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PAPER

Mapping Mobile Learning Adoption in Online Education: A BERTopic Review of TAM Studies (2020–2024)

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ABSTRACT

The study aimed to provide a comprehensive overview of the technology acceptance model (TAM) in online education while presenting application opportunities and barriers across various educational contexts. 301 empirical studies, retrieved in Web of Science (WoS) from 2020 until 2024, formed the basis of this research. The BERTopic model was used, which identified major topics and trends before the study conducted a thematic interpretation of the data. The study identified seven different topics and categorized them into collected information into three main themes, such as teacher-centered, student-centered, and technology and perception. The study uncovered key areas of concern and emerging trends, demonstrating potential uses of TAM in online education, including improving teaching effectiveness, promoting personalized learning, and creating a supportive learning ecosystem. Psychological resistance in teachers, together with the digital divide among students and TAM's constrained applicability, were found to be the major barriers for its implementation in online education.

KEYWORDS

online education, mobile learning, teacher adoption, student engagement, technology acceptance model (TAM), BERTopic model

1 INTRODUCTION

Advances in modern digital technologies have not only revolutionized the education system but have also significantly promoted the development of online education and mobile learning environments [1, 2]. Online educational and mobile learning platforms such as learning management systems (LMS) and massive open online courses (MOOCs), as well as AI-driven adaptive learning apps and digital resources, enable students and teachers to participate in educational experiences based on flexible environments. The COVID-19 pandemic has forced schools and universities around the world to adopt online and hybrid learning models and embrace these technologies [3, 4]. These changes have not only changed teaching methods but also brought about the important process of evaluating teacher-student technology

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interactions in real-life educational environments. Therefore, the key question now is what drives the willingness of teachers and students to adopt new technologies, especially mobile learning, and under what conditions will they adopt them?

The technology acceptance model (TAM) constructs a useful framework to answer these questions. The model explains user adoption behavior through users' beliefs about perceived usefulness (PU) and perceived ease of use (PEOU) [5]. Beliefs about PEOU and PU drive behavioral intentions (BI), which ultimately lead to actual usage behavior. TAM has been routinely used to examine the adoption of educational technology through the development of TAM2 and the unified theory of acceptance and use of technology (UTAUT) [6].

Technology acceptance and use has been widely studied in online education circles, among educators [7], students [3], and education administrators [1] in both formal and informal settings. Studies based on TAM in online education have examined technology adoption by examining its key variables [8, 9]. However, previously published reviews of TAM in online education have two major shortcomings. First, they have only focused on specific platforms and technologies and paid insufficient attention to other forms of online education, particularly mobile-driven learning. Therefore, existing research has not yet formed a holistic picture of the application of TAM in different online education technologies. Second, these studies rely primarily on qualitative analysis methods, which lack the precision and scalability of modern computational analysis. Therefore, a data-based approach is needed to explore TAM-related research in the field of online education.

2 LITERATURE REVIEW

2.1 Overview of technology acceptance model

Technology acceptance model serves as a foundational framework of information systems research to explain how individuals choose to adopt new technologies [5]. The TAM shows how both PU and PEOU influence BI toward actual usage behavior. The model offers a basic framework that succeeds in analyzing user decisions in technology adoption scenarios. Through multiple modifications, the TAM experienced growth during its developmental period. As such, the expanded version, TAM2 incorporates social influence together with cognitive instrumental processes [6], but another variant called UTAUT presents an extensive explanatory framework through incorporating multiple model constructs [10]. The model's operational scope became more versatile through these additions. The original TAM continues to be extensively utilized within educational technology and online learning research spaces even after other adaptations were developed. The model works well for studying user conduct in structured educational frameworks because of its organized design and distinct components. In this study, the original framework of TAM serves as an established base to map TAM-focused research in online education through topic modelling.

2.2 Application of TAM in online education

Online education refers to an educational model that delivers teaching content and organizes learning interactions through digital platforms, enabling learners to access educational resources remotely, synchronously or asynchronously [11]. Online education involves delivering educational content through digital and mobile platforms, such as LMS, MOOCs, apps, and AI-powered adaptive learning tools. With advancements in technology and the COVID-19 pandemic accelerating its adoption, online education has evolved, offering greater flexibility, interactivity, and personalization [12, 13]. However, at its core, online education remains technology-driven, with the acceptance and use of technology by key stakeholders, including students and educators, playing a critical role in shaping the effectiveness of educational activities [14]. Given this, researchers have increasingly explored the factors influencing the adoption and integration of online education technologies through the lens of TAM. Table 1 summarizes recent findings from TAM-based studies, highlighting the key factors driving the development and adoption of online education technologies.

Table 1. Empirical studies of TAM in online education

Context	Key Finding	Source
Formal education	University students' behavioral intention to use Edmodo (LMS) is significantly influenced by PU and PEOU; external factors such as user experience shape these variables.	Unal and Uzun [15]
	In higher education, PU and PEOU strongly predict students' behavioral intention and actual usage of e-learning systems; expectation-confirmation factors enhance BI.	Al-Nuaimi et al. [16]
	High school students' preferences for digital comics in classrooms are driven by perceived enjoyment, PU, and PEOU, highlighting the role of engagement in learning activities.	Chang and Chiu [17]
	K-12 teachers' online teaching work engagement and continuance intention are influenced by PU and institutional support, underlining the importance of resource availability.	Huang et al. [18]
	Academics' PU and PEOU are influenced by app design, emotional anxiety, and collaboration challenges; although 37% of the participants regarded EOPA (English Oral Presentation App) as useful, many reported usability difficulties and emotional resistance.	Barrett et al. [19]
Informal education	M-learning supports skill improvement and personal development through flexible and accessible systems. PU and PEOU strongly predict BI, and ease of use enhances overall satisfaction.	Alsswey et al. [20]
	E-learning platforms used during the COVID-19 pandemic facilitated self-directed learning. Social norms, PU, and PEOU were key factors influencing acceptance and sustained usage.	Alqahtani et al. [3]

Formal education is the educational system where authorities maintain predefined curricula, such as K-12 schools as well as higher education institutions. On the other hand, informal education is where digital platforms, such as those delivered by m-learning apps and e-learning systems, are used to enable a flexible, self-directed, and interest-based education. The adoption motivations function differently between these two settings. Formal educational institutions combine their organizational backing with systems integration to achieve optimal learning results through LMS and classroom technology implementations [18]. The emphasis in informal education lies on simplicity and adaptation capabilities of m-learning apps to promote convenience and skill development [19, 20]. Changes in the strength of influence between PU, PEOU, and BI depend on the context when formal education focuses on institutional resources and support structures, yet informal education uses individual motivations and sociocultural influence [3]. TAM's ability to assess technology adoption patterns in different educational environments receives explanation through its specific factors, which lead to comprehensive research on its application for online learning.

2.3 TAM for online education: Insights from current review studies

The application of TAM continues to grow in online education research because it provides essential comprehension about user interactions with digital and mobile learning technology platforms under diverse educational settings. Rather than focusing on a single platform, the core variables of TAM enable researchers to examine various technological usage methods and adoption conditions across multiple platforms. Studies in both formal and informal learning environments have contributed to a growing body of knowledge, clarifying the role of TAM in online education. This increased interest has also led to the emergence of review studies aimed at synthesizing empirical findings and identifying broader research trends. Table 2 summarizes several key review studies in this area, highlighting their central insights and the impact they have had on current understanding of TAM in online education.

Table 2. Review studies of TAM in online education

Source	Key Finding	Contribution
Al-Emran et al. [8]	TAM is widely applied in mobile learning (M-learning). PU and PEOU are key predictors, and BI directly influences technology adoption.	Provides a comprehensive overview of TAM in M-learning, offering theoretical foundations for mobile learning technology design. Reinforces the relevance of TAM for mobile education contexts.
Granić and Marangunić [9]	Comprehensive review of TAM in education. PU and PEOU significantly impact LMS and blended learning adoption, but TAM has limitations in explaining complex technology adoption.	Offers a broad perspective on TAM in education, identifying gaps in current research and suggesting directions for extending TAM to complex technologies. Strengthens the theoretical underpinnings of TAM for diverse educational tools.
Al-Nuaimi and Al-Emran [21]	Systematic review of TAM in LMS adoption. PU and PEOU strongly predict BI, while external support (e.g., training) significantly influences technology adoption intention.	Emphasizes the importance of external support (e.g., training) in enhancing the applicability of TAM to LMS optimization. Further clarifies the role of TAM in formal educational settings like LMS adoption.
Mustafa and Garcia [1]	TAM is integrated with other models (e.g., UTAUT), highlighting the moderating role of external factors such as social influence and cultural context on PU and PEOU.	Highlights the necessity of integrating TAM with other models to address cross-cultural applications and enrich the explanatory power of TAM. Extends its scope to broader online education frameworks.

Although existing reviews have explored TAM's application across various technological contexts, they often focus on specific forms of online education, neglecting others. This limited scope hinders a comprehensive understanding of how TAM functions across diverse educational settings and fails to fully address the growing convergence of formal and informal learning in today's technology-driven environments. In addition, most of these reviews rely on conventional qualitative synthesis methods, such as thematic coding and manual classification, which may lack the objectivity and scalability needed to capture the structural patterns and evolving directions of TAM-related research. The BERTopic model serves as the analysis tool in this study to perform topic modelling on TAM research related to online education, which was published between 2020 and 2024. This data-driven approach allows researchers to analyze key themes, topic relationships, and their temporal dynamics. This study fills methodological and thematic gaps existing in previous reviews of the technology acceptance model through contextual analysis to better understand TAM functions in modern online education contexts.

3 METHODOLOGY

3.1 Data collection and selection

Web of Science (WoS) was chosen as the main database for literature collection because it is a comprehensive academic database covering multiple disciplines and is therefore considered very suitable for this study [22]. Referring to previous research methods, a sophisticated search strategy (including search terms aimed at collecting empirical studies applying TAM in online education) was developed as follows:

((TS = ("online education") OR TS = ("distance education") OR TS = ("e-learning") OR TS = ("artificial intelligence education") OR TS = ("Internet education")) AND (TS = ("technology adoption model") OR TS = ("technology acceptance model") OR TS = ("technology application model"))) AND LA = (English)) AND DT = (Article).

Finally, the retrieved articles were screened to include only empirical studies that applied TAM in the context of online education. In addition, to capture the diversity of online education practices and research, a classification framework, based on the definition from Bozkurt et al. [12] and the dominant patterns observed in the collected studies, was constructed. Only English articles that explicitly incorporated at least one of the frameworks and were published between January 2020 and July 2024—a period suitable for examining developmental trends and polarization within the field—were included. The conference papers, monographs, and book chapters were excluded. After the inclusion and exclusion, a total of 301 peer-reviewed journal articles were included in the final analysis. Details of the data, please revise in the supplementary appendix.

3.2 Data analysis and BERTopic modelling

This study employed BERTopic to extract key topics and emerging patterns from TAM-related literature in online education. BERTopic was chosen for its context-aware capabilities, addressing the limitations of traditional methods like keyword network analysis and LDA, which struggle with incomplete keyword detection and lack contextual understanding [23]. By integrating BERT embeddings, transformer models, and category-based TF-IDF, BERTopic produces semantically coherent topic clusters. It outperforms LDA in identifying complex, context-rich patterns in unstructured academic data and demonstrates strong adaptability to varying topic densities and data types [24]. Finally, a follow-up topic analysis was conducted to interpret the contextual meaning of each cluster. This two-stage approach offered a structured, in-depth view of the current research landscape and the evolving application of TAM in online education.

4 RESULTS

4.1 Topic distribution analysis

The document-topic distribution visualization revealed seven distinct clusters identified by the BERTopic model: Topic 0 (teacher technology adoption), Topic 1 (online learning perception), Topic 2 (technology for learning enhancement), Topic 3 (student learning model adoption), Topic 4 (perception in TAM), Topic 5 (intention in TAM), and Topic 6 (social and emotional support in learning).

These clusters highlight the breadth and diversity of research focus areas, offering a structured view of how TAM is applied across different educational contexts and stakeholder perspectives.

Among the identified topics, Topic 0 emerges as the largest cluster, reflecting a dominant research emphasis on teachers' adoption and implementation of technology. Figure 1 illustrates distinct thematic separations, with Topic 4 appearing more isolated—highlighting its unique focus on theoretical aspects of technology acceptance frameworks. In contrast, Topic 2 and Topic 5 are positioned closer together, suggesting overlapping concerns related to technology-enhanced learning and BI. Meanwhile, clusters such as Topic 6 and Topic 3 show wider dispersion, indicating that discussions within these themes encompass a broader and more varied range of perspectives.

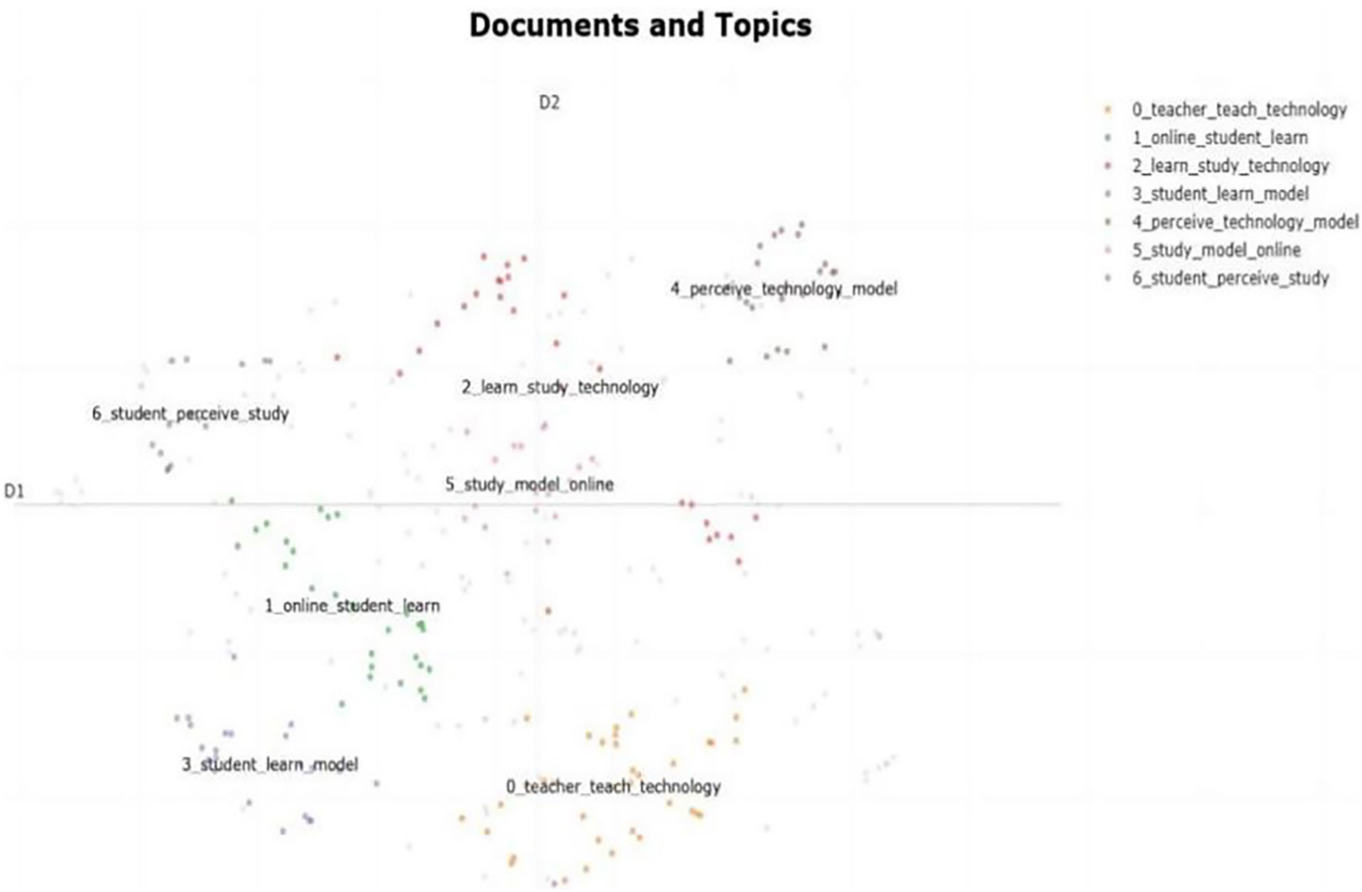

Fig. 1. Distribution of documents and topics

4.2 Content analysis of topics

Through manual interpretation of the BERTopic results (see Figure 2) and thematic analysis, three overarching themes were identified, reflecting the primary areas of focus within TAM-related research in online education: teacher-centric, student-centric, and perception and intention. Each theme encompasses specific topic clusters, characterized by distinct sets of representative keywords and core content. The following subsections provide an in-depth exploration of these themes, outlining their conceptual boundaries and thematic significance within the broader literature.

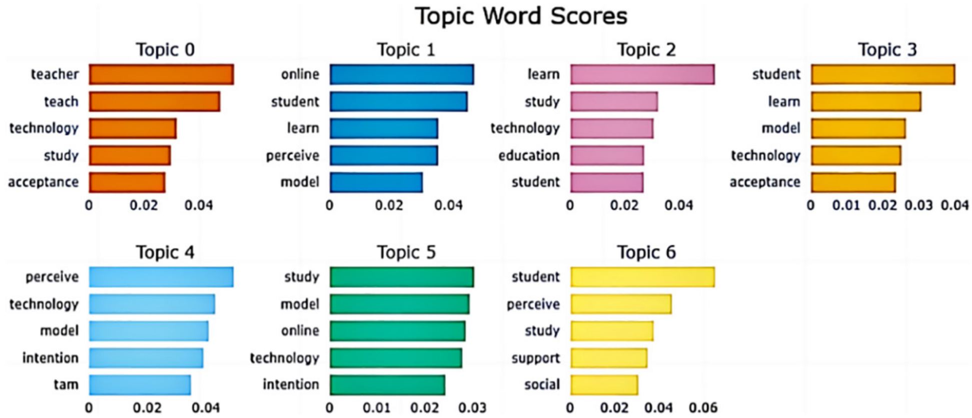

Fig. 2. Distribution of topic words

Teacher-centric theme. Teachers serve as central agents in the digital transformation of education, shaping how technology is adopted, implemented, and integrated to enhance instructional effectiveness [25]. In the context of online education—specially following the COVID-19 pandemic—their role has become increasingly critical in promoting personalized learning and equitable access.

This theme is defined by keywords such as teacher, teach, technology, study, and acceptance, and reflects a strong scholarly focus on the factors influencing teachers' acceptance of technology and how it is incorporated into their instructional routines.

Table 3 synthesizes representative studies that explore these dimensions, offering insight into the complex drivers behind technology integration in teaching. The literature reveals two core areas of analysis: 1) Macro-level factors influencing adoption, which include: Technological characteristics (e.g., ease of use, system reliability); External support (e.g., institutional backing, training); and individual and social factors (e.g., attitudes, peer influence). 2) Micro-level practices and impacts, which examine how technology is applied in daily teaching and its outcomes on pedagogical strategies and student engagement.

Table 3. Dimensions and factors influencing teachers' adoption

Dimension	Factors	Key Finding	Source
Technological characteristics	Perceived usefulness and ease of use	Technology improves teaching quality and reduces barriers in complex environments.	Walker et al. [26]
	Relative advantage	New tools are adopted when their advantages surpass traditional methods.	Koutromanos et al. [27]
	Technology accessibility	Accessible resources like virtual labs promote technology integration.	Kim and Song [28]
	Perceived enjoyment	Engaging tools encourage adoption through positive experiences.	Zou et al. [29]
External support	Institutional support and facilitating conditions	Resources, support, and training are crucial for adoption.	Zuo et al. [30]
	Professional development	Training programs build confidence and readiness for integration.	Moodley et al. [31]
	Crisis adaptation	Necessity and institutional flexibility drive rapid adoption.	Shi and Guo [32]
	Specific support	Tailored resources promote effective adoption in specialized fields.	Gabbiadini et al. [33]
Individual and social related factors	Self-efficacy and AI perception	Confidence and positive perceptions enhance successful adoption.	Şahin et al. [34]
	Emotional and psychological factors	Addressing emotional challenges is critical for successful adoption.	Panisoara et al. [35]
	Societal and cultural expectations	Societal norms and expectations influence adoption behaviors.	Sun and Zou [36]

The inherent features of technology known as technological characteristics define how usable technology appears to students and teachers in educational settings. PU together with ease of use stand as basic drivers which improve teaching quality and eliminate barriers to adoption [37]. The effectiveness advantages of new tools drive teachers toward better instructional methods according to [27]. Teachers can use technology accessibility to connect through virtual labs since these resources become easily accessible [28]. User experiences that provide enjoyment lead to positive adoption attitudes through an interactive and gratifying technological experience [38].

Teachers need institutional and systemic resources as external support to effectively use technology for their work. Institutions must provide both administrative support and technical training alongside other enabling factors to promote teacher adoption behaviors [30, 39]. Through professional development programs, teachers gain enhanced capabilities that build their integration readiness [31]. The adoption of technology at a quick pace became possible through necessary institutional flexibility during the COVID-19 pandemic [32]. STEM-specific support shows the necessity of tailored resources in promoting effective adoption, particularly in specialized educational fields [33].

Individual and social factors refer to the psychological and sociocultural dimensions influencing adoption. Self-efficacy and AI perception increase confidence and positive attitudes toward advanced tools, enabling successful integration [34]. Conversely, technostress and emotional labor may hinder adoption, highlighting the importance of addressing emotional and psychological barriers [35, 40]. Moreover, societal and cultural expectations shape behavior by aligning teacher actions with prevailing norms [36].

At the micro level, technology integration focuses on practical applications and their pedagogical impact. Teachers employ tools such as virtual labs for science instruction [28], MOOCs for scalable and flexible delivery [31], and flipped classrooms to promote collaborative, student-centered learning [27]. Other widely adopted mobile-assisted methods and collaborative platforms, enhance teachers' engagement in exercising their professional agency [30]. In particular, mobile-enabled tools such as the mobile app [8, 15], ClassDojo [38], and Chatbot [41] have gained traction for their portability, ease of use, and support for real-time interaction. These technologies not only reshape instructional practices but also redefine teaching models—blended learning increases flexibility by combining online and face-to-face instruction, and mobile-enhanced teaching facilitates seamless communication, just-in-time feedback, and adaptive instructional pacing. Furthermore, AI-driven personalized learning systems tailor content to individual needs, improving inclusivity and learning outcomes.

Beyond these macro-and micro-level considerations, ethical concerns related to AI adoption are gaining prominence. Issues such as algorithmic bias, fairness, and trustworthiness pose significant risks to equity in education [42]. These concerns underscore the need for robust ethical frameworks to guide the responsible use of AI in teaching, ensuring safe and inclusive learning environments for both educators and students.

Student-centric themes. Student-centric themes emphasize learners' experiences, perceptions, behaviors, and the support mechanisms shaping their engagement in online education. This theme captures how students perceive and interact with technology, adopt innovative learning models, and benefit from support systems that enhance learning processes. It encompasses four main topics: students' perceptions of online learning (Topic 1), adoption and integration of learning models (Topic 3), the role of technology in improving learning behaviors (Topic 2), and the impact of social and emotional support on student outcomes (Topic 6). Collectively, these topics highlight the multifaceted nature of students' interactions with technology and their pathways to academic success.

Topic 1 explores the relationship between students' online learning experiences and their perceptions of online education, using keywords such as online, student, learn, perceive, and model. Students shape their online educational perceptions through interaction with educational tools, platforms, and learning models. Gamified platforms, especially when integrated with microlearning tools, enhance engagement and satisfaction among students [43]. PU and PEOU are key factors influencing users' acceptance of online systems and the formation of positive perceptions [44]. Flexibility and learning effectiveness in blended further contribute to positive perceptions when learners experience adaptable environments in blended and asynchronous models [45, 46]. Student acceptance of e-learning platforms and their positive perceptions directly relate to their confidence, prior experience, and system flexibility [47].

Topic 3 investigates how students adopt and integrate learning models into their academic practices. Keywords such as student, learn, model, technology, and acceptance reflect this focus. The literature identifies three key dimensions: modes of interaction and engagement, integration into learning processes, and supportive factors.

Students adopt diverse interaction strategies, including exploratory engagement, collaboration, and personalized use. For example, graduate students explore CAQDAS tools to meet specific research goals [48], while chatbot technologies provide immersive language learning through simulated interaction [41]. Mobile-based tools further support academic engagement. For instance, WhatsApp has been integrated into communication routines to enhance collaborative learning and student participation [49], while AI-assisted mobile applications for language learning have demonstrated strong perceived usefulness and enjoyment in supporting language knowledge and skills acquisition [19, 29, 50]. Effective adoption also depends on seamless integration into academic routines. Map-based systems aid resource organization and promote sustainable learning [51], and MOOCs allow for flexible, self-paced skill development [52]. Engagement is further supported by system usability, instructor guidance, and platform quality. Well-designed systems and effective instructional support are critical in maintaining student involvement, as seen in the sustained use of mobile learning tools and platforms like Edmodo [15].

Topic 6 highlights the essential role of social and emotional support in shaping student engagement and outcomes in online learning environments. Keywords include student, perceive, study, support, and social. Two critical dimensions emerge: social interaction and emotional support.

Social interaction fosters collaboration, knowledge exchange, and a sense of belonging. Group awareness tools support peer interaction and build emotional connections [53], while social networking platforms promote dynamic engagement between students and instructors [54]. In addition, subjective norms—the expectations of peers and educators—encourage students' sustained participation in online learning [55]. The impact of social interaction is further amplified by emotional support, which addresses students' psychological needs, mitigates stress, and fosters resilience. Emotional encouragement reduces anxiety and boosts acceptance of e-learning by creating a sense of security [56]. Emotional resilience and satisfaction also enhance persistence and long-term success [34]. Leadership programs that integrate emotional support help students build self-regulation and navigate complex learning scenarios [57].

In contrast to other student-centric topics, Topic 2 focuses on how technology actively shapes learning behaviors and cognitive strategies. Representative keywords include learn, study, technology, education, and student, highlighting the transformative role of digital tools. Technologies such as ClassCraft enhance student engagement and promote the development of effective learning strategies through gamification [43], while chatbots facilitate individualized, immersive learning experiences [41]. MOOCs support self-directed learning and skill acquisition [52], and adaptive systems like map-based platforms optimize resource management and foster consistent academic performance [51]. However, some studies note gaps in evaluating the long-term impact of these tools. While models like blended and asynchronous learning improve flexibility, their direct influence on behavioral change remains underexplored [45]. Much of the literature continues to emphasize usability and adoption factors—such as system design and accessibility—over measurable learning outcomes [16]. This focus highlights a broader research gap: the need for empirical studies that assess how TAM-based approaches can enhance not just engagement but actual learning behaviors and outcomes in online education.

Perception and intention in TAM for online education. This theme explores the core constructs of the TAM, focusing on PU, PEOU, and BI within online education contexts. It combines theoretical insights with empirical evidence to examine how perceptions influence user intentions and how these, in turn, drive technology adoption. The TAM framework is widely employed to explain user behaviors across a variety of digital learning environments. This theme comprises two topics: Topic 4, which investigates perception-related variables and their underlying mechanisms within the TAM framework, and Topic 5, which emphasizes BI as a predictor of technology adoption in online education.

Topic 4 centers on the theoretical foundations of TAM, originally proposed by Davis [5], which explains how user perceptions influence BIs and ultimately drive technology use. Representative keywords include perceive, technology, model, intention, and TAM. Within the model, PU and PEOU are foundational variables that shape user attitudes and willingness to adopt technology. Tools perceived as useful motivate users by demonstrating clear advantages, such as improving efficiency, supporting collaboration, and enhancing learning outcomes [29, 32]. At the same time, PEOU minimizes cognitive load and technological barriers, increasing accessibility and user satisfaction. These interrelated perceptions play a central role in influencing BI and, by extension, adoption behaviors within online learning environments.

BI serves as the mechanism that links perception to adoption in TAM. Technologies that are perceived as beneficial tend to generate stronger intentions to adopt due to their efficiency and functionality [58], while ease of use reduces friction, encouraging users to engage with digital tools [59]. The interaction between perception and intention is further shaped by mediated and moderated pathways. Mediators, such as self-efficacy and attitude, translate perceptions into intention by increasing users' confidence and fostering positive mindsets toward technology [49]. Moderators, such as cultural norms and contextual conditions, adjust the strength of this relationship across different learning environments [60]. In some cases, BI itself contributes to a feedback loop, whereby initial intentions enhance subsequent perceptions through increased experience and confidence with the technology [61].

Building on these insights, Topic 5 examines BI as a critical driver that facilitates the transition from user perceptions to actual technology adoption. Key terms associated with this topic include intention, adoption, technology, model, and study. BI not only mediates the perception–adoption relationship but also directly predicts usage.

This topic contributes practical insights into how online education systems can be designed to align with users' motivational and cognitive processes.

In online education, strong BI leads to effective integration of digital tools into teaching and learning practices. For instance, Zhao et al. [62] showed that educators with high BI successfully adopted collaborative tools, which boosted student engagement. Almusharraf and Bailey [59] similarly found that PU enhances intention by emphasizing efficiency, ultimately facilitating adoption. Moreover, intention is reinforced by factors such as self-efficacy and prior experience, which enhance users' readiness to engage with technology. Acting as a bridge between perception and adoption, BI is shaped by both internal motivators and external enablers. Perceptions of ease and usefulness foster intention, which in turn drives concrete adoption behaviors. Environmental and institutional supports—such as training, peer influence, and technological infrastructure–further amplify this effect by creating conditions that align users' perceptions with successful outcomes [61].

5 DISCUSSION

This discussion examines three interrelated themes identified through BERTopic and manual synthesis—teacher dynamics, student learning experiences, and core TAM constructs. Each reflects a distinct yet connected dimension of technology acceptance in online education, offering insights into key tensions, opportunities, and implications for research and practice. Building upon these themes, the discussion further advances a contextualized theoretical framework and explores the international transferability of findings across diverse educational systems.

5.1 Teacher-centric perspectives: Efficiency vs. emotional resistance

In the teacher-centered teaching field, the application of the TAM provides an important opportunity to promote the teaching reform of online and mobile learning. A recurring theme in the study is teachers' perception of improved teaching efficiency. When technology is considered to help simplify administrative affairs or improve teaching responsiveness, it often inspires teachers to adopt a more positive attitude. This phenomenon is highly consistent with the conclusions of existing studies. PU is considered to be one of the key variables affecting teachers' willingness to use technology [18]. At the same time, PEOU cannot be ignored, especially in situations where technology tools can be compatible with teachers' existing teaching goals and workflows. As Walker et al. [26] pointed out, when technology presents a familiar teaching model, its ease of operation is more easily recognized by teachers, which helps to enhance the willingness to integrate. These tools are not only not seen as a disruption to daily teaching but have become a natural extension of it.

However, the above advantages do not mean that the application of TAM in the teacher context is barrier-free. A particularly prominent challenge in the study is the emotional resistance of teachers to technological change. Many teachers expressed concerns about the weakening of their teaching autonomy or the psychological fatigue caused by frequent technological updates. In existing studies, although the importance of technical training and institutional support has been emphasized [1], this study found that there is still a lack of systematic discussion on the complex relationship between teachers' emotional state and professional identity. For example, professional burnout, loss of control over teaching, or powerlessness in the face of emerging technologies often become key variables affecting their adoption behavior. In some situations, even if teachers have recognized the usefulness and ease of use of technology, their behavioral intentions may be inhibited if deep-seated anxiety and discomfort are not eliminated. This reminds us that technology acceptance is not only a rational judgment process but also a dynamic negotiation of emotional, identity, and practical tension.

In addition to emotional issues, structural inequality also constitutes an important obstacle to technology adoption. In resource-poor educational environments, teachers often lack stable digital infrastructure or continuous professional development support. This gap between theoretical acceptance and practice directly challenges the explanatory power of the TAM model in the context of unequal institutions. Traditional models focus on individual cognitive variables, but in actual operations, structural factors such as institutional support, financial investment, and policy environment also play an important role. Therefore, understanding teachers' technology adoption behavior should go beyond the classical framework and expand to the multiple interactions of emotional readiness, structural constraints, and specific institutional contexts.

5.2 Student-centric dimensions: Personalization, mobile-learning, and uneven access

Student-centered insights reveal both progressive trends and persistent barriers. Among the most notable developments is the capacity for personalized learning. Adaptive platforms allow students to engage at their own pace and according to their learning preferences, thereby fostering autonomy and motivation. This aligns with existing studies suggesting that PU enhances learner satisfaction and engagement [20]. Additionally, collaborative, gamified tools promote social presence and cognitive engagement, contributing to richer virtual learning experiences [38]. Moreover, mobile-assisted apps and wearable devices further empower student-centered learning by offering real-time feedback, flexibility, and ubiquitous access [49, 50]. These tools, such as "apps" and "smart technologies," reinforce students' PEOU and sense of agency, particularly in informal or asynchronous contexts [19]. Although personalized and mobile-tech-enhanced learning shows great promise, not all students have equal access to such learning opportunities. The digital divide still poses a significant obstacle, especially for students from disadvantaged or resource-poor backgrounds. The lack of stable network connection and suitable terminal equipment not only weakens their ability to participate in online learning but also subjectively reduces their perception of the "usefulness" of related technologies. Once the technology shows unstable or inaccessible characteristics during use, students are likely to regard it as an "inefficient tool," resulting in a negative experience. Especially in the area of mobile learning, frustrations caused by intermittent access or technical instability can directly undermine students' PEOU and PU, potentially leading to disengagement or discontinuity in learning. In this context, the "rational choice" assumption on which TAM is based faces challenges. The TAM emphasizes that users make adoption decisions based on the perceived usefulness and ease of use of technology, but in actual educational situations, students' use behavior is often restricted by objective conditions rather than being completely voluntary. This also shows that if structural inequality factors are not taken into account, TAM may have biases or blind spots in explaining technology adoption behavior.

In addition, social-emotional competence in online environments is still insufficient for users. Although virtual platforms allow users to interact with each other, it is usually difficult to replicate the strong and immediate interpersonal connection generated in face-to-face communication. This lack of emotion may not only weaken learning motivation and sense of belonging but also have a potential impact on students' long-term learning outcomes. However, there is currently a lack of systematic empirical research on the long-term impact of digital technology use on learning behavior and outcomes. Although many digital tools can improve user satisfaction and task performance in the short term, there is no sufficient evidence to show that they will have a lasting impact on students' cognitive development or learning strategies. Therefore, future research should go beyond the examination of immediate feedback and intention to use and adopt a longitudinal research design to continuously track students' behavioral changes, attitude evolution, and long-term trends in academic outcomes.

5.3 Rethinking perception and intention: Strengths and strains

In the context of online education, PU and PEOU have always been the core concepts of the TAM. Many research reviews have pointed out that these two variables are highly stable in explaining user BI and are key factors in predicting user technology adoption behavior [9]. When digital tools can effectively improve learning efficiency or simplify operating procedures, users are more likely to have a positive adoption intention. Similarly, if the technology interface is simple and easy to operate, the user's learning burden will be reduced, thereby enhancing their participation motivation and usage satisfaction [28]. In recent years, researchers have gradually introduced external factors such as social influence, organizational policies, and cultural expectations to enhance the model's explanatory power for complex educational scenarios [1]. This trend not only enriches the theoretical structure of TAM but also reflects the path of the model's continued evolution in different educational contexts.

However, our research also points out some long-standing structural problems. First, there is a significant gap between "cognition-behavior." Even if users have a positive evaluation of the usefulness and ease of use of technology, in practice they may not be able to continue using it due to factors such as system complexity, insufficient support resources, or mismatched teaching processes. This shows that perception alone is not enough to transform into stable adoption behavior. On this basis, we also observed another problem, that is, behavioral intention is statically treated. In fact, users' adoption intentions fluctuate over time, and when there is a lack of external incentives or continued support, their initial commitments are likely to be difficult to maintain. Therefore, research should pay more attention to the dynamic change mechanism of behavioral intentions, and explore the process of its enhancement, continuation, or decline through multi-time point tracking.

Although previous studies have introduced various external variables into the TAM framework, there remains a lack of a coherent path for integrating these factors into a unified model. To address this theoretical gap, the present study synthesizes its empirical themes and extends the explanatory scope of TAM by proposing a contextualized framework—Mobile-Enhanced TAM (see Figure 3). While the original TAM emphasizes PU and PEOU as determinants of BI, our findings indicate that mobile learning environments require broader sociotechnical considerations. In particular, structural barriers (SB) (e.g. unstable connectivity and limited access to devices) and affective constraints (AC) (e.g., anxiety or motivation loss) can significantly impede PEOU and, indirectly, PU. These barriers are especially salient in resource-constrained settings or among learners with limited digital fluency. The Mobile-Enhanced TAM framework also incorporates mobile affordance and contextual fit (MA&CF)—the capacity of mobile tools to support flexible interaction, timely feedback, and student-driven engagement—as a direct contributor to BI. Moving beyond short-term behavioral intention, the model introduces sustained mobile use (SMU) as an outcome variable, recognizing that digital adoption is often shaped by long-term engagement patterns, evolving perceptions, and emotional fatigue. Finally, institutional support (IS) is conceptualized as a moderating factor that can buffer the effects of structural and emotional constraints by providing equitable access, scaffolding mechanisms, and motivational support.

In contrast to existing extensions of TAM, such as TAM2 and UTAUT, the ME-TAM framework is uniquely tailored to mobile learning contexts characterized by instability, limited infrastructure, and emotional variability. TAM2 focuses on enhancing PU through social influence and cognitive instrumental processes, while UTAUT integrates variables like performance expectancy and facilitating conditions to explain technology usage across organizational contexts. However, both models assume relatively stable usage conditions and structured institutional support. ME-TAM introduces SB, AC, and MA&CF as central variables that address volatile, low-resource digital learning scenarios. Furthermore, it shifts the outcome variable from short-term behavioral intention to SMU, accounting for fluctuating motivation and emotional fatigue over time. These adaptations highlight the ME-TAM's specificity in addressing educational technology adoption in real-world mobile learning settings.

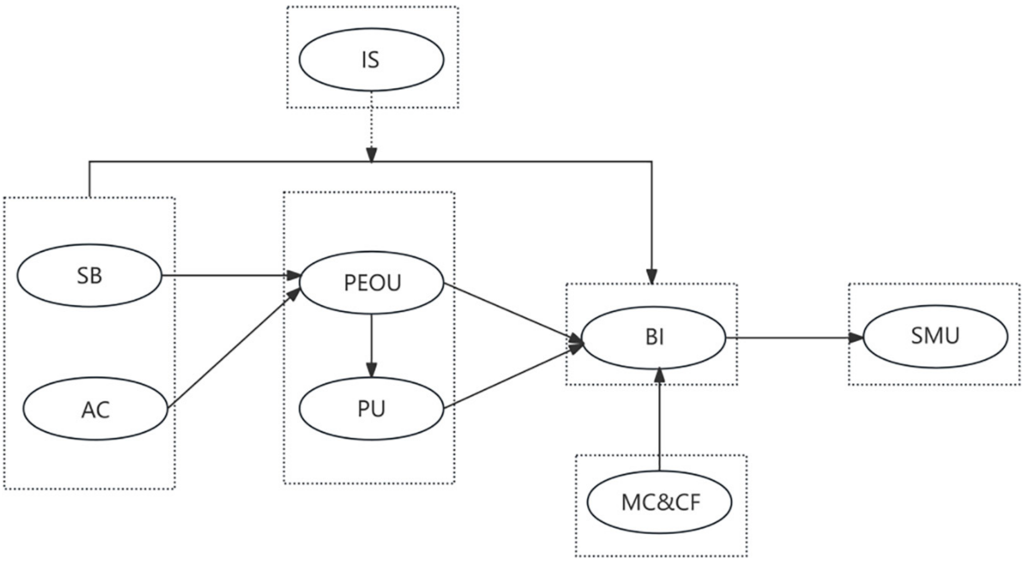

Fig. 3. Mobile-enhanced TAM

5.4 International applicability and contextual transferability

This study synthesizes technology acceptance research in online education and mobile learning from 2020 to 2024. The issue of whether these findings are applicable across other educational systems requires further scrutiny. Students' adoption behaviors are often constrained by structural barriers such as unstable internet connectivity, limited device access, and insufficient institutional support—factors that significantly shape PEOU and PU. In resource-poor or multilingual settings, these conditions may distort the adoption pathway, diminishing behavioral intention and actual usage. Our proposed ME-TAM provides a versatile interpretive framework for various scenarios. For instance, mobile affordance can be locally realized through lightweight apps, offline functionalities, or teacher-mediated delivery. Personalization may be achieved through micro-units, SMS-based scaffolding, or culturally responsive interfaces. Emotional and motivational barriers—such as anxiety or disengagement—also deserve greater consideration in low-support environments, where users may experience fatigue or helplessness toward mobile learning. Institutional support, as a moderating variable in the ME-TAM, is crucial in alleviating structural and emotional barriers by providing dependable infrastructure, user training, and culturally pertinent guidance. Moreover, the model's incorporation of prolonged mobile usage underscores the need for enduring engagement, which is frequently challenging to sustain in inadequately supported environments.

6 CONCLUSION

This study utilized the BERTopic model to analyze TAM-related research in online education, identifying key themes across teacher dynamics, student experiences, and core TAM constructs of perception and intention. Each thematic area encompasses distinct topics that shed light on critical aspects of technology adoption in educational settings. The findings offer a nuanced understanding of technology adoption, highlighting both its potential and limitations. Effective integration depends not only on technological functionality but also on emotional, contextual, and structural factors. These findings provide practical implications for various stakeholders: policymakers should invest in inclusive mobile learning infrastructure and support policies that address digital inequality; educators are encouraged to integrate adaptive, student-centered technologies while receiving institutional training to manage emotional and technical challenges; students should be supported through access to responsive learning environments and peer support mechanisms, which can significantly improve engagement and sustained adoption. As digital learning evolves, continuous strategic adaptation is essential for educators, policymakers, and institutions.

However, limitations of this study are still present. First, the study's scope was limited to the WoS English-language publications from 2020–2024, potentially excluding broader perspectives. Second, while BERTopic provides context-aware topic clustering, its outputs depend on specific model parameters and may oversimplify thematic boundaries. Future research should address these limitations by incorporating multilingual literature sources, expanding beyond the WoS index, and triangulating BERTopic outputs with qualitative or human-coded analysis to validate thematic interpretations. Additionally, exploring emerging technologies—such as VR, AR, and AI—within the TAM framework may further deepen insights into digital learning adoption.

7 DECLARATION OF INTEREST STATEMENT

No potential conflict of interest was reported by the author(s).

8 ETHICS APPROVE AND AI USAGE DECLARATION

Ethics approval was not necessary because this study did not use human beings, animals, or the acquisition of sensitive data. Additionally, this study used ChatGPT 4.0, an AI tool, to assist authors in managing their work and in translating and refining certain sentences. Related guidelines govern the use of AI tools.

9 DATA AVAILABILITY STATEMENT

Data used in this study can be obtained from the corresponding author upon request.

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