frontiers | Frontiers in Education

TYPE Systematic Review
PUBLISHED 01 November 2024
DOI 10.3389/feduc.2024.1436724

Check for updates

OPEN ACCESS

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RECEIVED 22 May 2024
ACCEPTED 07 October 2024
PUBLISHED 01 November 2024

CITATION
Galimova EG, Oborsky AY, Khvatova MA, Astakhov DV, Orlova EV and Andryushchenko IS (2024) Mapping the interconnections: a systematic review and network analysis of factors influencing teachers' technology acceptance.
Front. Educ. 9:1436724.
doi: 10.3389/feduc.2024.1436724

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Mapping the interconnections: a systematic review and network analysis of factors influencing teachers' technology acceptance

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This paper uses the Technology Acceptance Model (TAM) framework to examine elements affecting technology acceptance in teacher education. By means of network and cluster analysis, we investigate the distribution, interactions, and importance of components influencing technology adoption among pre-service and in-service teachers. Following the PRISMA method, a thorough search of Scopus and Web of Science databases produced 32 publications for in-depth study. Key interactions among TAM variables were found using network analysis done in RStudio with the igraph tool. Our results underline in teacher education settings the importance of perceived utility, attitudes toward technology, and perceived ease of use. The study revealed certain topic groups including psychological and social elements, knowledge and occupational relevance, and pragmatic uses in learning environments. While pointing up possible study gaps in this field, the network analysis offers insights into important factors and relationships impacting instructors' technology uptake. This study helps to create efficient professional development programs meant to improve instructors' technological integration skills and enable the successful application of instructional technologies in their respective fields. Our results provide insightful direction for teachers and legislators creating focused initiatives to increase technology acceptance in learning environments.

KEYWORDS

TAM, network analysis, technology integration, teacher education, technology adaptation variables

1 Introduction

Teachers progressively using digital tools and resources to enhance their teaching approaches has shown a consistent rise in the proliferation of technology in education in recent years (Backfisch et al., 2021). Understanding the elements influencing teachers' openness to adapt and accept technology would help to guarantee the effective acceptance of educational technologies (Panisoara et al., 2020). In this regard, the Technology Acceptance Model (TAM) (Davis, 1986) is a prominent theoretical framework extensively applied to examine users' technology acceptance and adoption.

Still, the current studies on teachers' technological acceptability show rather large gaps. For instance, there has not enough research on teachers' technology acceptability in rural locations and underdeveloped nations (Peng et al., 2023). Furthermore, little is known about the variations between elements influencing technology acceptability in different teaching environments (face-to–face, online, mixed) and at different educational levels (primary, middle, and high school) (Songkram and Osuwan, 2022). These inadequacies limit a thorough knowledge of the elements influencing teachers' technological acceptance.

The challenges teachers have bringing technology into their courses have significant effects on the outcomes of their instruction. For example, study (Rahali et al., 2022) found that students' digital literacy skills worsened when teachers improperly used tablet computers. In the same line, Sánchez-Mena et al. (2019) discovered that teachers' reluctance to welcome educational video games reduces students' interest and motivation.

This study aims to expand the corpus of information already in use by investigating the complex interactions of TAM factors in the framework of teacher preparation. One systematic review by itself might not be enough to completely find these intricate relationships. Therefore, our study is to illustrate the links between variables and find the most relevant components by means of network analysis approach. This method will offer a more complete picture of TAM's implementation in teacher preparation, therefore offering more information that might direct policies and interventions.

In particular, this research seeks to answer the following questions:

1. What is the distribution of the descriptive characteristics (year, type of participants, sample size, research topic, and methodology) of the reviewed studies?
2. Within the framework of the TAM, how are the relationships and connections between the factors affecting technology acceptance in teacher education characterized according to the network analysis results?
3. What are the centrality measures (degree, closeness, betweenness, and eigenvector centrality) of the variables identified in the network analysis and how do these measures reflect the importance of the variables in the network?
4. Under which thematic groups are the relationships between the variables of the TAM grouped according to the cluster analysis results, and what insights do these groups offer about technology acceptance in teacher education?

Dealing with these problems will assist one to understand the components of teachers' technology adoption in more complete manner. Better educational policies, more effective programs for teacher professional development, and more successful technology integration schemes can all be shaped by this understanding. For example, a study by Kukul (2023) showed that identifying factors that influence pre-service teachers' attitudes and intentions toward technology integration can improve the design of teacher education programs. Consequently, by analyzing the complex web of factors influencing teachers' technology acceptance, this research aims to provide guidance for more effective adoption and integration of educational technologies. The results of this study can help educators, policy makers and researchers to develop more targeted and effective strategies to support teachers' use of technology and consequently improve student learning.

2 Literature review

2.1 Technology acceptance model

TAM is one of the most influential and widely adopted theoretical frameworks for understanding and predicting user acceptance and usage behavior of information technologies. TAM was originally proposed by Davis (1986). It is based on the Theory of Reasoned Action (TRA) (Davis and Venkatesh, 1996; Na et al., 2022). Davis (1986) sought to develop a parsimonious model especially meant to explain and forecast the acceptability of information technology inside corporate environments. TAM is still a critical tool for understanding users' intentions to adopt a technology. Studies (Hong et al., 2021; Na et al., 2022; Saif et al., 2024; Wang et al., 2023) emphasize that TAM provides a fundamental framework that influences individuals' perceptions of new technologies and their intention to use them, especially with the proliferation of digital transformation and artificial intelligence technologies. TAM is used in many current studies on technology acceptance.

TAM suggests that two main ideas define a person's behavioral intention to utilize a technology: perceived utility and perceived simplicity of usage. Perceived usefulness refers to the degree to which an individual believes that using a particular system would enhance their job performance, while perceived ease of use refers to the degree to which an individual believes that using the system would be free of effort (Davis, 1989; Davis and Venkatesh, 1996; Kukul, 2023). According to TAM, perceived usefulness and perceived ease of use influence an individual's attitude toward using the technology, which in turn shapes their behavioral intention to use it. Behavioral intention is then proposed to be a strong predictor of actual system use (Davis et al., 1989; Ding et al., 2019). Since its launch, TAM has been pillar in knowledge of user acceptability of technology. TAM suggests that two elements mostly affect a person's acceptance and use of technology: perceived usefulness and perceived ease of use (Davis, 1989). Showcasing its adaptability and value in technology acceptance research, TAM has been extensively used, validated, and expanded throughout many technologies, user–groups, and settings over the years.

Despite the emergence of alternative models (for example, Unified Theory of Technology Acceptance, and diffusion of innovations), TAM remains a foundational and influential framework in the field of technology acceptance research. Its simplicity and ability to explain user behavior have made it a practical tool for researchers and practitioners alike. TAM continues to serve as a basis for understanding and predicting user acceptance across a wide range of technologies, including emerging fields such as artificial intelligence, virtual reality, and mobile applications (Chen et al., 2024; Ma and Lei, 2024; Rahali et al., 2022; Sánchez-Prieto et al., 2019b).

For instance, the study (Chen et al., 2024) explored pre-service teachers' behavioral intentions to adopt Immersive Virtual Reality

(IVR) in education using an TAM, finding that subjective norms from mentors and peers significantly influenced their intentions to use IVR. Similarly, Ma and Lei (2024) conducted a study rooted in the TAM to understand the factors influencing teacher education students' willingness to adopt artificial intelligence (AI) technologies for information-based teaching.

TAM has evolved significantly since its inception and continues to be a relevant and adaptable model in the digital age. Its extensions and alternative models have enriched our understanding of technology acceptance by incorporating a wider range of factors and contexts. As technology continues to advance and new innovations emerge, TAM and its derivatives will remain essential tools for researchers and practitioners seeking to understand and predict user acceptance and adoption behaviors.

2.2 Key constructs of technology acceptance model

TAM (Davis, 1989) identifies five core constructs that collectively shape an individual's acceptance, usage, and adoption of a particular technology or information system. These constructs are Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, Behavioral Intention to Use, and Actual System Use. This section review explores the evolution of these key constructs, their theoretical foundations, and their impact on technology adoption, drawing on a wealth of empirical studies.

2.2.1 Perceived usefulness

Perceived Usefulness (PU) is a fundamental concept in TAM, defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). It represents an individual's perception of the technology's potential to improve their performance or achieve their goals. Numerous studies have underscored the critical role of PU in technology acceptance. Venkatesh and Davis (2000) found that PU strongly predicted users' behavioral intentions and actual usage behavior across various contexts, including e-commerce and information systems. Legris et al. (2003) and King and He (2006) further reinforced the positive impact of PU on behavioral intention to use different technologies. PU has consistently emerged as a key determinant of technology adoption, influencing users' attitudes and intentions.

2.2.2 Perceived ease of use

Perceived Ease of Use (PEU) refers to an individual's belief that using a particular technology will be effortless or free from difficulty (Davis, 1989). Users are more inclined to adopt a technology that they perceive as user-friendly and straightforward to operate. PEU has been found to positively influence both PU and attitude. Teo and Milutinovic (2015) demonstrated that users' perceptions of ease of use can shape their attitudes toward technology. Additionally, Venkatesh (2000) highlighted the importance of PEU in facilitating initial user interactions, which can subsequently impact adoption decisions. While PEU is often mediated by PU, it remains a pivotal factor in shaping users' attitudes and intentions toward technology adoption (Venkatesh and Bala, 2008).

2.2.3 Attitude toward using

Attitude Toward Using (ATT) reflects users' overall affective or emotional predisposition toward adopting a particular technology (Davis, 1989). A favorable attitude indicates a positive evaluation of the technology, increasing the likelihood of adoption. Research has shown that both PU and PEOU influence ATT (Muñoz-Carril et al., 2020). When users perceive a technology as both useful and easy to use, they tend to develop a more positive attitude toward it. This positive attitude, in turn, strengthens their intention to adopt, as demonstrated by Sánchez-Mena et al. (2019). However, some scholars argue that the attitude construct may not be necessary in TAM, as its effect on behavioral intention is largely captured by PU and PEOU (Venkatesh and Davis, 2000).

2.2.4 Behavioral intention to use

Behavioral Intention to Use (BI) represents an individual's likelihood or readiness to engage in the actual use of a technology (Davis, 1989). It is considered the most proximal determinant of actual system use in TAM. A positive attitude toward using a technology enhances BI, as supported by the research of Lee et al. (2003), who found that users with a favorable attitude toward a website were more likely to intend to revisit it. BI has been extensively validated as a powerful predictor of technology adoption behaviors across diverse contexts (Gurer and Akkaya, 2022; Teo and van Schaik, 2012; Ursavaş et al., 2019).

2.2.5 Actual system use

Actual System Use (AU) refers to the observed behavior of individuals actively employing the technology (Davis, 1989). While BI is a strong predictor of AU, external factors can influence this relationship. Liu and Shi (2024) highlighted the role of accessibility, training, and social pressure in translating positive intentions into actual usage behavior. Measuring AU can be challenging, and some studies have relied on self-reported usage or proxies (Legris et al., 2003). Nevertheless, AU remains a critical outcome variable in evaluating the effectiveness of technology adoption interventions and the predictive accuracy of TAM (Venkatesh et al., 2003).

The TAM framework, with its five key constructs, has been instrumental in advancing our understanding of technology acceptance and adoption. Extensive empirical research has consistently reaffirmed the importance of PU, PEOU, ATT, BI, and AU across various technological contexts. As technology continues to evolve, TAM remains a valuable and adaptable model for researchers and practitioners seeking to predict and promote user acceptance of new innovations. Future research may explore the application of TAM to emerging technologies, such as artificial intelligence and virtual reality, and address potential limitations by incorporating additional constructs or considering contextual factors.

2.3 Comparison of technology acceptance model with other models/frameworks

The fast development of technology in education has produced several models and frameworks influencing technology acceptance in this discipline. Many researches have surfaced, each providing special insights on how these models could highlight the elements influencing the acceptability and application of instructional technologies. The literature reveals a complex landscape in which established models such as TAM (the focus of our study), the Unified Theory of Acceptance and Use of Technology (UTAUT and its extensions) (Venkatesh et al., 2003), the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991), Diffusion of Innovations (DOI) (Rogers, 2003), and the Theory of Planned Behavior (TPB) (Ajzen, 1985), and other frameworks such as Task-Technology Fit (TTF) (Goodhue and Thompson, 1995) and Technology-Organization-Environment (TOE) (Tornatzky and Fleischer, 1990) are compared and contextualized in various educational settings.

We examined the similarities and differences of TAM with other technology acceptance models. TAM was developed based on TRA and both models argue that individuals' attitudes and intentions influence their behavior (Davis, 1989; Fishbein and Ajzen, 1975). However, TRA is a general social psychology theory and covers a wide range of behaviors (Ajzen, 2020). TAM incorporates more specific factors and is particular to technological use (Davis, 1989). Like TAM, TPB is a development of TRA that holds that people's intentions define their conduct. TPB does, however, include another variable: "Perceived Behavioral Control," which speaks to the person's view of control over his/her conduct (Ajzen, 1991). TAM initially does not include this factor, but similar concepts were added in its later extensions (Venkatesh and Davis, 2000). UTAUT combines concepts from different technology acceptance models, including TAM (Venkatesh et al., 2003). In addition, UTAUT includes more variables such as "Performance Expectancy," "Effort Expectancy," "Social Influence," and "Facilitating Conditions." It also takes into account moderator variables such as gender, age and experience, making it more comprehensive than TAM (Venkatesh et al., 2003). Both TAM and DOI attempt to explain technology adoption (Wee et al., 2016). However, DOI examines how innovations diffuse at the level of organizations and social systems as well as individuals. DOI focuses on the characteristics of the innovation such as "Relative Advantage," "Compatibility," "Complexity," "Experimentation," and "Observability" (Rogers, 2003), whereas TAM focuses on the individual's perceptions of the technology (Malatji et al., 2020). Both models, TOE and TAM, examine the factors that influence technology adoption. However, TOE describes technology adoption at the organizational level and considers "Technological," "Organizational," and "Environmental" factors. TAM examines acceptance at the individual level and does not initially include organizational or environmental factors (Li, 2020). Both TTF and TAM aim to increase the use and performance of the two technologies (Vanduhe et al., 2020). TTF, however, emphasizes on the match between the technological features and the job requirements. Conversely, TAM worries about the personal impressions of the technology and how these impressions affect intention to use (Dishaw and Strong, 1999). While TTF focuses more on functional fit, TAM focuses on perceptual factors (Wu and Chen, 2017).

TPACK (Technological Pedagogical Content Knowledge) and TAM are two different frameworks that have an important place in the fields of educational technology and technology acceptance. These two models seek to understand the use of technology in educational settings, but their focus and approach are different. While TPACK describes the types of knowledge teachers need for effective technology integration (Mishra and Koehler, 2006), TAM explains the factors that influence individuals' intentions to accept and use technology (Davis, 1989). Both models emphasize the importance of technology use, but while TPACK focuses on how pedagogical and content knowledge intersect with technology, TAM focuses on factors such as perceived ease of use and utility.

CBAM (Concerns-Based Adoption Model) and TAM try to understand the process by which individuals adopt new technologies, but their approach and focus are different. CBAM treats technology integration as a process and assesses individuals' concerns, levels of use and the innovation itself (Hall and Hord, 2006). While CBAM addresses the change process from a broader perspective, TAM focuses more specifically on technology acceptance. While CBAM examines how individuals' concerns change over time, TAM focuses more on the factors that influence immediate decisions (Ensminger, 2016).

Consequently, while TAM focuses on individual acceptance and intention to use, models such as TOE and DOI also consider factors at the organizational and social systems level (Li, 2020). Models such as UTAUT and TPB include a larger number of variables and constructs than TAM, which offers a broader perspective (Al-Mamary et al., 2024; Rahman et al., 2017). Although TAM is based on the social psychology theories of TRA and TPB, it offers a technology-specific framework (Davis, 1989). TTF and TOE are more influenced by information systems and organization theories (Awa et al., 2017). Since the focus of the study is not to compare technology integration models, a brief review of common technology adaptation models related to the field of education has been made.

2.4 Extensions and modifications of the technology acceptance model

While TAM and its extensions have been widely adopted, some researchers have also identified potential limitations. Bagozzi (2007) and Venkatesh et al. (2003) argued that TAM oversimplifies the technology acceptance process by neglecting important factors that may influence an individual's decision to accept and use technology. These factors include social influences, facilitating conditions, and individual differences, such as personality traits and past experiences.

One of the early extensions of the model was proposed by Venkatesh and Davis (2000) with the introduction of TAM2. They argued that to fully comprehend perceived usefulness and usage intentions, additional theoretical constructs needed to be considered. TAM2 incorporated subjective norm, image, job relevance, output quality, and result demonstrability. For example, the inclusion of the subjective norm accounts for social influence, recognizing that an individual's technology usage can be influenced by the expectations and behaviors of their peers or social group (Venkatesh and Davis, 2000).

Building upon TAM2, Venkatesh and Bala (2008) developed TAM3, which further extended the model by focusing on the antecedents of perceived ease of use. TAM3 introduced constructs such as computer self-efficacy, perceptions of external control, computer anxiety, and computer playfulness. Computer self-efficacy, for instance, relates to an individual's belief in their ability to use computers effectively, which can influence their perception of the ease of use of a particular technology (Venkatesh and Bala, 2008).

Researchers have also proposed context-specific extensions, such as TAM for e-learning (Yuen and Ma, 2008) and TAM for mobile services (Shodipe and Ohanu, 2021), to address the unique characteristics of these technologies. Anxiety has also been explored as a modifier of TAM. Computer anxiety, as studied by Mohd et al. (2011), can negatively influence both perceived usefulness and perceived ease of use, hindering technology adoption. Belief also modifier of TAM. Digital competence belief (Antonietti et al., 2022) and pedagogical beliefs (Gurer and Akkaya, 2022; Liu et al., 2017) were examined for the effect on PU, ATT, and PEU.

The ongoing evolution of TAM through extensions and modifications has significantly expanded its explanatory power. These adaptations address specific contexts, integrate additional theoretical perspectives, and introduce new variables, ensuring the model's continued relevance in the dynamic field of technology acceptance research. The core constructs of TAM remain central, while the extensions provide a more nuanced understanding of user behavior across diverse technological landscapes.

2.5 The technology acceptance model in pre-service teacher education

TAM has been applied extensively in the context of pre-service teacher education to understand how future educators accept and integrate educational technologies into their teaching practices. This literature review synthesizes studies examining TAM within pre-service teacher education, focusing on factors influencing technology acceptance and the relationship between TAM constructs and technology integration.

2.5.1 Factors influencing pre-service teachers' acceptance of educational technologies

Several studies have explored the factors that shape pre-service teachers' acceptance of educational technologies through the lens of TAM. Teo (2009) found that perceived usefulness and perceived ease of use were significant predictors of pre-service teachers' behavioral intention to use computers in Singapore. Additionally, subjective norms and facilitating conditions played a crucial role in shaping their perceptions of usefulness and ease of use. Pynoo et al. (2011) examined the acceptance of a digital learning environment among pre-service teachers in Belgium, highlighting the importance of perceived usefulness, perceived ease of use, and subjective norms in determining their behavioral intention to use such tools. Wong et al. (2013) explored interactive whiteboard technology acceptance among pre-service teachers in Malaysia, revealing that perceived usefulness and perceived ease of use were significant predictors of behavioral intention, with self-efficacy and subjective norms as important antecedents.

Ma and Lei (2024) and Turan et al. (2022) further reinforced the significance of perceived usefulness and perceived ease of use in influencing pre-service teachers' willingness to adopt educational technologies. Additionally, personal innovativeness, self-efficacy, and Technological Pedagogical Content Knowledge (TPACK) have been identified as contributing factors to technology acceptance. Islamoglu et al. (2021) found a positive correlation between personal innovativeness and attitudes toward using technology in teaching, while Mishra and Koehler (2006) emphasized the integration of TPACK in teacher education programs to enhance pre-service teachers' technology integration skills.

2.5.2 Relationship between TAM constructs and technology integration in teaching practice

Several studies have investigated the link between TAM constructs and pre-service teachers' intentions and actual integration of technology in their teaching practices. Chen et al. (2024) and Philemon et al. (2022) found that perceived usefulness and perceived ease of use significantly influenced pre-service teachers' intentions to integrate technology in their future classrooms. Prieto et al. (2015) examined mobile learning acceptance among pre-service teachers, concluding that perceived usefulness and perceived ease of use were significant determinants of their behavioral intentions to use mobile technologies, which, in turn, influenced their intentions to integrate them into their teaching practices.

Teo and van Schaik (2012) highlighted the mediating role of attitude toward using in translating pre-service teachers' attitudes toward technologies into actual classroom practices. Additionally Thohir et al. (2023) found that TPACK significantly mediated the effects of perceived usefulness and perceived ease of use on technology integration intentions. These findings underscore the importance of integrating TPACK development into pre-service teacher education programs to foster effective technology integration.

Studies examining TAM in pre-service teacher education have provided valuable insights into the factors influencing technology acceptance and integration among future educators. Perceived usefulness, perceived ease of use, attitude toward using, personal innovativeness, and TPACK have emerged as significant determinants of pre-service teachers' technology adoption and integration behaviors. Integrating these findings into teacher education programs can better prepare pre-service teachers to effectively leverage educational technologies in their future classrooms.

2.6 The technology acceptance model in in-service teacher education

TAM has been applied in the context of in-service teacher education to understand how educators accept and integrate educational technologies into their teaching practices. This literature review synthesizes studies examining TAM within in-service teacher education, focusing on factors influencing technology acceptance, the impact of professional development and training, and the role of school culture and leadership.

2.6.1 Factors influencing in-service teachers' acceptance of educational technologies

Several studies have utilized the TAM framework to investigate the factors influencing in-service teachers' acceptance of educational technologies. Rahali et al. (2022) found that perceived usefulness, perceived ease of use, and attitudinal beliefs were significant predictors of in-service teachers' intentions to use technology. Sun (2022) explored e-learning technology acceptance among in-service teachers, concluding that perceived usefulness, perceived ease of use, and subjective norms significantly influenced their intentions to use e-learning tools in the classroom. Khlaif (2018) examined mobile learning acceptance among in-service teachers, highlighting the importance of perceived usefulness, perceived ease of use, and facilitating conditions in shaping their behavioral intentions to use mobile technologies for teaching.

Xu and Zhu (2020) reinforced the significance of perceived usefulness, perceived ease of use, and attitude toward using as determinants of in-service teachers' intention to adopt educational technologies. Additionally, factors such as self-efficacy, experience, and technology readiness have been found to influence technology acceptance. Ertmer et al. (2012) emphasized the role of self-efficacy in shaping in-service teachers' confidence in using technology for instruction, while Teo (2011) and Musyaffi et al. (2021) identified technology readiness as a significant predictor of their intention to adopt technology.

2.6.2 Impact of professional development and training on TAM constructs

Professional development and training programs have been shown to play a crucial role in shaping in-service teachers' perceptions and attitudes toward technology integration. Knezek and Christensen (2016) and Dahri et al. (2021) found that training programs positively influenced in-service teachers' perceived usefulness and perceived ease of use of educational technologies, leading to greater acceptance and integration. Šumak and Šorgo (2016) specifically explored the impact of training on interactive whiteboard acceptance, finding that it enhanced teachers' perceptions of usefulness and ease of use, which, in turn, influenced their intentions to integrate this technology into their classrooms.

Research on TAM in teacher in-service training have underlined that teachers' adoption of technology depends much on perceived utility, perceived ease of use, attitude toward use, self-efficacy, technological readiness, professional development, school environment, and leadership. Including these results into professional development initiatives helps to encourage good technology integration into classroom environments. Still, the body of current research has significant holes. First, there is a dearth of a comprehensive knowledge of the interactions among various elements influencing technology acceptability. For example, although studies such as Teo and van Schaik (2012) and Ursavaş et al. (2019) have examined the relationships between factors, they have not fully uncovered the complex web of these relationships. Second, comparative analyses of how the influence of these factors varies across different educational levels (primary, middle, and high school) and various teaching contexts (face-to-face, online, and blended) are limited (Songkram and Osuwan, 2022). The present work is to investigate the complicated interactions among TAM factors utilizing the network analysis technique in order to close these voids. This method could offer a more all-encompassing and complete picture of the elements affecting instructors' technology acceptance. Network analysis will allow us to identify which factors play a central role, which factors are closely interrelated and which factors remain more isolated. Consequently, this study aims to fill an important gap in the literature by analyzing the complex network of factors influencing teachers' technology acceptance. The findings can contribute to improving the quality of education and student achievement by providing guidance for more effective adoption and integration of educational technologies.

3 Methodology

This study used a systematic approach to investigate the interrelationships between variables within TAM in the field of teacher education. Systematic review processes (Petticrew and Roberts, 2008) were rigorously followed. After the research questions, database selection was made to collect data. Scopus and WoS databases were selected. According to Sönmez (2020), WoS covers more than 10,000 journals and consists of seven different citation databases containing different information collected from journals, conferences, reports, books, and book series. According to Shareefa and Moosa (2020), the Scopus database contains more content than other databases. Google Scholar does not produce consistent search results. Considering these reasons, Scopus and WoS databases were deemed sufficient for a broad scope and to access publications above certain quality criteria. Searches in the database were performed on April 2024. In the process of obtaining and selecting publications, PRISMA protocol (Moher et al., 2015) were adhered to.

3.1 Data collection process

3.1.1 Search query for Scopus

ITLE-ABS-KEY (("technology acceptance model" OR TAM) AND ("Teacher* education" OR "Teacher* training"))

3.1.2 Search query for WoS

"Technology Acceptance Model" OR "TAM") AND ("Teacher* education" OR "Teacher* training")

To acquire data for the investigation, an extensive exploration was conducted utilizing specific keywords in the Scopus and Web of Science (WoS) databases. As shown in Figure 1, the initial quest retrieved 89 publications from Scopus and 109 publications from WoS. Subsequently, the publications sourced from both databases were amalgamated, revealing that 42 of them were duplicates. These redundant publications were then eliminated from the roster to sustain the uniqueness of the dataset.

The subsequent phase encompassed a thorough examination of the titles and abstracts of the articles, culminating in the selection of 51 publications. During this juncture, various exclusion criteria were implemented: publications predating 2010 were disregarded, as were studies exclusively focusing on qualitative data, meta-analyses, systematic review studies, and studies not directly linked to teacher education, such as those centered on university students. Furthermore, publications not in English were also omitted. To perform network analysis a correlation or beta coefficient between two variables is required. Therefore, qualitative analysis, review and meta-analysis studies that do not contain such data were excluded. All citeria listed in Table 1.

In the next stage, the full texts of the remaining studies were obtained. Two researchers from the study team examined these texts meticulously. In this way, data analysis reliability was ensured. Studies without beta values for the relationships between variables were excluded from the scope of this study. After this comprehensive review process, 32 publications were selected for in-depth analysis.

3.2 Data analysis

The 32 selected publications were meticulously reviewed to create an inventory of variables operationalized in studies on TAM. Variables are listed in each study. Variables were categorized as independent (Variable A) and dependent (Variable B). For example, if there is an arrow from the variable "Perceived Usefulness" to the variable "Attitudes to Technology" in the SEM model examined and this path was supported in the study, "Perceived Usefulness" was determined as variable A and "Attitudes to Technology" was classified as variable B. In order to determine the level of association between the data, beta coefficients were recorded. This first stage was crucial in laying the groundwork for the subsequent network analysis by identifying the direction and strength of the connections. All variables listed in Appendix. The network data were then formulated by combining the links between variables to quantify the frequency of each link across studies. This approach enabled an assessment of the importance of particular relationships within the TAM research area. For example, a recurring link between "Perceived Usefulness" (PU) and "Behavioral Intention" (BI) across several studies would imply that there is a consensus on this relationship in this field. Using the igraph (2.0.3) package in Rstudio (2023.12), a network graph was created to visually represent these links. RStudio is a powerful and user-friendly integrated development environment (IDE) for the R programming language. This software provides comprehensive tools for data manipulation, statistical analysis and graphical representation (RStudio Team, 2023). Each node in the generated Network Graph (As shown in Figure 5) symbolizes a variable, while each edge shows a hypothesis being tested between two variables. The thickness of the edges was directly proportional to the frequency of a given link, offering a visual insight into the most and least studied relationships within the TAM. We found the relative importance of each variable in the network by use of many metrics of network centrality including degree, closeness, betweenness, and eigenvector centrality. These centrality assessments allowed to pinpoint crucial factors influencing teachers' acceptance and usage of technology significantly. Using the igraph library, we also applied the Spinglass community discovery approach to find any subgroups or clusters inside the network that would reflect varying themes or focal points in the TAM research. By grouping variables based on the strength of their connections, this sophisticated method exposed the fundamental network architecture. By stressing the most important factors and often investigated relationships, network analysis therefore gave a sophisticated knowledge of cooperative research efforts in TAM studies in teacher education. Together with measured centrality, the visual network graph clearly indicated the main areas of research interest and possible directions for next investigation.

4 Findings

The findings offer a thorough study of TAM application in teacher education. Thirty-two publications were evaluated using a thorough study and a meticulous selection process. These studies expose the several applications of TAM in educational research as well as the vast spectrum of participants—including pre-service and in-service instructors. The sample sizes of the studied publications ranged from 85 to 2011, showing TAM research's availability of both general and more context-specific reviews. Our results provide direction for increasing acceptance and integration of instructional technologies as well as clarify the complex network of components influencing instructors' technology acceptability. The extensive study shown below highlights the significance of the basic TAM structures and reveals contemporary trends and prospective gaps in the body of information on technology acceptance in teacher education.

These studies (listed in Appendix) are categorized based on participant classification, distinguishing between in-service and pre-service educators, and encompass a broad spectrum of subjects, reflecting the manifold applications of TAM in educational studies. Regarding participant classification, the investigations demonstrate a balanced distribution between in-service and pre-service teachers, albeit with a slightly more pronounced emphasis on the involvement of pre-service educators. This signifies a notable scholarly curiosity in unraveling the perceptions and intentions toward technology among prospective teachers, a pivotal aspect in their readiness for the contemporary, technology-driven educational environment.

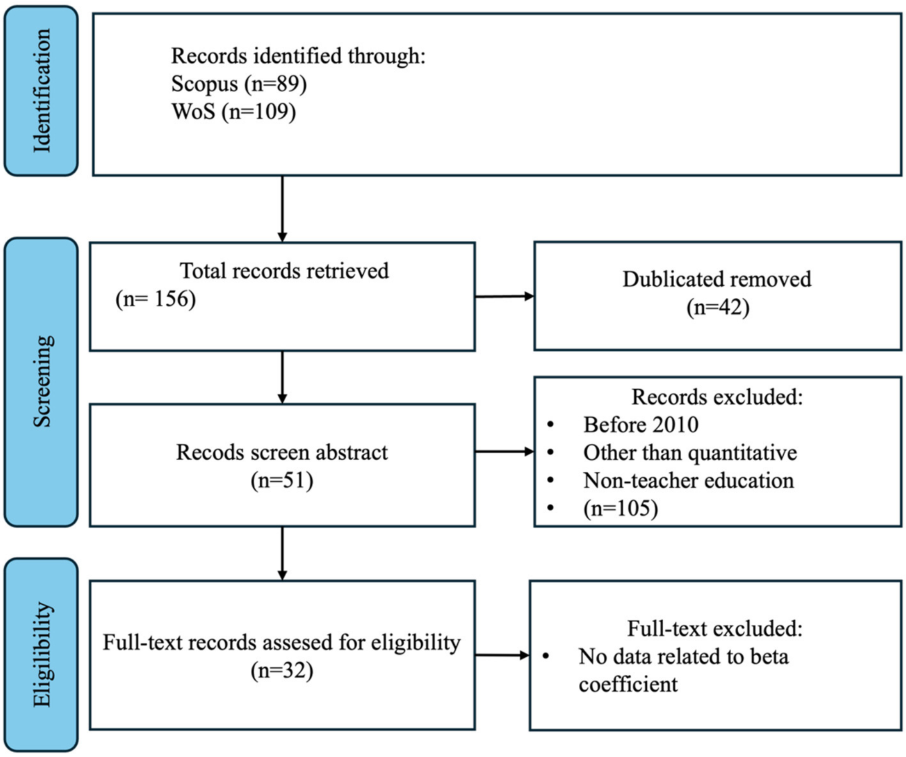

FIGURE 1
Data collection process.

4.1 Descriptive information about the studies

The sample sizes in the investigations exhibit considerable variability, with certain studies featuring a substantial number of participants, such as the inquiry by Antonietti et al. (2022) involving 2011 in-service teachers, which explores the utilization of digital educational platforms amidst the COVID-19 crisis. Conversely, other research endeavors entail smaller sample sizes, exemplified by the work of Alshehri with 85 in-service teachers, concentrating on acceptance of using blackboard. This diversity in sample sizes indicates a wide methodological spectrum within TAM studies, encompassing both extensive and more context-specific investigations.

The publications originate from a diverse array of outlets, spanning from journals dedicated to language instruction to those with a broader focus on educational technology, underscoring the interdisciplinary essence of TAM research in teacher education. To conclude, the table exhibits a robust and multifaceted body of scholarly work leveraging TAM to delve into a plethora of factors influencing the adoption of technology among teaching professionals. The studies vary in magnitude, breadth, and emphasis, portraying a rich and varied research landscape dedicated to comprehending and enriching the incorporation of technology in educational environments for present and future educators.

The distribution of the selected publications by year (as shown in Figure 2) shows that there were one and two publications between 2012 (De Smet et al., 2012; Teo and van Schaik, 2012) and 2018 (Camadan et al., 2018). There was a slight increase from 2019, reaching the highest number of 8 in 2022. Since these numbers do not express all the studies in the field, it is not possible to accept them as a train in the field. However, it shows that further statistical studies on TAM, such as SEM, are ongoing.

The classification of the subjects of research articles utilizing the TAM in the realm of teacher training illustrates a wide array of topics with varying scopes (as shown in Figure 3). The topic of "Digital Application" emerges as the most prevalent subject with ten publications, signifying a notable interest in the acceptance and utilization of digital tools in teacher education. This is succeeded by "Non-specific technology," which is present in six publications, indicating a general examination of technology acceptance without a specific platform focus. Particular technologies like Learning Management Systems (LMS), AI Technology, Information and Communication Technology (ICT), mobile learning, online instruction, tablet use, and video games are explored less frequently, each referenced in only two or three publications. This suggests a more concentrated yet less prevalent interest in distinct tools and platforms in the landscape of educational technology. Furthermore, emerging and specialized technologies such as applications, games, and virtual reality have the least representation in the data, each mentioned in only one publication, signaling that these areas are still in the early stages of exploration. On the whole, the diverse range of topics mirrors a vibrant field, encompassing extensive inquiries into general attitudes toward technology alongside

TABLE 1 Inclusion and exclusion criteria.

Criteria type	Inclusion criteria	Exclusion criteria
Publication type	Peer-reviewed journal articles	Conference papers, book chapters, theses
Publication language	English	Languages other than English
Publication year	Between 2010-2024	Publications before 2010
Research focus	Studies using TAM in the context of teacher education	Studies using TAM in contexts other than teacher education
Participant type	Pre-service or in-service teachers	Students, administrators, or other educational stakeholders
Methodology	Quantitative studies (reporting relationships between variables with beta values)	Qualitative studies, mixed-method studies
Data analysis	Studies using Structural Equation Modeling (SEM), Partial Least Squares (PLS), or regression analysis	Studies limited to descriptive statistics or correlation analyses
Technology type	Educational technologies (e.g., learning management systems, mobile learning tools, educational software)	Non-educational technologies
Accessibility	Studies with full text accessible	Studies with only abstract accessible
Originality	Original research articles	Systematic reviews, meta-analyses

specific examinations of particular tools and advancements in teacher education.

Figure 4 shows Structural Equation Modeling (SEM) as the dominant approach, used in 24 publications, due to its ability to model complex relationships in technology acceptance studies. Partial Least Squares SEM (PLS-SEM) appears in seven works, valued for handling exploratory research and limited samples. Regression analysis, used in only one study, proves less suitable for TAM's complexity. This methodological trend indicates a preference for robust frameworks capable of analyzing the intricacies of technology acceptance in education.

4.2 Network analysis results

In this network (Figure 5), every variable is illustrated as a vertex, and the edges connecting the vertices symbolize the explored connections between these variables. The significance of a vertex—evidenced by its magnitude—indicates the frequency of scrutiny of the variable across diverse studies.

The central and most extensive vertices in the network are Perceived Usefulness (PU) and Attitudes to Technology (ATT), highlighting their significance and the regularity of examination in TAM-related teacher education studies. The relation between PU and Perceived Ease of Use (PEU) stands out prominently, having been researched 28 times, demonstrating researchers' interest in how technology usability influences its perceived value. The interaction between PEU and PU was determined to be significant in 28 studies (for example Muñoz-Carril et al., 2020; Sánchez-Mena et al., 2017). Beta values range from 0.167 (Ursavaş et al., 2019) to 0.731 (Al-Abdullatif, 2022). The relation between PU and Attitude (ATT) is particularly notable, as it has been the subject of investigation in 21 instances, indicating the keen attention of researchers to the impact of technology usefulness on attitudes. The correlation between PU and ATT was found to be statistically significant in 21 research studies. The beta coefficients exhibit a range from 0.15 (Sun, 2022) to 0.757 (Sánchez-Mena et al., 2019).

Similarly, the robust association between ATT and Behavioral Intention (BI), with 20 links, accentuates the emphasis on how teachers' attitudes toward technology can forecast their inclination to use it in academic environments. The significance of the interaction between ATT and BI was found to be notable across 20 research studies. Within these studies, the Beta coefficients varied, spanning from 0.148 (Chen et al., 2024) to 0.858 (Turan et al., 2022). The relation between PEU and ATT is particularly noteworthy, having been the subject of investigation in 16 instances, reflecting researchers' keen interest in the impact of technology usability on user attitudes. The connection between PEU and ATT was established as statistically significant across 16 research studies. The beta coefficients vary from 0.138 (Sun, 2022) to 0.753 (Teo and Milutinovic, 2015).

In 13 studies, the relationship between PU and BI was explored, with beta values from 0.108 (Lazar et al., 2020) to 0.845 (Mayer and Girwidz, 2019). This range suggests that the impact of PU on BI may depend on various factors, and further research is needed to identify consistent patterns. Ten studies have examined the link between SN and PU, with beta values ranging from 0.147 (Ma and Lei, 2024) to 0.552 (Saini and Abraham, 2019). This variation suggests that the relationship between SN and PU may be influenced by a variety of factors, and a more comprehensive understanding is required. Also with ten studies, the relationship between SN and BI has shown beta values from 0.102 (Ursavaş et al., 2019) to 0.476 (Songkram and Osuwan, 2022). This range suggests a complex and context-dependent relationship that warrants further investigation to identify consistent patterns.

Seven studies have investigated the interaction between SE and AU, with beta values spanning from 0.181 (Peng et al., 2023) to 0.633 (Backfisch et al., 2021). This variation suggests that the impact of SE on AU may be influenced by a range of factors, and further analysis could provide valuable insights. With seven studies as well, the relationship between SN and PEU has shown beta values from 0.435 (Alshehri, 2024) to 0.786 (Al-Abdullatif, 2022). This range suggests a strong but complex relationship that may be influenced by various factors. A more nuanced understanding of this interaction is warranted. For SE and PU, the seven studies have yielded beta values from 0.19 (Alshehri, 2024) to 0.482 (Backfisch et al., 2021). This variation suggests that the relationship between SE and PU may be influenced by multiple factors, and further research is needed to identify consistent patterns. Also with seven studies, the relationship between PU and AU has shown beta values ranging from 0.097 (Sun, 2022) to 0.431 (Backfisch et al., 2021). This suggests a weak to moderate relationship that may be influenced by various factors.

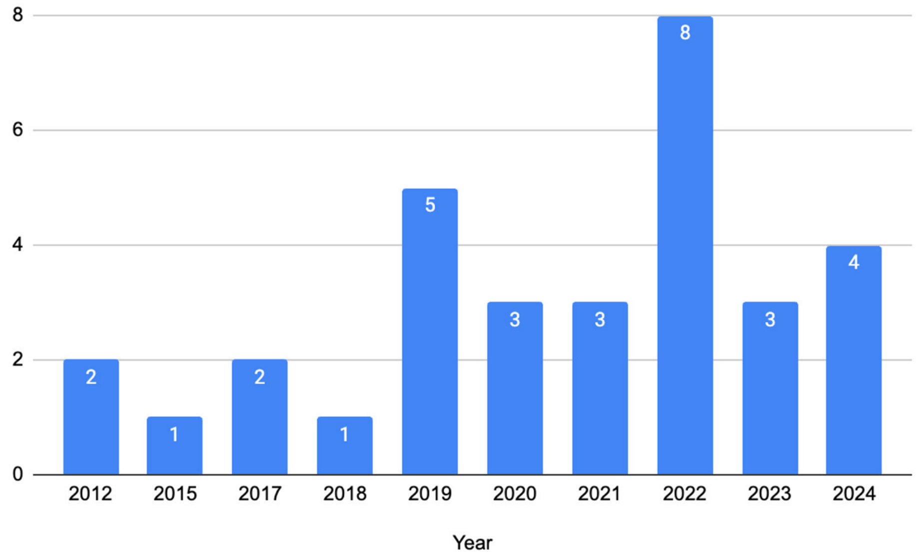

FIGURE 2
The number of publications over years.

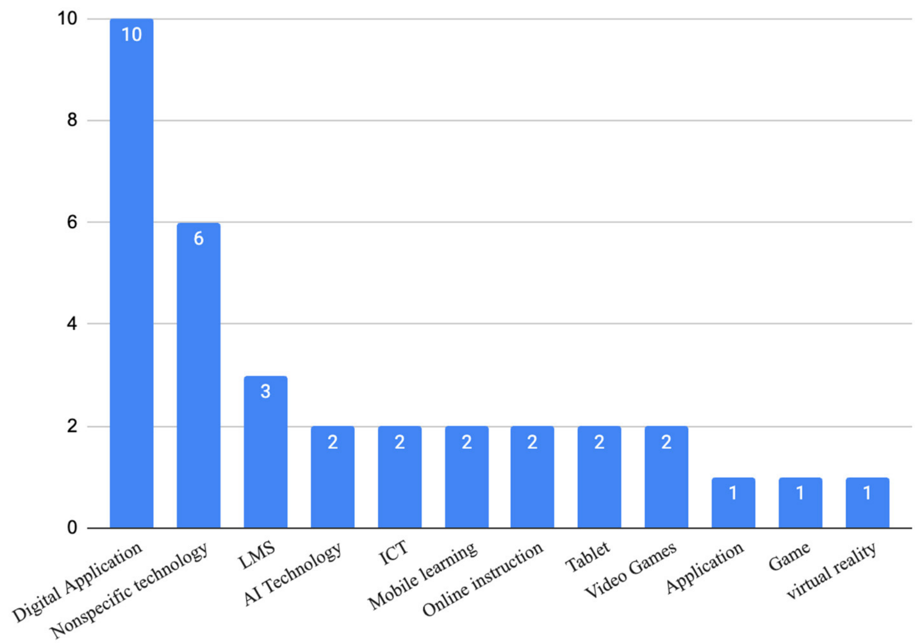

FIGURE 3
Distribution of theme.

Further analysis could help identify the conditions that strengthen this association.

The network also unveils that certain relationships are less frequently explored. For example, the links involving Competence (COM), Training (TRA), and Anxiety (ANX) are relatively scarce, indicating potential gaps or areas for expansion in the existing research corpus. Distinct or singular relationships, such as those between Psychological Wellbeing (PWB) and PU, or Satisfaction (SAT) and Job Relevance (JR), are evident in the network. These isolated connections indicate specialized research domains within TAM application in teacher education that may necessitate further investigation due to their infrequent scrutiny. Additionally, the network highlights specific pairs of variables that researchers commonly analyze together, like PEU and ATT, implying a specific research focus on how ease of use influences attitudes toward technology. Finally, the presence of context-specific elements such as Domain Knowledge (KNOW), Job Relevance (JR), and Experience (EX) within the network reflects the nuanced considerations relevant to teacher education.

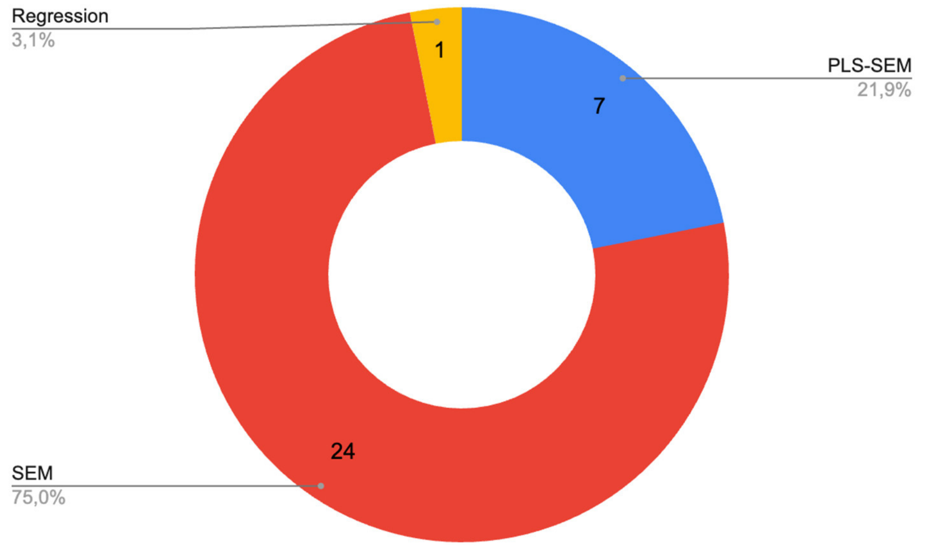

FIGURE 4
The distribution of approaches.

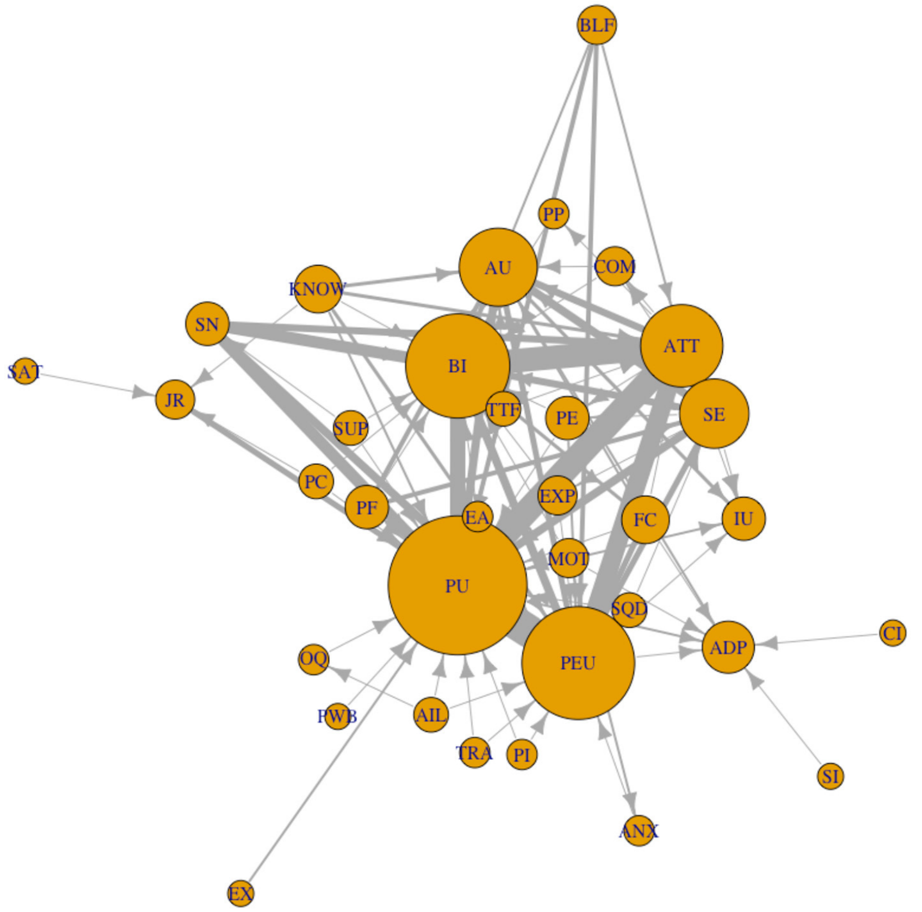

FIGURE 5
Network analysis of variables in TAM.

TABLE 2 Network statistics for each variable.

Variable	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality
ADP	0.212	3.300	0.063	0.059
AIL	0.091	0.379	0.000	0.029
ANX	0.061	0.317	0.000	0.014
ATT	0.424	1.941	0.152	0.870
AU	0.394	8.250	0.040	0.372
BI	0.576	3.000	0.006	0.712
BLF	0.121	1.000	0.000	0.165
CI	0.030	2.357	0.000	0.001
COM	0.121	5.500	0.012	0.035
EA	0.061	0.330	0.000	0.025
EX	0.030	0.314	0.000	0.031
EXP	0.121	0.402	0.006	0.045
FC	0.182	1.833	0.000	0.142
IU	0.152	NaN	0.000	0.080
JR	0.121	0.244	0.019	0.080
KNOW	0.182	1.000	0.000	0.141
MOT	0.121	0.375	0.000	0.028
OQ	0.061	0.347	0.000	0.016
PC	0.091	0.363	0.000	0.028
PE	0.152	0.465	0.018	0.072
PEU	0.636	0.351	0.204	0.882
PF	0.152	0.688	0.000	0.111
PI	0.061	0.384	0.000	0.029
PP	0.061	2.357	0.002	0.024
PU	0.818	0.388	0.142	1.000
PWB	0.030	0.347	0.000	0.015
SAT	0.030	0.226	0.000	0.001
SE	0.333	1.500	0.024	0.334
SI	0.030	2.357	0.000	0.001
SN	0.152	0.452	0.008	0.441
SQD	0.091	1.179	0.000	0.034
SUP	0.091	0.702	0.000	0.033
TRA	0.061	0.384	0.000	0.029
TTF	0.091	1.833	0.000	0.035

For KNOW and PU, the two studies have yielded beta values of 0.471 (Mayer and Girwidz, 2019) and 0.856 (Liu and Shi, 2024). This suggests a strong and consistent relationship between KNOW and PU in these studies, although further research with a larger sample of studies is needed to confirm this pattern. In two studies, the relationship between FC and AU was explored, with beta values of 0.316 (Sun, 2022) and 0.32 (Camadan et al., 2018). This suggests a relatively consistent and moderate relationship between FC and AU, although further research is needed to confirm this pattern. Two studies have also examined the link between BLF and ATT, with beta values of 0.163 (Liu et al., 2017) and 0.616 (Gurer and Akkaya, 2022). This variation suggests that the impact of BLF on ATT may depend on various factors, and further analysis is needed to understand this relationship fully. For PE and PEU, the two studies have yielded beta values of 0.467 (Sánchez-Prieto et al., 2019a) and 0.518 (Zhang et al., 2023). This suggests a strong and consistent relationship between PE and PEU in these studies, although further research with more studies is needed to confirm this pattern. In the same number of studies, the relationship between BLF and BI was explored, with beta values of 0.105 (Antonietti et al., 2022) and 0.239 (Chen et al., 2024). This variation suggests that the impact of BLF on BI may depend on contextual factors, and further research is needed to uncover consistent patterns.

The network analysis offers a thorough depiction of the intricate research landscape concerning technology acceptance in teacher education. It underscores the predominance of certain variables like PU and ATT while also identifying the less-explored paths involving other influential factors. The intricate network of relationships demonstrates the dynamic interactions among various elements influencing technology acceptance among educators, presenting abundant opportunities for further exploration of the less-investigated variables.

4.3 Moderator variables

Degree centrality quantifies the number of direct links a node possesses, with PU emerging as the most central node, indicating its strong connectivity to various other factors in TAM research (in Table 2). PEU and BI also exhibit notable degree centralities, highlighting their significant contributions within the scholarly network. Closeness centrality denotes a node's proximity to all other nodes in the network, suggesting its capacity for efficient interactions with the entire system. Notably, AU displays the highest closeness centrality, implying its potential for swift impact on, or susceptibility to influence from, other variables, despite an apparent inversion in values. Betweenness centrality signifies a node's role as a mediator in the network, with PEU holding the highest betweenness centrality, positioning it as a critical intermediary governing information flow among nodes. Eigenvector centrality considers the connections of a node's neighbors, reflecting the node's influence in the network. PU boasts the highest eigenvector centrality, indicating its association with other highly influential variables and its pivotal position within the network. Since there is no arrow from IU to other variables and arrows come from other variables to itself, the "Closeness centrality" value could not be calculated. Certain variables such as TRA and SAT exhibit low centrality metrics across the board, hinting at their peripheral status within the ongoing research network. Such findings may suggest these variables are either emerging topics yet to establish robust relationships with others or occupy specialized niches within TAM applications in teacher education.

To summarize, the analysis underscores the central roles of PU, ATT, and PEU in the network, with PU reigning as the most dominant influencer overall. Variables like AU also emerge as crucial due to their potential to serve as pivotal nodes of influence. Discrepancies in centrality measures for other variables reveal diverse roles and varying degrees of impact within the research network, signaling distinct areas of emphasis and avenues for future exploration in the realm of TAM in teacher education.

4.4 Cluster analysis result

Figure 6 enriched through the utilization of the Spinglass technique from the igraph package in R, illustrates the identification of communities or clusters in the network that portray groupings of interlinked variables in studies employing the TAM in the realm of teacher education. The Spinglass method for community detection is grounded in physics principles, leading to the clustering of nodes in a manner that simulates the spin states of particles, thereby forming clusters based on the intensity and density of connections.

Within the network structure, each node serves as a representation of a variable, with the connections serving to depict the relationships under examination among them. The color-coded regions signify distinct communities that have been identified within the network.

A distinct community, Cluster 1, emerges as a relatively smaller entity encompassing OQ and AIL, potentially denoting specialized domains within the scope of TAM application. These variables may signify emerging factors of significance or specialized areas of inquiry.

Cluster 2 comprises variables like MOT, ANX, SI, and ADP, pointing toward a community that emphasizes the psychological and social dimensions of technology adoption. The inclusion of Adoption in this cluster underscores the intricate relationship between personal and social elements in the decision-making processes related to technology utilization in educational settings.

Grouping together KNOW, JR, PC, and SAT, Cluster 3 underscores an emphasis on the compatibility of technology with existing knowledge and occupational requirements, alongside the overall contentment derived from technology employment, all of which are crucial in comprehending the integration of technology in pedagogical practices.

The most expansive community, Cluster 4, incorporates pivotal TAM variables such as ATT, PEU, and PU, alongside BI and additional variables like FC, SN, and SUP. This cluster stands at the core of TAM exploration in teacher education, encompassing fundamental facets of technology acceptance, ease and utility of technology, and the intention to engage with it.

Lastly, Cluster 5 is affiliated with SE, COM, AU, and an array of other factors that could potentially influence the practical and self-assessment dimensions of technology utilization, including EXP and PF.

The categorization of variables into clusters unveils the multifaceted landscape of TAM exploration within teacher education. The clusters serve as indicators of thematic focal points within the research domain, including psychological and social dimensions, knowledge and vocational relevance, core TAM constructs, as well as practical utilization and self-evaluation. Such clustering endeavors can guide forthcoming research trajectories by shedding light on which variable groupings tend to interact more frequently and which necessitate deeper scrutiny.

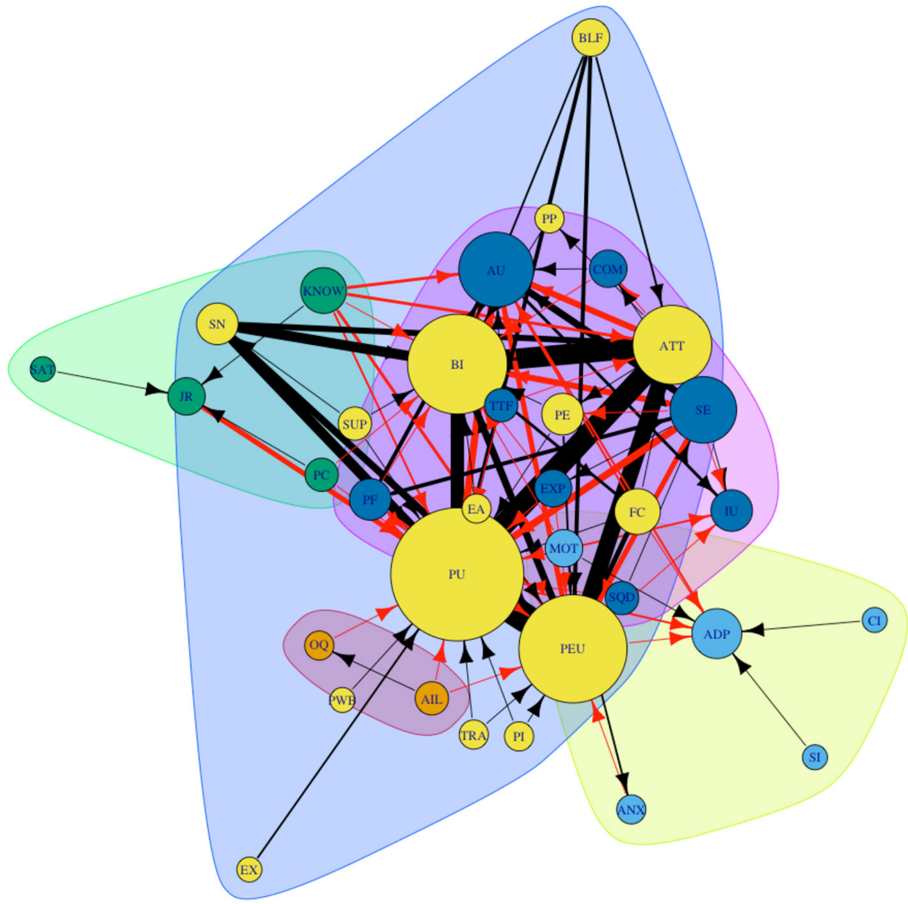

FIGURE 6
Cluster based on network analysis of variables in TAM.

5 Discussion

This study sought to establish a thorough knowledge of the ideas by means of an analysis of the relationships among the factors applied in teacher education under TAM. Our study attempted to find the most significant factors and relationships influencing teachers' technology adoption by means of network analysis approach, thereby analyzing the intricate interactions among the elements inside the TAM framework. We will review our results in view of the body of current literature, debate the theoretical and pragmatic consequences of our work, and offer suggestions for next studies in this part on discussion. We will first go over the main results of our network analysis then look at the relevance of the clusters and major variables we found. We will then assess our study's contributions to the domains of teacher preparation and technology integration, and last we will go over the limits of our study and future research paths.

The descriptive findings of our study show that TAM research in teacher education continues to be used in the field of teacher education. In systematic review studies on TAM in the field of education (Al-Qaysi et al., 2020; Granić and Marangunić, 2019), TAM continues to be used as a technology adaptation framework. When we look at the distribution of research topics, we see that digital applications are the most common area of study. This is in line with Lai and Bower (2019) observations on the diversity of technology use in education. On the other hand, new technologies such as artificial intelligence and virtual reality are less studied, suggesting that these areas are just beginning to be explored in teacher education, as Chen et al. (2024). Methodologically, the general application of SEM is in accordance with Scherer et al. (2019) views on the rising relevance of SEM for modeling complicated interactions in educational technology research. These results imply that, although more study on the integration of new technologies is needed, research on technology acceptance in teacher education is developing in terms of both breadth and approach.

Our findings emphasize the importance of perceived usefulness, attitudes toward technology, and perceived ease of use within the TAM framework, aligning with prior studies that have recognized these elements as fundamental determinants of technology acceptance. Our findings are compatible with other studies findings (King and He, 2006; Sun, 2022; Teo and Milutinovic, 2015; Venkatesh and Bala, 2008). For example, Venkatesh and Bala (2008) also considered "Perceived Usefulness" and "Perceived Ease of Use" as the main variables. The importance of these variables in our network analysis underlines their enduring importance in influencing the adoption and use of educational technologies by teachers. In fact, as stated in Davis (1989), the concepts of "Perceived Usefulness" and "Perceived Ease of Use" form the basis of the TAM model.

The strong link between ATT and Behavioral Intention (BI) is in line with Teo's (2011) study examining teachers' technology use intentions. This confirms that teachers' attitudes toward technology play an important role in shaping their intention to use. The associations of the Subjective Norm (SN) variable with PU and BI support the importance of social influences emphasized by Venkatesh and Davis (2000) in their TAM2 model. The less examined relationships that emerged in our network analysis (e.g., links related to Competence and Education) are in line with Ertmer and Ottenbreit-Leftwich (2010) observations on the complex nature of technology integration in teacher education and suggest that these areas need further exploration.

Our network analysis results for moderator variables reveal the complex interplay of factors influencing technology acceptance in teacher education. Perceived Utility (PU) variable has the highest degree and eigenvector centrality, confirming the critical role of this factor in teachers' technology acceptance. This result conforms with the meta-analysis by Scherer et al. (2019) and validates the fundamental presumptions of Davis's (1989) original TAM model. Perceived Ease of Use (PEU) has a high betweenness centrality that implies this variable serves as a link between several network components. This validates Venkatesh and Bala's (2008) stressed in the TAM3 model the notion that PEU has several antecedents and implications. The high proximity centrality of the Actual Use (AU) (Hsu et al., 2021; Lay et al., 2013; Shodipe and Ohanu, 2021) variable points to the possibility for this variable to be fast changed by other network elements. This outcome is in line with the study (Ranellucci et al., 2020) on the relationship between pre-service teachers' intentions and actual technology use. These findings show the several nature of technology acceptance in teacher education and provide important guidance on the path of further research. Especially PU and PEU's vital roles suggest that although the possible impact of less-studied variables should not be ignored, teacher preparation programs should focus on these aspects. Although the TAM has been widely employed and validated, our study also uncovers potential deficiencies and areas that have not been thoroughly explored within the network analysis. For example, variables like training (Quintana-Ordorika et al., 2024), satisfaction (Philemon et al., 2022), and competence (Peng et al., 2023) demonstrate lower centrality metrics, indicating their peripheral standing within the research network. These findings suggest that while certain variables are firmly established in the literature, others may represent emerging topics that have not yet established robust connections with other factors. This presents an avenue for future research to delve into these less-explored areas and augment the comprehensive understanding of technology acceptance among teachers.

Our cluster analysis results reveal the multidimensional nature of TAM research in teacher education. The five clusters identified show that the factors affecting technology acceptance are grouped under different thematic groups. The fact that Cluster 2 includes variables such as motivation, anxiety and social influence supports the importance of social influences emphasized by Venkatesh and Davis (2000) in the TAM2 model. This finding also confirms Bagozzi's (2007) suggestion that TAM should consider social influences more. The coexistence of variables such as content knowledge, job suitability and perceived compatibility in Cluster 3 is in line with Mishra and Koehler's (2006) idea of integration of technology, pedagogy and content knowledge in the TPACK framework. This emphasizes the importance of professional knowledge and context in teachers' technology acceptance. The fact that Cluster 4 includes the core variables of TAM (ATT, PEU, PU, and BI) shows that Davis (1989) original model is also valid in the context of teacher education. Still, the fact that this cluster also includes social customs and supporting factors emphasizes the need of considering technological adoption from a broader perspective as advocated by Venkatesh et al. (2003) in the UTAUT model. In Cluster 5, the co-occurrence of factors such as self-efficacy, competency, and actual use matches the results of Ertmer et al. (2012) on the crucial part of self-efficacy and beliefs in teachers' technology integration practices. This cluster structure suggests that acceptance of technology in teacher preparation consists in a complex mix of psychological, social, cognitive, and contextual aspects. These findings underscore the need of future research and teacher education programs to incorporate this multidimensional structure and imply the necessity of a complete approach to help technological integration.

5.1 Policy implications and future research directions

Our network analysis provides interesting data that can direct educational projects aimed to increase technological integration in classrooms. The outcomes underline the need of targeted interventions and wise policy decisions to help teachers adopt and effectively use educational technologies. One of the main policy ramifications results from the central relevance of perceived usefulness and perceived simplicity of use in our network analysis. Programs for professional development emphasizing on raising teachers' confidence and competency in using technology should be given top priority by policy makers. These courses should not only teach technical abilities but also show the useful advantages of technology integration in many educational environments. School systems might set up mentoring initiatives, for instance, whereby tech-savvy teachers help their peers thereby promoting peer learning and technology acceptance. Our results further underline the need of removing obstacles to technology acceptance connected to infrastructure and support. Schools should make continuous technological help available to their staff and make strong investments in a technology infrastructure. Establishing dedicated IT support teams in colleges or forming agreements with technology corporations could help to ensure flawless integration and troubleshooting.

The cluster analysis results suggest that technological acceptance is shaped by a complex interaction of psychological, social, and contextual aspects. Policymakers should approach technology integration holistically, weighing social, and organizational characteristics in schools together with technical features. This can involve the development of cooperative learning environments whereby educators might exchange their technological integration best practices and experiences. Our research also exposed several gaps in the body of knowledge that demand more investigation.

(1) Contextual factors: Further investigation is required to examine the variability of technology adoption across diverse educational levels, topic domains, and cultural contexts. (2)

Emerging technologies: With the introduction of emerging technologies like artificial intelligence and virtual reality in educational environments, research should examine the applicability of current technology acceptance frameworks to these advances. (3) Integration with pedagogical practices: Future research ought to investigate the incorporation of technology acceptance models with pedagogical knowledge and practice frameworks, such as TPACK (Mishra and Koehler, 2006). (4) Student outcomes: Although our study focused on instructors' adoption of technology, subsequent research should investigate how this acceptance impacts students' learning results and engagement.

By addressing these research deficiencies and enacting evidence-based policies, we may cultivate a more conducive atmosphere for technology integration in education, thereby enhancing teaching methodologies and students' learning experiences in the digital era.

6 Conclusion

This paper shows network analysis of TAM in teacher education, therefore revealing the intricate interactions among the elements affecting technology acceptance. Our results imply that teachers' technology acceptance is mostly influenced by perceived utility, opinions on technology, and perceived simplicity of usage. Network analysis revealed how these underlying constructs interact in shaping technology acceptance in teacher education. Our study makes important contributions to the existing literature on technology acceptance in teacher education. Our network analysis approach provides a more nuanced picture of the connections between different factors, revealing that some relationships are stronger than others and that certain sets of variables tend to cluster together. These insights have allowed us to create more focused and efficient strategies to support the integration of technology into the educational process. In summary, by providing guidance for the creation of professional development initiatives and teacher education programs, the research findings may enable a more successful integration of technology into educational environments. This could finally help to improve the methods used to teach and learn for learner.

While this study provides a nuanced understanding of the research landscape and key variables within TAM, it also has certain limitations. The analysis relied on the availability and accessibility of published studies, which may have resulted in the exclusion of relevant research not indexed in the selected databases. Additionally, the study focused specifically on teacher education, and the findings may not be generalizable to other contexts or user groups. Furthermore, the dynamic nature of the field and the continuous evolution of educational technologies may render certain aspects of the study outdated over time.

Future research should aim to address these limitations by employing more comprehensive data sources and considering a broader range of contexts and user groups. Given the rapid advancements in educational technologies, ongoing updates and expansions of the TAM framework are necessary to capture emerging technologies and their unique characteristics. Additionally, further exploration of the less-studied variables and relationships identified in this study, such as training, satisfaction, and competence, could reveal important insights into the technology acceptance process. Finally, the practical implications of this study suggest that professional development programs for teachers should focus on enhancing their perceptions of usefulness and ease of use, as well as addressing psychological and social factors that influence technology adoption.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

EG: Writing – original draft, Writing – review & editing. AO: Writing – original draft, Writing – review & editing. MK: Writing – original draft, Writing – review & editing. DA: Writing – original draft, Writing – review & editing. EO: Writing – original draft, Writing – review & editing. IA: Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Acknowledgments

Generative AI technologies are used in order to check grammatical errors and to increase readability of the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2024.1436724/full#supplementary-material

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