachers, and offer accessible support services. Pedagogical interventions should include digital literacy training and structured orientations for new technologies (Cattaneo et al., 2022; Ng, 2012).

Strengthening Authenticity and Industry Alignment

Given VET's emphasis on real-world skill application, technologies must provide authentic, industry-relevant practice environments. Tools such as VR/AR simulations, interactive training modules, and AI-driven competency assessments should be designed to mirror workplace scenarios. Authenticity enhances perceived usefulness, engagement, and long-term acceptance (Garzón et al., 2021; Thomann et al., 2024).

Supporting Diverse Learner Profiles

VET institutions serve learners with varied educational backgrounds, ages, and skill levels. Designing for inclusivity requires adjustable difficulty levels, simplified interfaces, personalised learning pathways, and supportive feedback mechanisms. Tailoring technologies to learner diversity increases accessibility and sustained engagement (Al-Emran et al., 2023).

Vocational education as a distinctive context for technology acceptance

This review highlights several mechanisms unique to VET:

- 1) Authenticity as a driver of technology acceptance
- 2) Industry alignment as a shaping force in perceived usefulness
- 3) Heightened dependence on usability due to procedural learning demands
- 4) Significant learner variability in digital readiness
- 5) Strong contextual influence of instructors, institutions, and training environments

These findings reinforce the need for VET-specific acceptance frameworks that reflect learners' practical and workplace-oriented experiences (Kleinert, 2014; Moodie, 2016).

Limitations and scope for future research

This review focuses on studies from 1989 to 2025, potentially excluding some niche works. The dominance of cross-sectional quantitative studies limits causal inference. Cultural representation is uneven, with Western and Chinese contexts most visible. Variability in methodological quality across studies also affects comparability.

Directions for future research on technology acceptance in TVET

Future studies should:

- 1) Develop integrated theoretical models combining behavioural, cognitive, emotional, and contextual mechanisms.
- 2) Conduct longitudinal and mixed-methods research to capture acceptance processes over time.
- 3) Expand cross-cultural analysis to build globally relevant acceptance models.
- 4) Examine how cognitive load, engagement, and emotional states mediate technology use in VET.
- 5) Investigate technology acceptance in emerging VET technologies such as AI tutors, robotics, and immersive simulations.

Conclusion

This systematic review synthesised findings from approximately 100 studies published between 1989 and 2025 to advance understanding of learners' technology acceptance in technical and vocational education and training (TVET). The review demonstrates that technology acceptance in vocational education is fundamentally a multi-layered, learning-centred process shaped by the interaction of technical characteristics, individual psychological factors, environmental and institutional conditions, and cognitive–affective learning mechanisms. Rather than functioning solely as a behavioural precursor to technology use, acceptance in TVET is embedded within learners' cognitive processing, emotional experience, engagement, and perceived learning effectiveness.

By integrating behavioural, psychological, cognitive, affective, and contextual perspectives, this review moves beyond intention-based explanations and highlights the distinctive

acceptance mechanisms operating in vocational learning environments. In particular, authenticity, procedural skill demands, workplace relevance, industry alignment, and learner diversity emerge as central contextual features that reshape how technologies are perceived, experienced, and adopted in TVET. These findings underscore that acceptance mechanisms developed for general or academic education settings cannot be assumed to transfer directly to vocational contexts.

The integrated conceptual framework proposed in this study provides a theoretically grounded structure for understanding technology acceptance as a learning-integrated process situated within vocational education. The framework offers a foundation for future empirical research to examine acceptance dynamics across technologies, learner groups, and cultural settings, and supports more context-sensitive design of educational technologies and instructional practices in TVET.

Despite its contributions, this review has several limitations. The predominance of cross-sectional quantitative studies constrains causal inference, and the uneven representation of cultural contexts limits global generalisability. Future research should employ longitudinal, experimental, and mixed-methods designs to examine how acceptance evolves over time, investigate cross-cultural variation in acceptance mechanisms, and explore emerging technologies such as AI-supported systems, immersive simulations, and intelligent tutoring environments in vocational education.

As digital transformation continues to reshape vocational education, adopting learning-centred and context-sensitive approaches to technology acceptance will be essential for fostering meaningful engagement and effective skill development in TVET.

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