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TECHNOLOGY ACCEPTANCE MODEL (TAM) IN ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION (AIHEd): A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

This systematic literature review examines the application of the Technology Acceptance Model (TAM) to artificial intelligence adoption in higher education (AIHEd). Based on a comprehensive analysis of 23 empirical studies, the research investigates TAM characteristics in AIHEd, evaluates the model's explanatory power, and identifies significant external variables. The findings validate TAM's robustness in the AIHEd context, with core relationships showing high significance rates. Trust emerges as a critical factor unique to Artificial Intelligence (AI) adoption, significantly influencing all core TAM constructs. The analysis reveals perceived enjoyment, subjective norm, and trust as the most frequently examined and significant antecedents. The study identifies methodological challenges, particularly in measuring the relationship between behavioral intention and actual usage. The geographic concentration in research suggests the need for more diverse regional perspectives. These findings contribute to both theory and practice by validating TAM's applicability to AI adoption while highlighting the need for theoretical extensions incorporating trust. The study provides practical insights for higher education institutions implementing AI technologies and suggests directions for future research in this rapidly evolving field.

Keywords: Technology Acceptance Model, Artificial Intelligence, Higher Education, Systematic Review, AIHEd, SLR

1. Introduction

The proliferation of artificial intelligence (AI) in higher education represents a transformative force in contemporary educational landscapes (Zawacki-Richter et al., 2019). As AI technologies continue to reshape learning experiences (Holmes et al., 2019), empirical evidence increasingly validates their educational value. Recent studies have demonstrated AI's positive impact on student engagement (Lo et al., 2024) and learning outcomes across diverse educational contexts (Dai et al., 2024; Wu & Yu, 2024; Zheng et al., 2023). However, the realization of these benefits fundamentally depends on effective technology adoption, which currently exhibits notable disparities across institutions and regions (Singla et al., 2024). These adoption disparities risk exacerbating existing educational inequalities (UNESCO, 2021), underscoring the critical importance of understanding AI technology adoption patterns in higher education.

The Technology Acceptance Model (TAM), introduced by Davis Davis (1989), has emerged as the predominant theoretical framework for understanding technology adoption in educational settings (Granić, 2022). Its robustness has been validated across various educational technologies. Within the burgeoning field of AI adoption research, TAM remains the most frequently applied theoretical lens. Despite the growing number of studies applying TAM to Artificial Intelligence in Higher Education (AIHEd), a systematic understanding of TAM's role in this domain remains absent (Bond et al., 2024). Several critical gaps in the literature hinder our understanding of TAM's applicability in AIHEd.

Foremost, the empirical landscape of TAM research in AIHEd remains unclear. Existing studies have not systematically examined publication trends, journal distributions, sample demographics (countries, participant identities), and the specific AI technologies investigated. Without this comprehensive overview, it is difficult to assess the scope and focus of TAM-based AIHEd research (Granic & Marangunic, 2019).

Furthermore, uncertainty persists regarding the extent to which TAM's internal hypothesized relationships have been empirically tested and validated. While numerous studies have applied TAM to AI adoption in higher education, no existing research has quantitatively assessed the frequency with which TAM hypotheses are tested (hypothesis testing rate) or the extent to which they produce statistically significant results (significance rate). The hypothesis testing rate reflects the extent to which TAM's internal hypothesized relationships have been investigated in AIHEd studies, while the significance rate provides insight into the explanatory power of these relationships in predicting AI adoption (Lee et al., 2003). Without systematically compiled data on these statistical metrics, it remains unclear whether TAM constructs are consistently tested and whether they reliably explain AI adoption in higher education

Additionally, the incorporation of external variables into TAM for AIHEd and their empirical validation remain unclear. While many studies extend TAM by introducing additional variables (e.g., Al Darayseh, 2023; Lai et al., 2023; Rahman et al., 2023; Zou et al., 2023), there is no systematic synthesis of which variables have been incorporated, how frequently they have been tested, and whether they yield statistically significant results. Without this knowledge, it is difficult to determine which external factors consistently influence AI acceptance beyond traditional TAM constructs.

To address these research gaps, this study aims to systematically analyze the application of TAM in AI adoption research within higher education (AIHEd). The study pursues three interconnected objectives:

First, this research maps the empirical landscape of TAM research in AIHEd by systematically examining publication trends, journal distributions, sample demographics (countries, participant identities), and the specific AI technologies investigated. This analysis provides a structured overview of how TAM has been applied in AIHEd and identifies existing research patterns.

Second, the study evaluates the extent to which TAM's internal hypothesized relationships have been empirically tested and validated in AIHEd by quantifying hypothesis testing rates and significance rates reported in existing studies. This assessment determines the consistency of TAM's application and its predictive strength in explaining AI adoption in higher education.

Finally, this investigation identifies and assesses the significance of external variables incorporated into TAM for AIHEd by synthesizing which external factors have been integrated, how frequently they have been tested, and whether their relationships with TAM constructs have yielded statistically significant results. This objective clarifies the role of external variables in extending TAM for AI adoption in higher education and provides insights into their influence beyond the model's traditional constructs.

2. Literature Review

2.1. Artificial Intelligence in Higher Education (AIHEd)

Artificial intelligence (AI) has emerged as a transformative force in higher education. Drawing from Hwang et al.'s (2020) definition of Artificial Intelligence in Education (AIEd) "the use of AI technologies or applications in educational settings to facilitate teaching, learning, or decision-making" we define Artificial Intelligence in Higher Education (AIHEd) as the application of AI technologies in higher educational contexts to facilitate teaching, learning, or decision-making. This definition encompasses four key dimensions: (1) technology must be AI-based, (2) the educational context is specifically higher education, (3) target users include students, faculty, and administrative staff, and (4) the purpose is to enhance teaching, learning, or education-related decision-making processes. A recent meta-systematic review by Bond et al. (2024) has identified multiple significant benefits of AI integration in higher education. These benefits include the delivery of personalized learning experiences, enhanced understanding of student learning patterns, improved learning outcomes, reduced administrative burden for educators, increased educational equity, and more precise assessment and feedback mechanisms. The documented potential of AI to transform higher education underscores the importance of understanding factors that influence its adoption and implementation.

2.2. TAM in Education

Understanding the factors influencing the acceptance of AI in education is critical, as existing research demonstrates AI's potential to enhance educational processes (Urban et al., 2024). By recognizing and addressing these factors, educational institutions can more effectively integrate AI technologies.

Several Information Systems (IS) theories and models are used to understand IS acceptance, including the Innovation Diffusion Theory (IDT) by Rogers (1962), TAM by Davis (1989), the Theory of Planned Behavior (TPB) by Ajzen (1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). Among these, TAM is the most commonly adopted model in education (Granić & Marangunić, 2019a; Šumak et al., 2011) and the most frequently used model for assessing user acceptance of AI technologies (Kelly et al., 2023).

The original TAM framework comprises five core constructs: perceived usefulness (PU), perceived ease of use (PEU), attitude toward using (ATT), behavioral intention to use (BI), and actual system use (AU). Davis et al. (1989) define PU as "the degree to which a person believes that using a particular system would enhance his or her job performance," and PEU as "the degree to which a person believes that using a particular system would be free of effort." BI represents future intentions to adopt technology (Venkatesh & Bala, 2008), while AU typically measures actual usage frequency or duration (Venkatesh & Bala, 2008). ATT specifically addresses attitudes toward using technology, rather than attitudes toward the technology itself (Ajzen, 1991). Later iterations of TAM (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) eliminated ATT and posited that PEU directly influences BI.

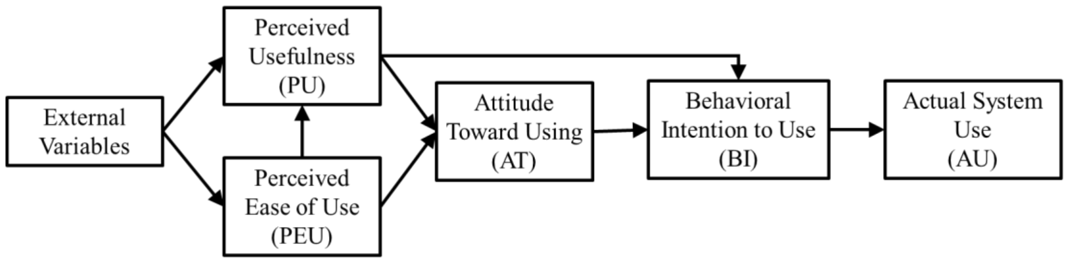

Figure 1: TAM Model (Davis et al., 1989)

The extensive use of the TAM model has led to numerous literature reviews (Al-Emran & Granić, 2021; Alomary & Woollard, 2015; Alshammari & Rosli, 2020; Chang et al., 2010; Chuttur, 2009; Doulani, 2019; Gupta et al., 2022; Lee et al., 2003; Legris et al., 2003; Marangunić & Granić, 2015; Mortenson & Vidgen, 2016; Silva, 2007; Turner et al., 2010; Yucel & Gulbahar, 2013) that have significantly contributed to our understanding of TAM's applications. Lee et al.'s (2003) comprehensive review of TAM research in general technology acceptance systematically documented the empirical validation of relationships between major TAM variables. Their analysis of hypothesis testing results showed that the relationship between perceived ease of use (PEU) and behavioral intention (BI) was significant in 63 out of 82 studies. Similarly, the relationship between behavioral intention (BI) and actual use (AU) showed significance in 13 out of 15 studies. Other hypothesized relationships, such as those between PU-BI and PEU-BI, also demonstrated consistent statistical significance across reviewed studies. Scherer et al. (2019) conducted a meta-analytic structural equation modeling (MASEM) study synthesizing 124 correlation matrices from 114 empirical TAM studies in education.Their findings confirmed that TAM effectively explains technology acceptance in educational settings, with PU and PEU as strong predictors of BI and AU.

Research using the TAM model in education covers a wide range of topics, including technology adoption (Granić & Marangunić, 2019b), online learning (Mustafa & Garcia, 2021), mobile learning (Al-Emran et al., 2018; Liu et al., 2024; Mugo et al., 2017), learning management systems (Cavus et al., 2022), higher education (Rosli et al., 2022), e-learning (Abdullah & Ward, 2016), and technology adoption by teachers (Scherer et al., 2019). Despite the varied themes, several consistent findings emerge regarding study subjects, sample regions, research methodologies, TAM applications, and commonly used external variables. Students are the most frequently surveyed subjects, higher education is the most examined level, Asian countries dominate sample regions, quantitative methods are predominantly used, and TAM is often employed in an extended form. These findings deepen our understanding of TAM's application in education.

However, differences exist in the types of technologies studied and the most common external variables. For example, Mustafa and Garcia (2021) found that course information, satisfaction, system quality, and academic performance are essential external variables in online learning. In contrast, Rosli et al., (2022) identified self-efficacy, subjective norms, experience, and enjoyment as critical variables in higher education technology adoption. Similarly, Abdullah & Ward (2016) highlighted self-efficacy, subjective norm, enjoyment, computer anxiety, and experience in e-learning adoption. These differences suggest that the characteristics of different educational technologies influence the external variables extending TAM.

While existing reviews have covered TAM's application in various educational technologies, a gap remains in the literature regarding its application in AI in higher education domain. This gap prevents us from identifying the most common external variables in TAM studies and understanding the outcomes of hypothesis tests in AI in higher education domain. Therefore, examining the prevalent external variables in studies applying TAM to AI in higher education and evaluating the results of these hypothesis tests is necessary.

3. Method

3.1. Search Strategy and Protocol

The literature search encompassed four comprehensive academic databases: Web of Science Core Collection (WOS), Scopus, Education Resources Information Center (ERIC), and IEEE Xplore. The search protocol integrated three conceptual components. The first component focused on Technology Acceptance Model terminology, including "TAM" and "technology acceptance model". The second component encompassed artificial intelligence terms such as "artificial intelligence", "machine intelligence", "intelligent support", "intelligent virtual reality", "chatbot*", "machine learning", "automated tutor", "personal tutor*", "intelligent agent*", "expert system", "neural network", "natural language processing", "intelligent tutor*", "adaptive learning system*", "adaptive educational system*", "adaptive testing", "decision trees", "clustering", "logistic regression", "adaptive system*", "Chatbot*", and "ChatGPT*". The third component covered educational context indicators including "education", "learner", "student", "teacher", and "instructor". This comprehensive search framework was informed by established systematic reviews in technology acceptance (Granic & Marangunic, 2019), artificial intelligence (Bond et al., 2024; Labadze et al., 2023), and educational research (Labadze et al., 2023).

Database-specific search strings were strategically developed to optimize each platform's unique search capabilities. For Web of Science, topic (TS) fields were utilized for content matching and Web of Science category (WC) fields for subject classification. Scopus searches incorporated title, abstract, keyword, and author fields (TITLE-ABS-KEY-AUTH) for comprehensive coverage. ERIC searches were configured with peer-review filters, while IEEE Xplore searches were optimized for abstract-level matching. The search was executed on April 8, 2024, without temporal restrictions, targeting peer-reviewed content in English.

3.2. Eligibility Criteria

The screening process followed a two-phase approach with hierarchical criteria. The first phase established initial screening requirements. Studies were required to be published in

English to ensure accurate interpretation and analysis. The temporal scope extended from 1986, marking the introduction of TAM by Fred Davis (1986), through 2024. To maintain scholarly rigor, only peer-reviewed articles from academic journals were considered.

Meanwhile, the second phase implemented detailed content eligibility criteria. For inclusion, studies must have examined AI technologies or applications as the subject of technology adoption research. These AI applications needed to be specifically employed for educational purposes. The theoretical framework must have utilized either the original TAM or an extended version (TAM+) as its core model. Studies were required to be situated within higher educational contexts and employ quantitative empirical methodologies with hypothesis testing. Furthermore, all studies must have incorporated the three core TAM variables: Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Behavioral Intention (BI).

Studies were excluded based on several criteria: examination of non-AI technologies, application of TAM in non-higher educational contexts, utilization of AI technologies outside educational purposes, and use of theoretical models other than TAM as the primary framework. Opinion pieces, editorial content, and non-empirical research were removed from consideration. Articles lacking hypothesis testing results or missing any of the three core variables (PU, PEU, BI) were excluded. Additionally, retracted articles and those suspected of plagiarism were eliminated from the analysis.

3.3. Study Selection Process

The initial database search yielded 516 articles, with distinct distributions across databases: Web of Science Core Collection (n=167), Scopus (n=282), Education Resources Information Center (ERIC) (n=34), and IEEE Xplore (n=33). The preliminary screening process involved removing 157 duplicate entries identified through cross-database comparison. Additionally, 4 book chapters were excluded to maintain the focus on peer-reviewed journal articles and conference proceedings, resulting in 355 unique publications for further evaluation. The title and abstract screening phase rigorously applied the established inclusion criteria, leading to the exclusion of 278 papers that did not meet the specified requirements. The remaining 77 papers underwent a comprehensive full-text assessment, resulting in the exclusion of 41 additional articles. This systematic screening process identified 36 articles for detailed quality evaluation.

3.4. Quality Assessment Protocol

The quality appraisal of the 36 articles followed evaluation criteria from recent studies by Claro et al. (2024) and Zhao et al. (2021). The assessment incorporated quality criteria across three dimensions: (1) Theoretical dimension examined whether concepts were clearly defined, research objectives were explicitly specified, and the study design effectively aligned with achieving these objectives. (2) Methodological dimension assessed whether research instruments were clearly described and based on the study design, whether the instruments were validated, whether the instruments were provided with face validity, and whether the sample was adequately described with sufficient size for the proposed analyses. (3) Findings dimension evaluated whether research questions were comprehensively answered, and whether conclusions were clearly described and supported by the results.

Each criterion was evaluated using a three-point scale: "Yes, complies" (1 point), "Partially complies" (0.5 points), and "Does not comply" (0 points). Publications needed to achieve a minimum score of 7 points across the nine criteria to qualify for inclusion in the analysis. This quality assessment process resulted in the exclusion of 13 articles that fell below the quality threshold, yielding 23 articles for final analysis. This data extraction process is illustrated in a PRISMA flow diagram (Page et al., 2021) in Figure 2.

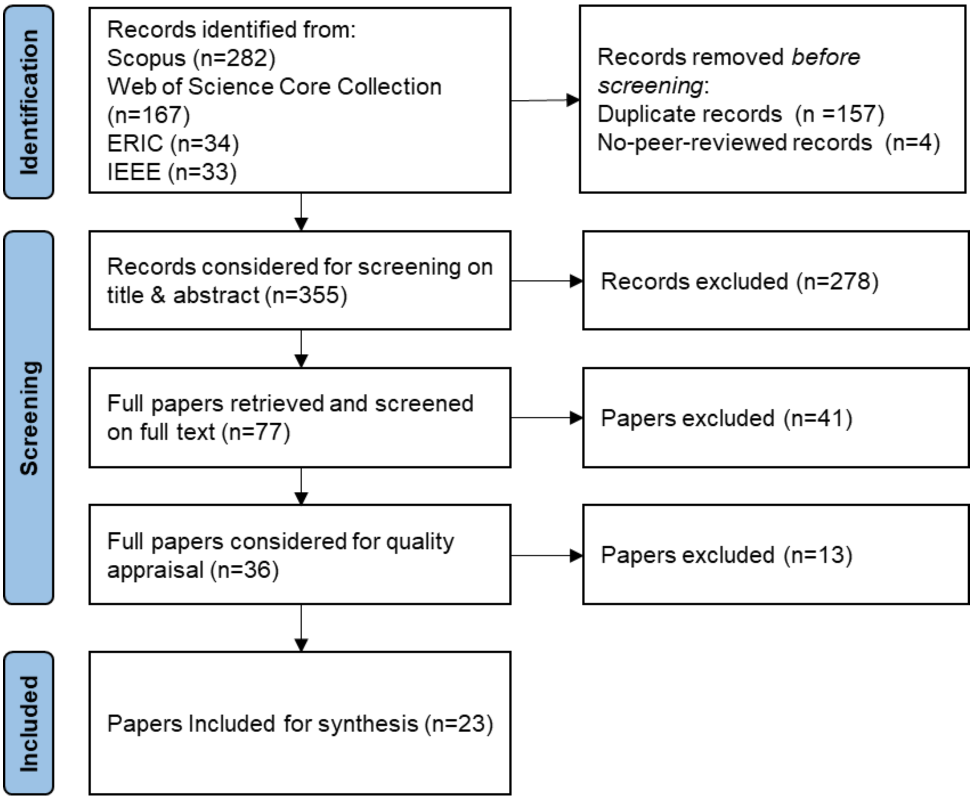

Figure 2: PRISMA Flow: Data Extraction Procedure

3.5. Coding Process of Included Articles

A specific coding scheme for data extraction, detailed in Table 1, was developed. Independent coding by researchers ensured accurate data collection, and discrepancies were resolved through regular meetings.

Table 1: The coding scheme of data extraction

Author	The name(s) of the article's author(s)
Year of Publication	The year the article was published
Source of Literature	The journal or conference where the article appeared
Geographical location	The country or region where the study was conducted
Participant Identity	The roles or positions of individuals participating in the study.
AI Technology	The type of AI technology investigated.
Predictor Variables	Identifies the factors predicting the core constructs of PEU, PU, ATT, and BI.
Hypothesis Testing Outcomes	The results of the hypothesis tests.

3.5. Statistical approaches

Descriptive statistical methods were employed to analyze the empirical application of TAM in AIHEd, following Lee et al. (2003) and Xue et al. (2024). The analysis mapped publication trends, journal distributions, sample demographics (e.g., country, participant type), and AI technologies studied, providing an overview of TAM research patterns. Additionally, hypothesis testing rates and significance rates were quantified to assess the consistency and predictive strength of TAM in AI adoption. External variables incorporated into TAM were also examined by evaluating their frequency and statistical significance.

4. Results

4.1. Mapping the Empirical Landscape of TAM Research in AIHE (Objective 1)

In this section, we systematically examine the publication trends, journal distributions, sample demographics, and the AI technologies investigated in the studies reviewed. This provides a structured overview of how TAM has been applied in AIHEd and highlights existing research patterns. The analysis identifies key trends in the application of TAM.

In terms of publication trends, the temporal analysis revealed a rapidly growing research interest in AI technology adoption in higher education. Specifically, 12 studies were published in 2024, 9 studies in 2023, and only 2 in 2022. This indicates a significant increase in publications over the past two years, reflecting the rising academic focus on AI adoption in higher education.

Regarding journal distributions, the studies were published across 7 different scholarly journals, reflecting a diverse academic interest in the field. *Education and Information Technologies* published the highest number of articles (n=3), followed by *International Journal of Human-Computer Interaction*, *Computer Assisted Language Learning*, *Computers and Education: Artificial Intelligence*, and *International Journal of Educational Technology in Higher Education* with two articles each. Other journals, such as *Psychology Learning and Teaching* and *IEEE Access*, contributed single articles, showcasing the multidisciplinary appeal of this research area.

In terms of sample demographics, the analysis of the 23 studies revealed research spanning across 13 countries, with a dominant representation from Asia. China contributed the largest number (n=7), followed by the UAE (n=3) and Bangladesh (n=2). Other regions, such as Europe, also provided contributions, with Germany (n=2) and Turkey (n=1). Geographically, the study shows significant global diversity, demonstrating the widespread interest in this topic. Regarding participant identities, the majority of studies (n=16) focused on students as the population, while pre-service teachers were examined in three studies. Additionally, two studies explored learners and two focused on teachers, emphasizing the importance of understanding student perspectives in the context of educational research. It is important to note that these participants refer to those in the studies reviewed, not participants in our own research.

In terms of AI technologies investigated, the studies covered a wide range of applications, with ChatGPT being the most frequently studied technology (n=8). AI-powered chatbots, including academic advising chatbots, were featured in two studies. Other technologies explored included GPT applications, AI-based teacher-bots, AI-based robots, voice assistants, AI-based applications, AI-powered speech evaluation programs, and smart learning platforms, illustrating the extensive scope of AI technologies in education.

4.2. Evaluating the Internal Relationships of TAM in AIHEd (Objective 2)

This section assesses the extent to which TAM's internal hypothesized relationships have been empirically tested and validated in AIHEd. We quantify the hypothesis testing rates and significance rates reported in the studies, evaluating the consistency of TAM's application and its predictive strength in explaining AI adoption in higher education. This assessment provides insights into the validity and robustness of TAM's internal constructs within the AIHEd context.

Table 2 summarizes the results of testing 23 hypotheses related to TAM in the AIHEd domain. Figure 3 illustrates both the testing rates and significance rates for these original TAM hypotheses. Among the hypothesized relationships, PU→BI demonstrates the highest testing rate (87%), followed by PEU→BI (78%), and PEU→PU (55%). The relationship BI→AU shows the lowest testing rate at 33%. Regarding significance rates, three relationships—PU→AT, AT→BI, and BI→AU—achieve 100% significance. Other relationships show varying levels of significance: PEU→PU (87%), PU→BI (80%), PEU→AT (75%), and PEU→BI (72%). Table 3 shows the summary of these hypotheses.

Table 2: The Results of Hypothesis Testing between major TAM variables

Authors and year	PEU toPU	PEU toAT	PEU toBI	PU toAT	PU toBI	AT toBI	BI toAU
(Al Shamsi et al., 2022)	YES	X	YES	X	YES	X	YES
(Albayati, 2024)	YES	YES	NO	YES	NO	YES	X
(Algerafi et al., 2023)	YES	X	YES	X	YES	X	X
(Alrishan, 2023)	X	X	YES	X	YES	X	X
(Awal & Haque, 2024)	X	X	YES (-)	X	NO	X	YES
(Ayanwale & Molefi, 2024)	X	X	NO	X	NO	X	X
(Bilquise et al., 2023)	X	X	YES	X	NO	X	X
(Dehghani & Mashhadi, 2024)	YES	X	YES	X	YES	X	X
(Esiyok et al., 2024)	YES	X	YES	X	YES	X	YES
(Gado et al., 2022)	X	YES	X	YES	YES	YES	X
(Lai et al., 2023)	NO	X	NO	X	YES	X	X
(Liu et al., 2024)	YES	X	NO	X	YES	X	YES
(Liu & Ma, 2024)	YES	NO	X	YES	X	YES	YES
(Liu & Huang, 2024)	YES	X	YES	X	YES	X	X
(Ma & Lei, 2024)	YES	X	YES	X	YES	X	X
(Masa'deh et al., 2024)	X	YES	X	YES	YES	YES	X
(Pillai et al., 2024)	NO	X	YES	X	YES	X	YES
(Rahman et al., 2023)	X	YES	X	YES	X	YES	X
(Sukkeewan et al., 2024)	YES	YES	YES	YES	YES	YES	X
(Tiwari et al., 2023)	X	NO	X	YES	X	YES	X
(Zhang et al., 2023)	YES	X	YES	X	YES	X	X
(Zou et al., 2023)	YES	X	NO	X	YES	X	X
(Zou & Huang, 2023)	YES	YES	YES	YES	YES	YES	X

Note: The symbols in the results column indicate: YES = significant positive test result; YES (-) = significant negative test result; NO = non-significant test result; X = no hypothesis test conducted. Abbreviations: PEU = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude; BI = Behavioral Intention; AU = Actual Use.

Table 3: Summary of Hypotheses between Major TAM variables

Hypotheses	PEU →PU	PEU →AT	PEU →BI	PU →AT	PU →BI	AT →BI	BI →AU
Positive-Significant hypothesis	13	6	12	8	16	8	6
Negative-significant hypothesis	0	0	1	0	0	0	0
Non-significant hypothesis	2	2	5	0	4	0	0
Not tested	8	15	5	15	3	15	17
Total	23	23	23	23	23	23	23

Hypotheses	PEU →PU	PEU →AT	PEU →BI	PU →AT	PU →BI	AT →BI	BI →AU
Total hypotheses examined	15	8	18	8	20	8	6
Total no. of significant hypothesis	13	6	13	8	16	8	6
Hypothesis testing rates (%)	65	35	78	35	87	35	26
Significance rate of hypothesis (%)	87	75	72	100	80	100	100

Note. PEU = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude; BI = Behavioral Intention; AU = Actual Use.

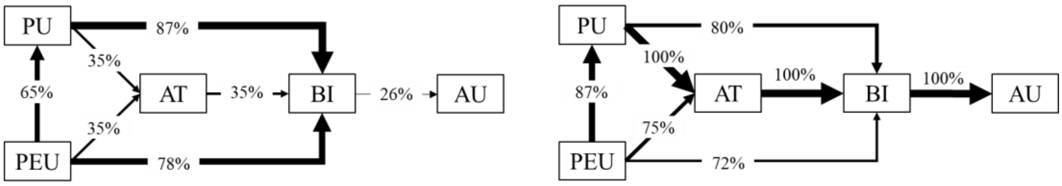

Figure 3: Testing Rates (Left) and Significance Rate (Right) of TAM Internal Hypotheses in AIHEd

4.2. Identifying and Assessing the Role of External Variables in TAM for AIHEd (Objective 3)

In this section, we identify and evaluate the external variables incorporated into TAM for AIHEd. This section synthesizes which external factors have been integrated into TAM, the frequency with which they have been tested, and the statistical significance of their relationships with TAM constructs. We assess the impact of these external variables on extending the traditional TAM framework for AI adoption in higher education, offering insights into their role and influence.

Figure 4 presents a comprehensive overview of all antecedents and their hypothesis testing outcomes for each TAM core construct in AIHEd. The three most frequently examined antecedents across all TAM constructs were perceived enjoyment (N=12, 9 significant tests, 75% significance rate), subjective norm (N=11, 8 significant tests, 73% significance rate), and trust (N=9, 8 significant tests, 89% significance rate). For Antecedents of PU, subjective norm emerges as the most frequently tested variable (N=5), showing an 80% significance rate (4 significant tests). Perceived enjoyment (N=3) and output quality (N=2) follow in testing frequency, both achieving 100% significance rates. Additional antecedents include computer self-efficacy, system quality, information quality, and perceived fairness, though tested less frequently. Among Antecedents of PEU, subjective norm leads in testing frequency (N=6) with a 67% significance rate (4 significant tests), followed by self-efficacy (N=4, 50% significance rate) and anxiety (N=3, 33% significance rate). The analysis also identified other antecedents such as facilitating conditions, computer experience, and compatibility, each with varying testing frequencies and significance rates. For Antecedents of ATT, credibility was tested twice, showing 100% significance rate. Other variables including anxiety, compatibility, and facilitating conditions were also examined, though less frequently. Regarding Antecedents of BI, trust (N=5) and subjective norm (N=4) were most frequently tested, demonstrating strong significance rates of 80% and 75% respectively. The analysis also revealed additional antecedents including perceived risk, computer anxiety, and facilitating conditions, each contributing to our understanding of behavioral intention in AIHEd contexts.

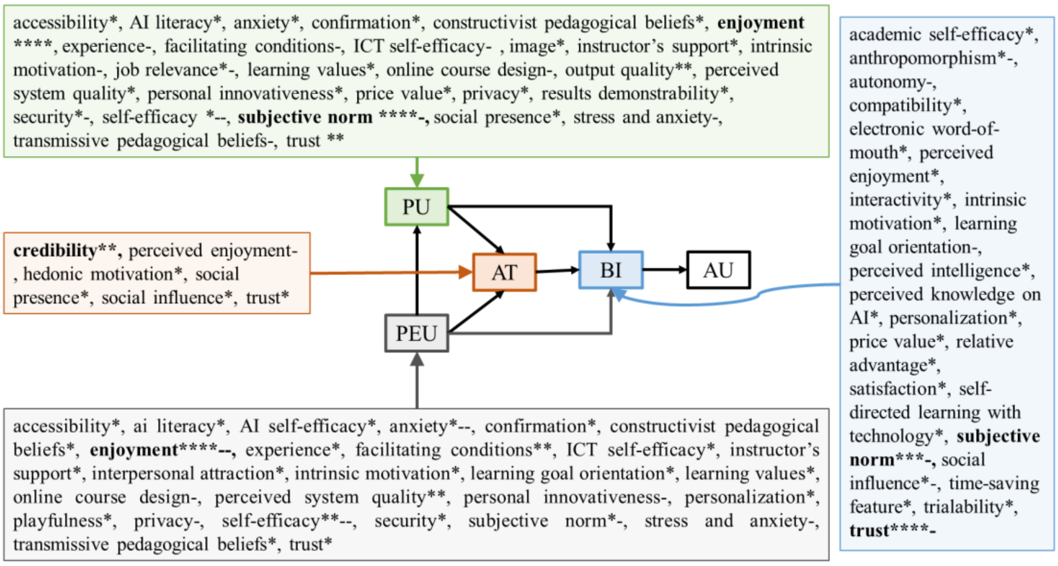

Figure 4: Hypothesis Testing Outcomes of the Antecedents of the TAM Core Constructs in AIHEd

Note: Each * indicates a significant test result; the more *, the more significant results. Each - indicates a non-significant test result; the more -, the more non-significant results.

5. Discussion

In this section, we discuss the main findings of the study, highlighting the significant insights derived from the empirical landscape of TAM research, the validation of TAM's internal relationships, and the role of external variables in extending TAM for AI adoption in higher education.

5.1. Empirical Landscape of TAM Research in AIHEd (Objective 1)

The analysis shows a significant surge in research interest, with over 90% of studies published in 2023 and 2024. This growth reflects the rapid emergence of AI technologies in higher education, particularly following the release of ChatGPT. The geographical distribution reveals a strong predominance of studies from Asia, especially China, which is consistent with patterns observed in previous non-AI technology adoption research (Xue et al., 2024). This suggests that traditional trends in technology adoption continue to shape AI adoption studies in higher education.

However, the heavy concentration of research in Asian regions limits the global representativeness of findings, potentially overlooking cultural and institutional variations in AI adoption. Future research should explore the moderating effects of macro-level factors such as cultural dimensions, national economic development, and types of educational systems. Cross-cultural and cross-institutional analyses would help clarify how these factors influence the relationships between TAM constructs and AI adoption, leading to a more comprehensive understanding of AI adoption in diverse educational contexts.

5.2. Internal Relationships of TAM in AIHEd (Objective 2)

The analysis of original TAM hypotheses reveals several important findings. The high significance rates for core relationships (PU→AT, AT→BI, BI→AU at 100%) strongly validate TAM's applicability in the AIHEd context. However, the varying testing rates, from 87% (PU→BI) to 33% (BI→AU), align with patterns observed in earlier TAM research (Lee et al., 2003). The lower testing rate for BI→AU is particularly noteworthy, as it represents a critical gap in understanding the translation of adoption intentions into actual usage behaviors. This limited testing of the BI→AU relationship likely stems from methodological challenges. Theoretically, measuring this relationship requires two time points: one for measuring behavioral intention (BI) and a later point for measuring actual usage (AU) (Jeyaraj et al., 2023). However, most studies employ anonymous cross-sectional surveys, which make it difficult to match individual responses across time points. While some researchers attempt to assess both BI and AU through single-time surveys, this approach contradicts the temporal nature of the BI→AU relationship, as current usage cannot logically represent future behavioral intentions. To address this methodological challenge, future studies should either employ longitudinal designs with participant matching mechanisms or develop alternative constructs that better capture the temporal relationship between intention and behavior.

5.3. External Variables in TAM for AIHEd (Objective 3)

Our research reveals that perceived enjoyment, subjective norm, and trust are the three most frequently utilized antecedents of TAM. The prominence of enjoyment and subjective norm aligns with findings by Abdullah and Ward (2016) in e-learning and Rosli et al., (2022) in higher education. This consistency is likely due to subjective norm being an antecedent for PU in both TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), while enjoyment is an antecedent for PEU in TAM3. A notable discovery of this study is the significant role of trust, which is not only one of the top three most frequently used antecedents but also the only one that significantly predicts all four core constructs: PEU, PU, AT, and BI. This contrasts with previous studies in other educational domains, such as Mustafa and Garcia (2021) in online learning and Abdullah and Ward (2016) in e-learning, where trust was not among the most frequently used antecedents. This suggests that trust plays a uniquely critical role in AI acceptance in education. In traditional TAM frameworks, particularly TAM3, trust is not explicitly included as a construct. Given its significant predictive power across all four TAM constructs in the AIHEd context, future iterations of TAM should incorporate trust to better explain AI acceptance and use in education. This inclusion could address gaps in understanding user acceptance of AI technologies, where issues of data privacy, security, and reliability are paramount. As AI applications in education evolve, understanding the role of trust will be crucial for developing effective strategies to foster acceptance and integration of these technologies in educational environments.

5.4. Significance of Research Findings

Through achieving the first research objective of mapping the empirical landscape of TAM in AIHEd, this study establishes the field as a growing research hotspot, with a significant increase in the volume of publications in recent years. This trend underscores the rising academic interest in AI adoption in higher education. The study offers valuable guidance for new researchers, particularly in terms of selecting relevant journals for publication, highlighting key journals in the field. Additionally, it identifies critical research gaps, including the predominance of studies focusing on student populations, the geographical concentration in Asia, and the limited examination of AI technologies beyond ChatGPT. These gaps suggest important directions for future research, such as exploring non-student populations, expanding research to regions outside Asia, and investigating other AI technologies used in higher education.

In meeting the second research objective of evaluating TAM's internal relationships in AIHEd, this study affirms the stability of TAM’s core hypotheses within the context of AI adoption in education. The findings reinforce the reliability of TAM as a theoretical framework for understanding how AI technologies are adopted in educational settings. However, the study also highlights areas where TAM may need refinement, especially in capturing the relationship between behavioral intention and actual usage of AI technologies. This suggests that future research should refine TAM to better address the complexities and unique aspects of AI adoption in higher education, providing further empirical support for model adjustments.

In achieving the third research objective of identifying and assessing the role of external variables in TAM for AIHEd, this study demonstrates the importance of factors such as trust, perceived enjoyment, and subjective norm in influencing AI adoption decisions. These findings highlight the need to extend the TAM framework to include these external variables, offering a more comprehensive understanding of the factors that shape AI technology acceptance. The study also emphasizes the relationships between these external variables and TAM constructs, suggesting that these factors play a crucial role in the adoption process and should be considered in future research and practice to improve the model’s explanatory power and relevance in educational contexts.

6. Limitations and Future Research

This systematic literature review has several limitations that suggest directions for future research. In terms of literature search, we only included English-language publications, potentially missing valuable research published in other languages. Future reviews should expand the language scope to include databases from various regions, providing a more comprehensive understanding of AI adoption patterns. Additionally, given the rapidly evolving nature of AI technology in higher education, our focus on peer-reviewed journal articles may have excluded emerging research published in conference proceedings or preprint platforms, limiting our ability to capture the most recent developments in this fast-moving field. Given the field's rapid development, researchers should consider including conference proceedings and preprint articles to capture emerging trends.

Methodologically, while this systematic literature review approach provides valuable insights into research patterns and hypothesis testing outcomes, it lacks the quantitative rigor of meta-analysis. This limitation prevents us from estimating effect sizes and examining potential moderating effects across studies. Future studies should employ meta-analytic approaches to provide quantitative assessments of effect sizes and examine potential moderating effects. Furthermore, although our analysis suggests the importance of incorporating trust into traditional TAM frameworks, our approach cannot statistically evaluate which specific model extension would be most effective. The systematic literature review methodology prevents us from comparing competing models that integrate trust in different ways. To address this limitation, future research should employ meta-structural equation modeling (meta-SEM) to statistically compare competing TAM extensions that incorporate trust in different ways, helping identify the most effective theoretical framework for understanding AI adoption in higher education.

7. Conclusions

This systematic literature review advances understanding of AI adoption in higher education through the TAM framework by synthesizing 23 empirical studies. Our analysis validates TAM's applicability in the AIHEd context while revealing several distinctive features. First, the high significance rates of core TAM relationships, particularly PU→AT, AT→BI, and BI→AU (all at 100%), demonstrate the model's robustness in explaining AI adoption. Second, we identify trust as a crucial factor unique to AI adoption, significantly influencing all core TAM constructs - a pattern not observed in previous educational technology studies. Third, our findings highlight the consistent importance of both hedonic (enjoyment) and social (subjective norm) factors in AI adoption decisions.

The temporal and geographical analysis reveals rapidly growing research interest, with over 90% of studies published in 2023-2024, though with notable geographic concentration. This pattern reflects both the accelerating integration of AI in higher education and the need for more diverse regional perspectives. As AI continues to transform higher education, understanding its adoption patterns becomes increasingly critical for ensuring equitable and effective implementation. This review provides a foundation for future research while offering practical insights for institutions navigating the complex landscape of AI integration in higher education.

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