**Systematic Review**

**UNDERSTANDING AI ADOPTION IN HIGHER EDUCATION: A SYSTEMATIC REVIEW OF TECHNOLOGY ACCEPTANCE MODEL, TECHNOLOGY READINESS INDEX, AND THE INTEGRATED TECHNOLOGY READINESS AND ACCEPTANCE MODEL**

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| **ABSTRACT**Artificial Intelligence (AI) has transformed various domains, including education. To reap the benefits of AI tools in education, it is critical to understand the factors affecting their adoption by users. Various Information Systems theories have been applied in this context, the most widely used being Davis’ Technology Acceptance Model (TAM) and Technology Readiness Index (TRI). This systematic literature review (SLR) synthesizes findings from 25 studies based on the TAM (n= 20), the TRI (n= 3), and the integration of TAM and TRI (n= 2), also known as the Technology Readiness and Acceptance Model (TRAM) or TRI-TAM. The objective is to examine the adoption of Artificial Intelligence (AI) technologies in higher education. While conducting SLR, we adhered to PRISMA guidelines to ensure transparency and reproducibility of search results. Data extraction focused on key parameters like study design, analysis technique, technological focus, population studied, sample size used, theoretical lens applied, factors explored, and the key findings. The findings reveal that cognitive factors, Perceived Usefulness (PU), and Perceived Ease of Use (PEOU) are the most significant predictors of Behavioural Intention (BI) to adopt AI. Findings also reveal the use of AI-specific constructs such as AI Literacy, AI Explainability, and Co-Creation Intention. The actual use of technology has been rarely measured, indicating a recurring intention–actual use gap. The review also highlights crucial research gaps, such as a lack of longitudinal studies, use of only self-reported measures, underrepresentation of inclusive education professionals and decision-makers, and absence of cross-cultural comparisons. Thus, this review maps the evolving landscape of AI adoption in higher education and outlines a clear agenda for more robust, inclusive, and theoretically grounded future research. |

**Keywords:** Artificial Intelligence, Higher Education, Technology Acceptance Model (TAM), Technology Readiness Index (TRI), Technology Readiness and Acceptance Model (TRAM), Systematic Literature Review, PRISMA.

**1. INTRODUCTION**

Artificial Intelligence (AI) as a transformative technology has permeated every domain, including education. AI technologies in general and generative AI in particular offer various pedagogical affordances, triggering their widespread use in educational contexts. Given the moderately technical nature of operating AI tools, educators and students often face challenges in their adoption (Lin et al., 2017). To reap the benefits of AI tools in education, it is critical to understand the factors affecting their acceptance by the users; otherwise, it will result in the underutilization of AI capabilities (Mugo et al., 2017). If these capabilities are utilised properly, it will result in enhanced performance, save time, and cost economy (Sharda et al., 1988). Information Systems (IS) theories were propounded to explain why users adopt certain technologies. Some prominent IS theories are the Technology Acceptance Model (TAM), the Diffusion of Innovations theory, the Contingency Theory, and models such as DeLone and McLean IS Success Model. However, the TAM is the most dominant one (Lin et al, 2007. Its popularity can be gauged from the fact that since its inception and publication by Fred A. Davis in the reputed journal MIS Quarterly in 1989, it has received more than one lakh citation, reiterating its usefulness and suitability in different contexts. Given the substantial influence TAM has in understanding technology acceptance, it is crucial to explore its role in emerging fields such as Artificial Intelligence in higher education. Therefore, this study seeks to understand the role of TAM and its application in AI technologies acceptance in higher education through a systematic literature review. This will help in understanding factors crucial to the role of AI technologies in higher education. Given AI tools’ pedagogical affordances, they qualify as learning technologies, and therefore, TAM serves as a credible theoretical framework to assess their acceptance among academicians and students.

**1.2. RESEARCH QUESTIONS**

The review was guided by the following research questions:

RQ1. How has the Technology Acceptance Model (TAM) been used to study AI adoption in higher education?

RQ2. To what extent has the Technology Readiness Index (TRI) been applied in explaining user readiness and acceptance of AI in higher education?

RQ3. Explain users’ acceptance and adoption of AI technologies in higher education using TRAM.

RQ4. What are the key constructs, user groups, and methodological trends across TAM, TRI, and TRAM-based studies in higher education?

RQ5. What are the conceptual and empirical gaps in current research, and what directions can future studies take to deepen our understanding of AI acceptance in higher education?

RQ1 to RQ4 are addressed in the findings section, particularly in Sections 4.4 to 4.8, which examine the application of TAM, TRI, and TRAM models in terms of key constructs, outcomes, and theoretical integrations. RQ5 is addressed in Section 5, where methodological, theoretical, and population-level gaps are synthesised, offering directions for future research.

**2. LITERATURE REVIEW**

**2.1. THE TECHNOLOGY ACCEPTANCE MODEL (TAM)**

TAM has been postulated as a robust and parsimonious framework to examine the wide range of behaviours of technology users (Marikyan & Papagiannidis, 2024). It posits that perceived usefulness (PU) and perceived ease of use (PEOU) of technology positively influence the user’s behavioural intention (BI) to use that technology. BI, in turn, is a significant predictor of actual use of that technology (Kelly et al., 2023). TAM is one of the simplest and most frequently used models to explain technology acceptance/ adoption or usage by individuals and organisations. Its strength lies in the fact that it can be extended to other variables or can be used in conjunction with other technology adoption models (Venkatesh et al., 2003). Regression and correlation results showed that usefulness mediates the effect of ease of use on usage.

**2.2. EXTERNAL FACTORS INFLUENCING TAM IN HIGHER EDUCATION**

Besides its core constructs (PU, PEU, attitude, BI, and AU), TAM can be extended to accommodate other external factors, too, which have been integrated with TAM across different contexts and technologies. These factors have been listed below:

**Organisational Support:** It is one of the most important factors that influence technology adoption and has a significant positive influence on users’ behavioural intention to adopt AI in higher education (Sharma et al., 2024)

**Social Influence:** It refers to the influence on an individual’s behaviour by others. It is equivalent to the constructs of social factors, image construct, and subjective norms used in other IS theories (Rana et al., 2024). It significantly influences PU and PEOU in online learning format (Ismatullaev & Kim, 2024).

**Trust:** It is an important factor that has been found to exert a significant impact on users’ BI both directly and indirectly while adopting AI-based healthcare technologies and in academia (Rana et al., 2024).

**Facilitating Conditions:** It refers to the availability of resources and necessary infrastructure and support required for technology uptake. The availability of necessary infrastructure and institutional support motivates users to adopt technology (Cabellos, 2024).

**Hedonic Motivation:** Hedonic motivation emphasises the pleasurable and enjoyable aspects of technology adoption. The Hedonic System Acceptance Model (HSAM) states that technology adoption is not only guided by pragmatic factors like PU and PEOU, but enjoyment and emotional satisfaction derived from technology adoption are also crucial (Van der Heijden, 2004; Qu & Wu, 2024).

**2.3. APPLICATION OF TAM IN EDUCATION**

TAM has been widely used by researchers in educational settings to predict users’ intention to adopt technologies (Al-Emran et al., 2018; Teo, 2019). It has been applied to study acceptance of artificial intelligence-enabled e-learning (Kashive & Powale, 2020); in measuring acceptance of AI-driven assessments by students (Benito et al., 2019); in measuring acceptance of AI tools by teachers (Choi et al, 2019); in measuring acceptance of AI-based teacher bots (T-bots) (Pillai et al, 2024), acceptance of ChatGPT (Al-kfairy, 2024; Almogren, 2024); use of generative AI in teaching (Calleja & Camilleri, 2025), and use of ChatGPT for research (Adewale, 2025). Prior to these studies, TAM was widely utilised to measure adoption of e-learning (Ali et al., 2018), online learning (Panigrahi et al., 2018), and mobile learning (Mittal et al., 2020). Few other studies that have applied TAM in understanding adoption or acceptance of advanced other technologies in education include the use of chatbots for language learning; use of AI chatbots in higher education (Rahman et al., 2025), and podcasts as a source of learning (Merhi, 2015). Its widespread use by researchers in educational settings to study the adoption of a variety of technologies suggests its robustness and validity (Alzoubi, 2024).

**2.4. LIMITATIONS OF TAM IN EMERGING TECHNOLOGY CONTEXTS**

TAM focuses on why the user accepts or rejects specific technology. The main criticism against TAM is that it does not measure the success of technology adoption but merely predicts the user's behavioural intention as a proxy for actual usage of the technology. Additionally, the construct perceived usefulness (PU) and perceived ease of use (PEOU) are subjective in nature, implying that technology usage depends on an individual’s belief. It is not an objective phenomenon; hence, if the user perceives that the technology is not useful to him, he will not use it even though the technology improves performance. In the same vein, they may miscalculate the advantages offered by technology and adopt them even if they are inefficient. Thus, it can be said that people act according to their beliefs about technology. Therefore, it is essential to find out why performance beliefs are not consistent with objective reality (Davis, 1989). Although TAM has been the preferred model applied to understand various types of technology adoption, such as computer-based instruction, online learning, mobile learning, virtual learning, etc., its explanatory power can be enhanced by integrating it with Parasuraman and Colby’s Technology Readiness Index 2.0 (TRI 2.0).

**2.5. TECHNOLOGY READINESS INDEX AND ITS ROLE IN CAPTURING PSYCHOLOGICAL READINESS**

TAM and its extensions, TAM 2 and TAM 3, are quite effective in explaining technology adoption, but they primarily focus on cognitive beliefs formed during or after exposure to the specific technology or application, implying that TAM variables are system-specific (Godoe & Johansen, 2013). It ignores why a user finds the technology useful or easy to use. It does not address mental readiness or preparedness, or the user’s disposition that influences initial perceptions of technology. To overcome this limitation, Parasuraman and Colby’s Technology Readiness Index(TRI) could serve as a valuable complementary framework (Parasuraman, 2000). TRI measures a user’s innate predisposition to embrace or resist new technologies. It measures their personality on four dimensions: optimism, innovativeness, discomfort, and insecurity. A person with a high degree of optimism and innovativeness (positive traits or motivators) will embrace the new technology with ease, while a person with a high degree of discomfort and insecurity (negative traits or inhibitors) is less likely to embrace new technology (Walczuch et al., 2007). TRI measures readiness but not perceptions regarding the use of specific technology. Therefore, integrating TAM and TRI will help to overcome the inherent imperfection of either of these theories.

 Table 1: TRI traits and their definitions

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| **Factor** | **Definition** |
| Optimism | “A positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives.” |
| Innovativeness |  “A tendency to be a technology pioneer and thought leader.” |
| Discomfort | “A perceived lack of control over technology and a feeling of being overwhelmed by it.” |
| Insecurity | “Distrust of technology and scepticism about its ability to work properly.” |

Source: Adapted from Parasuraman (2000)

**2.6. UPDATED PSYCHOLOGICAL MEASURES IN TECHNOLOGY ADOPTION: INTRODUCING TRI 2.0**

Since its conceptualisation in 2000, the Technology Readiness Index (TRI) was revised and renamed TRI 2.0 (Parasuraman & Colby, 2015). This updated version assesses users' optimism, innovativeness, discomfort, and insecurity levels through a 16-item index. Although TRI 2.0 is a shortened version of TRI 1.0, it is based on the same theoretical framework as TRI 1.0. These changes were required because some of the items in TRI 1.0 had become obsolete and did not cater to new and more advanced technologies, such as aviation and the mobile sector (Smit, 2018).

**2.7. INTEGRATING TRI AND TAM**

The TAM has certain limitations that can be attributed to different contexts wherein it is applied, diverse users, and deficiencies within the models themselves (Rahimi & Oh, 2024). With the introduction of TRI in the year 2000, researchers have integrated it with TAM to capture not only system-specific (addressed by TAM) but also individual-specific (addressed by TRI) factors. It theorises that the impact of technology readiness (optimism, innovativeness, discomfort, and security) on use intention is mediated by PU and PEOU. The rationale behind integrating TRI with TAM is that TRI augments the TAM, and the integrated model, Technology Readiness and Acceptance Model (TRAM), has better explanatory power since TRI accounts for the individual differences in technology adoption (Goede & Johansen, 2013; Lin et al., 2017). Integrated Technology Readiness and Acceptance Model (TRAM) has been widely reported as a better model than either TAM or TRI when they are used alone (Lin et al., 2007; Koivisto, 2016; Wook et al., 2017; Lai & Lee, 2020; Desmaryani et al., 2024).

**3. METHODOLOGY**

**3.1. SEARCH STRATEGY**

For the Systematic Literature Review, studies that employed the Technology Acceptance Model (TAM), the Technology Readiness Index (TRI), and studies that employed both TAM and TRI were investigated. These research studies were accessed from Scopus (official name SciVerse Scopus), which was introduced in 2004 by Elsevier. The most extensive database includes research articles, books, conference proceedings, editorials, etc. Also, about 99.11% of the journals indexed in Web of Science are indexed in Scopus (Singh et al., 2021). Therefore, choosing the Scopus database is a sensible option because it is not only the largest database but also offers multidisciplinary coverage of articles, ease of use, time saving, quality of outcomes, and possible effect on research findings (Boyle & Sherman, 2006). Moreover, almost two-thirds of the articles published are covered in both Web of Science and Scopus (Vieira & Gomes, 2009). This review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021). These studies were accessed in a stepwise manner using three search strings, each catering to the specific theories:

* For TAM-based studies: TITLE-ABS-KEY ("technology acceptance model" OR "TAM") AND TITLE-ABS-KEY ("higher education" OR "university" OR “college” OR “Tertiary Education”) AND TITLE-ABS-KEY ("artificial intelligence" OR "AI")
* For TRI-based studies: TITLE-ABS-KEY ("technology readiness index" OR "TRI" OR “TRI 2.0”) AND TITLE-ABS-KEY ("higher education" OR "university" OR “college” OR “Tertiary Education”) AND TITLE-ABS-KEY ("artificial intelligence" OR "AI")
* For integrated TRAM-based studies: TITLE-ABS-KEY ("TRAM" OR "TRI-TAM") AND TITLE-ABS-KEY (“Technology Acceptance Model" OR "TAM”) AND TITLE-ABS-KEY ("technology readiness index" OR "TRI" OR “TRI 2.0”) AND TITLE-ABS-KEY ("higher education" OR "university" OR “college” OR “Tertiary Education”) AND TITLE-ABS-KEY ("artificial intelligence" OR "AI")

All the co-authors decided against applying a timeline filter to ensure comprehensive coverage of research studies. However, we restricted our search to journal articles written in English. Table 2 outlines the inclusion and exclusion criteria applied in this SLR.

**3.2 INCLUSION AND EXCLUSION CRITERIA OF RESEARCH STUDIES**

The inclusion and exclusion criteria for the selected studies are outlined in Table 2.

Table 2: Inclusion and Exclusion Criteria

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| **Criteria** | **Inclusion Criteria** | **Exclusion Criteria** |
| Publication Type | Peer-reviewed journal articles | Policy documents, Review papers, Editorials, Conference papers, Pre-prints, Grey Literature |
| Domain of the Study | Higher Education | School, K-12  |
| Study Design | Empirical studies using qualitative, quantitative, or mixed methods | Reviews and Meta-analysis studies |
| Dependent Variable | Behavioural intention to use AI, Acceptance of AI, Continued usage of AI, Intention to use AI, and Adoption of AI in education/learning/teaching context | Studies examining unrelated dependent variables |
| Population | Educational leaders, Faculty/Academicians, and Students in higher education | Populations not associated with higher education. |
| Discipline | All academic disciplines | None |
| Publication Period | Till May 2025 (inclusive of Articles in Press) | None |
| Publication Language | English-language | Non-English publications |

**3.3 SCREENING PROCESS**

Initial search in Scopus database resulted in 130 TAM-based studies, 18 TRI-based studies, and 5 TRITAM-based studies. In the first stage, we reviewed the abstracts of these studies to confirm their suitability. Upon reviewing, it was found that 65 TAM-based studies were suitable for further analysis, but only 4 TRI-based and 3 TRITAM-based studies met our criteria. In the next stage, we delved into full paper screening those studies with 15 or more Scopus citations. This resulted in 20 TAM-based studies, 3 TRI-based studies, and 2 TRAM-based studies, which were finally included for further analysis.



 **Figure 1:** PRISMA Framework of the study

**4. RESULTS AND FINDINGS**

The studies included in the analysis (n=25) were subjected to full-text screening and in-depth review. The authors created a data extraction table for the studies included to organise key information from each study. This table consisted of the following elements: study title, author(s) and year of publication, study design (qualitative, quantitative, or mixed method), analytical technique, technological focus, country of study, population, sample size, dependent variable(s), extended constructs and or theoretical lens, independent variable(s), TAM/ TRI / TRAM constructs, and key findings. Tables 1, 2, and 3 present the key elements of studies included in the review.

Table 3: Systematic Literature Review (SLR) Table of TAM-based Studies

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Authors** | **Study Design** | **Analysis Technique** | **Technological Focus** | **Country** | **Population** | **Sample Size** | **Dependent Variable** | **Extended Constructs/Theoretical Lens** | **Independent Variables/ TAM Constructs** | **Key Findings** |
| ‘Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers' Perspectives Using Structural Equation Modelling’ | Wang et al. (2021) | Quantitative | Structural Equation Modelling | AI technologies | China | Teachers | 311 | Continuance Intention to teach with AI | Anxiety (AN), Self-Efficacy (SE) | AN, SE, attitude toward use (ATU), perceived ease of use (PEU), and perceived usefulness (PU) | Intentions to use AI predicted by ATU, SE, PEU, PU, AN |
| ‘Chat-GPT: Validating Technology Acceptance Model (TAM) in the education sector via ubiquitous learning mechanism’ | Saif et al. (2024) | Quantitative | SEM using Smart PLS | Chat GPT's AI content | Pakistan | Students | 156 | ChatGPT Usage | Stress, Anxiety/Social Exchange Theory | PEU, PU, BI, Attitude | Stress and anxiety lead to ChatGPT usage via ubiquitous learning; PU & PEOU shape attitude and increase actual use. |
| ‘Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis’ | Zhang et al. (2023) | Quantitative | SEM using R | AI-based educational apps | Germany | Pre-service teachers | 452 | Acceptance | AI Self-Efficacy, Perceived Enjoyment, AI Anxiety, Job Relevance, Subjective Norm/ TAM 3 | PEOU, PU, BI | PEOU and PU are strong predictors; gender differences noted in AI Anxiety and Perceived Enjoyment |
| ‘Understanding key drivers affecting students' use of artificial intelligence-based voice assistants’ | Shamsi et al. (2024) | Quantitative | PLS-SEM | AI-based voice assistants | UAE | University Students | 300 | Actual Use | Subjective Norm, Enjoyment, Facilitating Conditions, Trust, Security | BI | Enjoyment, trust, and PEOU influence PU; facilitating conditions and trust shape PEOU; subjective norm and security have no impact PU |
| ‘Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator’ | Duong et al. (2023) | Quantitative | CFA and regression using SPSS, AMOS | ChatGPT | Vietnam | University Students | 1389 | Actual Use | Effort Expectancy (EE), Performance Expectancy (PE), Knowledge Sharing**\***PE = PU | EE = PEOU (Contextual renaming) | EE, PE, BI, Actual Use | Performance and effort expectancy impact BI & Actual Use; knowledge sharing moderates BI and actual use |
| ‘Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education’ | Pillai et al. (2024) | Mixed method  | Nvivo + PLS-SEM | AI-based teacher-bots | India | Educators (Principals, Directors, Deans, Professors) & Students | 1425 (45 educators, and 1380 students) | Adoption Intention (ADI) and Actual Usage | Personalisation, Interactivity, Perceived Trust, Anthropomorphism, Perceived Intelligence | PU, PEOU, BI (renamed as ADI), ATU | All TAM variables impact ADI → ATU; human-teacher preference for learning, negatively moderates this link |
| ‘Investigating student acceptance of an academic advising chatbot in higher education institutions’ | Bilquise et al. (2024) | Quantitative | PLS-SEM causal modelling | AI-driven advising chatbot | UAE | Students | 207 | BI | Unified Theory of Acceptance and Use of Technol (UTAUT), AI-driven self-service technologies models, the Service Robot Acceptance (sRAM) model, and the intrinsic motivation Self-Determination Theory (SDT) model. | PU, PEOU, BI, Actual Use | Functional elements, PEOU, and social influence drive BI; PU, autonomy, and trust do not affect chatbot acceptance. |
| ‘Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study’ | Dahri et al. (2024) | Mixed method  | SPSS-SEM + qualitative analysis using post-reflection technique | ChatGPT for Metacognitive Self-Regulated Learning (MSRL) | Malaysia | Pre-service teachers | 300 | Behavioral Intention | Personal Competence, Social Influence, AI Trust, AI Enjoyment, AI Intelligence, Attitude, MSRL | Perceived AI Usefulness | All constructs positively impact ChatGPT acceptance for MSRL |
| ‘Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model’ | Al-Abdullatif et al. (2023) | Quantitative | PLS-SEM | Chatbots | Saudi Arabia | Students | 432 | Attitude and Acceptance | Perceived Enjoyment, Perceived Risk, Perceived Value/ value-based model (VAM) | PU, PEOU | PU, PEOU, Enjoyment, Attitude and value positively affect acceptance; risk doesn't affect attitude or acceptance |
| ‘Understanding the Factors Influencing Higher Education Students' Intention to Adopt Artificial Intelligence-Based Robots’ | Algerafi et al. (2023) | Quantitative | SPSS + PLS-SEM | AI-based robots | China | Students | 348 | PU, PEOU, and Acceptance | TAM 3 constructs: Subjective Norm, Job Relevance, Output Quality, Anxiety, Self-Efficacy. Robot Anxiety; Robot self-efficacy; Perceived enjoyment; Perceived playfulness | BI, PEOU, PU | PU and PEOU significantly impact acceptance. Job relevance and robot anxiety were not significant for PU and PEOU, respectively. |
| ‘Effects and acceptance of precision education in an AI-supported smart learning environment’ | Hu (2022) | Quantitative and Qualitative | PLS-SEM and interview guide | AI-supported learning analytics dashboard (LAD) | Taiwan (not explicitly mentioned; inferred) | Students | 50 | Transfer of Learning | Output Quality and Transfer of Learning | BI, PEOU, PU | Output quality influenced learning transfer. PU and PEOU impacted BI. |
| ‘The factors influencing teacher education students' willingness to adopt artificial intelligence technology for information-based teaching’ | Ma & Lei (2024) | Empirical | SEM using SPSS and AMOS | AI technologies | China | Teacher education students | 359 | AI Literacy (AIL), Subjective Norms, Output Quality | BI | BI, PEOU, PU, Attitude | PU and AIL influence AI tech acceptance among educators |
| ‘Exploring the Acceptance and User Satisfaction of AI-Driven e-Learning Platforms (Blackboard, Moodle, Edmodo, Coursera and edX): An Integrated Technology Model’ | Saqr et al. (2024) | Quantitative | PLS-SEM | AI-driven learning platforms (Blackboard, Moodle, Edmodo, Coursera, and edX | Saudi Arabia | Students | 500 | Intention to Use e-learning | AI characteristics, student traits, Satisfaction/ Expectation-Confirmation Model (ECM) | BI, PEOU, PU, Attitude | PU and PEOU enhance satisfaction and attitudes; self-efficacy drives intention, but satisfaction has no direct impact on intention. |
| ‘Factors influencing pre-service special education teachers' intention toward AI in education: Digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness’ | Yao & Wang (2024) | Quantitative | SEM | AI in Education (AIEd) | China | Pre-service special education (SPED) teachers | 274 | Behavioral Intention | Digital literacy, Teacher self-efficacy | BI, PEOU, PU | Digital literacy significantly impacts teacher self-efficacy |
| ‘Artificial intelligence in Indian higher education institutions: adoption and perceptions’ | Sharma et al. (2024) | Quantitative | SEM | AI in HE | India | Academics, Students, Management staff | 411 | AI Adoption | Social Cognitive Theory (SCT), Human–Computer Interaction Theory (HCIT), Artificial Intelligence Self-Efficacy, Perceived Effectiveness, Organizational Support (OS), Perceived Risk | BI, PEOU | BI mediates the effects of efficacy, risk, OS, and PEOU on AI adoption; BI is the key adoption driver. |
| ‘Acceptance of Educational Use of AI Chatbots in the Context of Self-Directed Learning with Technology and ICT Self-Efficacy of Undergraduate Students’ | Esiyok et al. (2025) | Quantitative | PLS-SEM | AI chatbots | Türkiye (inferred) | Undergraduate Students | 414 | Actual Usage of Chatbots | ICT self-efficacy, self-directed learning with technology (SDLT) | PU, PEOU, BI | ICT self-efficacy affects PEOU; PU and PEOU impact BI; SDLT influences both BI and actual use. |
| ‘Investigating influencing factors of learning satisfaction in AI ChatGPT for research: University students' perspective’ | Almulla (2024) | Quantitative | PLS-SEM | ChatGPT | Saudi Arabia | Students | 262 | ChatGPT Adoption | Interaction learning, Collaborative learning, Interaction quality, Information quality, Learning motivation, Learning satisfaction | PU, PEOU, BI | PU and PEOU mediate between interaction learning and satisfaction; info quality drives continued use. |
| ‘ChatGPT in higher education: factors influencing user satisfaction and continued use intention’ | Yu et al. (2024) | Quantitative | SPSS-SEM | ChatGPT | United States | Students | 328 | Continued Use Intention | ChatGPT’s Compatibility, ChatGPT’s Efficiency, Satisfaction with ChatGPT | PU, PEOU | Compatibility positively influences PEOU; efficiency enhances PU. PU and PEOU drive satisfaction and continued use, and satisfaction significantly increases continued use intention. |
| ‘Exploring students' acceptance of an artificial intelligence speech evaluation program for EFL speaking practice: an application of the Integrated Model of Technology Acceptance’ | Zou et al. (2023) | Qualitative and Quantitative | Semi-structured interviews through an inductive method; SEM using SPSS and AMOS | Computer-assisted language learning (CALL), such as online learning, mobile learning, and learning management systems | China | Students | Qualitative=21 Quantitative= 218 | BI |  Intrinsic motivation (operationalised as perceived enjoyment (PE)) and extrinsic motivation (operationalised as perceived usefulness (PU))/ Motivational theory | PU, PEOU | PU and PE significantly predict BI; PEOU is not significant. Both intrinsic and extrinsic motivation influence BI. |
| ‘ChatGPT adoption and its influence on faculty well-being: An Empirical research in higher education’ | Cambra-Fierro et al. (2024) | Quantitative | CB-SEM | ChatGPT | Spain | Faculty | 401 | Adoption, Faculty Well-being | Perceived enjoyment, faculty well-being (composed of happiness, energy and stress) | PU, PEOU | PU and PEOU drive ChatGPT adoption, which enhances faculty well-being. |

# **Table 4: Systematic Literature Review (SLR) Table of TRI-Based Studies**

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Authors** | **Study Design** | **Analysis Technique** | **Technological Focus** | **Country** | **Population** | **Sample Size** | **DV** | **Extra Constructs/Theoretical Lens** | **Independent Variables/ TRI Constructs** | **Key Findings** |
| ‘What influences college students using AI for academic writing? - A quantitative analysis based on HISAM and TRI theory’ | Cui (2025) \* | Quantitative | SEM | AI tools for academic writing | China (inferred) | Students | 148 | Intention to use | Perceived usefulness, Perceived ease of use, Perceived enjoyment (PE), Intention to use, emotional engagement/ Hedonic Information System Acceptance Model (HISAM) | PU, PEOU, Perceived Enjoyment, Technological Optimism, Discomfort, Insecurity | Students’ intention to use AI tools is influenced by both cognitive (PU, PEOU) and emotional (PE, optimism) factors; PE significantly drives intention. Discomfort and insecurity have minor but notable emotional impacts on usage intention. |
| ‘Case study: exploring the role of current and potential usage of generative artificial intelligence tools in higher education’ | Chergarova et al. (2023) | Qualitative + Quantitative | Survey Method / Qualtrics software | AI tools (avatars, chat, detection, etc.) | USA | Faculty, researchers, and employees | 43 | Readiness | None | Optimism, Innovativeness, Discomfort, and Insecurity | Most participants used AI tools out of curiosity and occasional need, preferring free models. Tools were applied in creative, non-research tasks such as idea generation, coding, and presentations. Higher education stakeholders demonstrated strong readiness and enthusiasm for responsible classroom integration of generative AI tools. |
| ‘Enhancing college students’ AI literacy through human-AI co-creation: a quantitative study’ | Wen et al. (2024) | Quantitative | SPSS Amos  | AI content co-creation tools | China | Students | 401 | AI Literacy | AI Literacy, AI trust, AI Explainability, AI Personalisation, Co-creation behaviour, co-creation intention | Optimism, Innovativeness | TRI factors and trust in AI improve literacy, motivation, and co-creation with AI tools |

# \*Although Cui (2025) includes constructs commonly associated with TAM (PU, PEOU), the study explicitly adopts the Hedonic IS Acceptance Model (HISAM) and Technology Readiness Index (TRI) as its theoretical foundation. As TAM or TRAM frameworks were not referenced, the study was categorised under TRI-based studies.

# Table 5: Systematic Literature Review (SLR) Table of TRAM-Based Studies

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Authors** | **Study Design** | **Analysis Technique** | **Technological Focus** | **Country** | **Population** | **Sample Size** | **Dependent Variable** | **Extra Constructs/Theoretical Lens** | **Independent Variables/ TRI + TAM Constructs** | **Key Findings** |
| ‘Factors Influencing the Acceptance of ChatGPT in High Education: An Integrated Model With PLS-SEM and fsQCA Approach’ | Zhao et al. (2024) | Quantitative | Mixed-method / PLS-SEM + fsQCA | ChatGPT | China | Students | 298 | Acceptance of ChatGPT | TAM, Theory of Planned Behaviour (TPB); Discomfort, Insecurity, Attitude, SN, PBC | PU, PEOU, SN, Attitude, BI | Discomfort and insecurity reduce PU/PEOU; PU/PEOU shape attitude, which along with SN and PBC drives BI |
| ‘Evaluating the Intention for the Adoption of Artificial Intelligence-Based Robots in the University to Educate the Student’ | Roy et al. (2024) | Quantitative | SEM using SPSS | AI-based robots | India | Teachers & students | 445 (194 students and 251 teachers) | Attitude and Intention | Trust, Subjective Norms, and Perceived Behaviour Control/Theory of Planned Behaviour (TPB) | PU, PEOU, Attitude, Subjective Norm, Perceived Behavioural Control, TRI traits (e.g., optimism, discomfort) | PU, PEOU, and trust positively impact attitude; discomfort and insecurity do not negatively influence attitude |

**4. DISCUSSION OF FINDINGS**

**4.1. SUBJECT AREA DISTRIBUTION**

Figure 2 illustrates the subject area distribution of the studies included in the initial Scopus search (N = 130), based on Scopus classification. The subject area analysis reveals that a significant portion of AI in education research adopting TAM/TRI models has been published under the Social Sciences category (40.8%). This is followed by Computer Science (19.6%), Business and Management (5.3%), Engineering (4.9%), and Psychology (4.5%). Other areas, such as Arts and Humanities, Multidisciplinary studies, and Environmental Science, represent smaller fractions. The dominance of Social Sciences indicates that AI adoption in educational contexts is predominantly studied through behavioural and pedagogical lens. The significant presence of computer science and engineering suggests a parallel interest in the technical aspects of AI integration in education. Minimal representation of fields such as Health, Biochemistry, and Environmental Sciences indicates the need for interdisciplinary research.

 

 Figure 2. Subject area distribution of studies based on Scopus classification (N = 137)

**4.2 GEOGRAPHICAL AND CONTEXTUAL COVERAGE**

Most of the studies were conducted in Asia (India, China, Vietnam, Pakistan). In the Middle East, countries such as Saudi Arabia and the United Arab Emirates (UAE) are well represented. A smaller number of studies came from Europe (e.g., Germany, Spain) and North America (the United States). Earlier, much of the behavioral research has been conducted in Western countries, a trend noticed by Heine & Norenzayan (2010), who coined the term WEIRD (Western, Educated, Industrialized, Rich, and Democratic) societies to highlight overdominance of undergraduate students in the United States as study population in behavioral studies. However, our review reveals a contrasting trend: among the 25 included studies, a majority were conducted in Asian and Middle Eastern contexts, such as China, India, Saudi Arabia, and the UAE, with only two studies reported from the USA and one from Spain. This broader geographical spread reflects a growing interest in understanding AI adoption in non-Western educational systems, offering richer cultural perspectives that can help diversify the technology acceptance literature.

**4.3 Descriptive Profile of Reviewed Studies**

Table 6: Summary of study characteristics in the reviewed literature

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Research Methods** | **Frequency** | **Technology Focus** | **Frequency** | **Country** | **Frequency** |
| Qualitative |  | ChatGPT/ Generative AI | 7 | China | 8 |
| Quantitative |  | AI-based chatbots/AI-based voice assistants | 4 | India | 4 |
| Mixed method | 3 | AI Learning Platforms (LMS) | 2 | Saudi Arabia | 3 |
| Analysis Technique | *frequency* | AI Robots / Embodied AI | 2 | UAE | 2 |
| PLS-SEM (Smart PLS) | 12 | Speech AI / Evaluation Tools | 1 | Pakistan | 1 |
| SEM (SPSS/AMOS) | 6 | AI for Writing / Co-creation | 3 | Germany | 1 |
| Confirmatory Factor Analysis (CFA) | 2 | Theoretical integrations |  | Vietnam | 1 |
| Regression / PROCESS MACRO | 1 | TAM 2  | 5 | Malaysia | 1 |
| Population |  | TAM 3 | 7 | Türkiye (inferred) | 1 |
| Teachers | 8 | Unified Theory of Acceptance and Use of Technol (UTAUT)  | 4 | United States | 2 |
| Students | 19 | Theory of Planned Behaviour (TPB)  | 2 | Spain | 1 |
| Educational Leadership & Management | 1 each | Expectation-Confirmation Model (ECM)  | 1 |  |  |
|  |  | Social Cognitive Theory, Motivational Theory, and Self-Determination  |  |  |  |

Note: Frequencies indicate the number of studies using a particular method, framework, country context, or technology focus. Some studies fall into multiple categories.

**4.4 CONSTRUCTS EXPLORED ACROSS STUDIES**

*Behavioural Intention (BI):* The Table reveals that BI appears in all studies, highlighting its centrality in IS literature seeking to understand the adoption or acceptance of AI technologies by users in higher education.

*Perceived Usefulness (PU) and Perceived Ease of Use (PEOU):* PU and PEOU are reported in 23 studies, highlighting the importance of cognitive beliefs in explaining the adoption or acceptance of AI technologies by users in higher education.

*Actual Use/Continued Use:* These constructs appear less frequently than BI (only 8 studies), revealing an intention-behaviour gap. This indicates methodological weakness, as most researchers measure only intention as an outcome behaviour and do not measure use, which may be due to time constraints, difficulty in tracking actual use, or difficulty in follow-up. Measurement of actual use is crucial because what users intend is different from what users will do. Strong intention does not automatically lead to use behaviour or adoption. The use of satisfaction as a mediating variable indicates a post-use evaluative perspective; however, the absence of empirical validation of actual usage leaves the intention-behaviour gap unaddressed.

*Attitude & Perceived Enjoyment (PE):* Other constructs that have been studied frequently are attitude and perceived enjoyment, indicating the importance of attitudinal and affective factors in shaping users’ intention to adopt AI tools in higher education. Attitude is relevant as it is the direct predictor of BI and used as a mediating variable to explain the effect of PU and PEOU on BI. It measures users’ overall evaluation of technology. PE, on the other hand, goes beyond the concept of utility as captured by PU and PEOU and measures intrinsic motivation of the user towards the use of technology. Its incorporation by researchers in research is quite critical because intrinsic motivation plays a very important role in educational settings where learning is mostly self-directed.

These constructs serve as a bridge to link cognitive beliefs with BI and are consistent with hedonic-motivation system adoption models (HM-SAM) and UTAUT 2, which emphasise emotion and affect as core determinants of technology use in non-mandatory settings like higher education. In addition to these, some AI-specific constructs have also been studied, which include AI Literacy, AI Explainability, and Co-Creation Intention.

Table 7: Constructs by Domain, Frequency, and References

| **Domain** | **Construct** | **No. of Studies** | **Studies Reporting it** |
| --- | --- | --- | --- |
| **Cognitive Beliefs** | Perceived Usefulness (PU) | 23 | All TAM and TRAM-based studies and one TRI-based study (Cui, 2025) |
| Perceived Ease of Use (PEOU) | 23 | All TAM and TRAM-based studies and one TRI-based study (Cui, 2025) |
| Attitude | 8 | Wang et al. (2021); Saif et al. (2024); Dahri et al. (2024); Al-Abdullatif et al. (2023); Ma & Lei (2024); Saqr et al. (2024); Zhao et al. (2024); Roy et al. (2024) |
|

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| --- |
| **Behavioral Outcomes** |

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|  |
| --- |
| **Behavioral Intention (BI)/ Intention to Use** |

 |

|  |
| --- |
| **25** |

 | All 25 studies  |
| Actual Use / Continued Use | 7 | Saif et al. (2024); Shamsi et al. (2024); Duong et al., (2023); Pillai et al. (2024); Esiyok et al., (2025); Almulla (2024); Yu et al. (2024) |
| **Usage related/Post adoption** | Continued Use Intention\*\* | 1 | Yu et al. (2024) |
| **Affective States** | Enjoyment / Perceived Enjoyment | 8 | Zou et al. (2023); Cambra-Fierro et al. (2024); Cui (2025); Zhang et al. (2023); Shamsi et al. (2024); Dahri et al. (2024); Al-Abdullatif et al. (2023); Algerafi et al. (2023) |
| Anxiety | 4 | Wang et al. (2021); Saif et al. (2024) Zhang et al. (2023); Algerafi et al. (2023) |
| Motivation / Satisfaction \*\*\* | 6 | Bilquise et al. (2024); Almulla (2024); Zou et al. (2023); Wen et al. (2024); Yu et al. (2024); Saqr et al. (2024);  |
| **Dispositional Traits** | Optimism | 4 | Cui (2025); Wen et al. (2024); Roy et al. (2024); Chergarova et al. (2023) |
| Innovativeness | 2 | Wen et al. (2024); Chergarova et al. (2023) |
| Discomfort | 4 | Cui (2025); Zhao et al. (2024); Roy et al. (2024); Chergarova et al. (2023) |
| Insecurity | 4 | Cui (2025); Zhao et al. (2024); Roy et al. (2024); Chergarova et al. (2023) |
| **Trust and Risk** | Trust / AI Trust | 5 | Shamsi et al. (2024); Dahri et al. (2024); Pillai et al. (2024); Bilquise et al. (2024); Roy et al., 2024; Wen et al. (2024) |
| Perceived Risk  | 2 | Al-Abdullatif et al. (2023); Sharma et al. (2024) |
| **Social / Normative** | Subjective Norms (SN) | 6 | Zhang et al. (2023); Shamsi et al. (2024); Algerafi et al. (2023); Ma & Lei (2024); Zhao et al. (2024); Roy et al. (2024) |
| Social Influence | 2 | Bilquise et al. (2024); Dahri et al. (2024) |
| **Self-Beliefs** | Self-Efficacy | 7 | Algerafi et al. (2023); Saqr et al. (2024); Esiyok et al. (2025); Wang et al. (2021); Zhang et al. (2023); Sharma et al. (2024); Yao & Wang (2024) |
| Digital Literacy/ AI Literacy | 3 | Yao & Wang (2024); Wen et al. (2024); Ma & Lei (2024) |

\*\* Note: Continued Use Intention is conceptually distinct from Behavioral Intention and Actual Use. It reflects post-adoption retention intent and was coded under Usage-Related Constructs.

\*\*\* Motivation and Satisfaction were grouped in the synthesis as both constructs function similarly in the reviewed models, capturing users’ affective and experiential responses to AI-based tools.

**4.5 METHODOLOGICAL PATTERNS AND LIMITATIONS**

Table 8 presents methods and tools used in the reviewed studies. An analysis indicates research methodology adopted is primarily quantitative, with over 70% (n=18) of the studies employing structured surveys analyzed using the Structural Equation Modeling (SEM) technique via Smart PLS, SPSS, and AMOS software. Only one study is purely descriptive or qualitative. In contrast, six studies employ a mixed-method design, which adds theoretical depth and helps in a nuanced understanding of those factors not captured in surveys alone. None of the studies reviewed reported longitudinal designs and experimental interventions, indicating a methodological gap in evaluating causal inference or long-term user engagement with AI tools in educational contexts. This over-reliance on self-reported measures introduces a social desirability effect, which may inflate associations between constructs like PEOU and BI (Podsakoff et al., 2003)

Table 8: Methodological Overview of Included Studies

|  |  |
| --- | --- |
| **Method / Tool** | **Frequency in Your Table** |
| Quantitative (survey) | Dominant (~22/25) |
| Mixed method | 6 studies |
| Qualitative | 1 case study |
| PLS-SEM (SmartPLS) | 12 studies |
| CB-SEM (AMOS/SPSS) | 6 studies |
| Regression Technique/ MACRO | 2 studies |

**4.6 INTEGRATION OF THEORETICAL FRAMEWORKS**

Table 9 presents the theories and models used in conjunction with TAM. At least ten different theories have been integrated with TAM to explain AI adoption in higher education. Service Robot Acceptance Model (sRAM), which has been widely used in the hospitality industry, was applied by Bilquise et al (2024) to study the adoption of an academic advising chatbot by students. sRAM theory explains users’ acceptance of autonomous service robots. It is built upon TAM by integrating functional factors (e.g., perceived usefulness, ease of use) with relational factors (e.g., trust, rapport), and socio-emotional factors (e.g., anthropomorphism, warmth). It is to be noted that the use of sRAM in educational contexts signals a shift towards multi-dimensional acceptance models that not only address cognitive and affective factors but also relational aspects of working with AI (Wirtz, J. et al., 2018).

Another interesting observation is that all seven studies based on TRI and TRAM were published between 2022 and 2025, reflecting the recent academic interest in investigating the effect of psychological readiness in the context of AI adoption. Most studies focused on student populations, with only one examining faculty readiness. This trend confirms that TRI and TRAM are emerging frameworks in the AI-in-education literature, with considerable room for further empirical development.

Table 9: Theoretical models integrated alongside TAM/TRI in the reviewed studies

|  |  |  |
| --- | --- | --- |
| **Theory / Model** | **Frequency** | **Notes** |
| **TAM 3** (Technology Acceptance Model 3) | 2 | Explicitly named in two studies with constructs: Subjective Norm, Job Relevance, Anxiety, Output Quality, and Self-Efficacy. |
| Unified Theory of Acceptance and Use of Technology (**UTAUT)** | 2 | Includes constructs like Facilitating Conditions, Effort Expectancy, Performance Expectancy |
| **Self-Determination Theory (SDT)** / Motivation Theory | 2 | Used to explain perceived enjoyment, intrinsic/extrinsic motivation |
| **Expectation-Confirmation Model (ECM)** | 1 | Used in combination with Satisfaction |
| **Value-Based Adoption Model (VAM)** | 1 | Associated with Perceived Value, Risk, and Enjoyment |
| **Social Cognitive Theory (SCT)** | 1 | Alongside AI Self-Efficacy and Organisational Support |
| **Social Exchange Theory** | 1 | Used in a study involving anxiety and stress |
| **HCI Theory (Human-Computer Interaction)** | 1 | Part of a broader theoretical integration |
| **Service Robot Acceptance Model (sRAM)** | 1 | Used in the context of anthropomorphism, trust, and intelligence |
| **Self-Directed Learning with Technology (SDLT)** | 1 | Mentioned in one study with ICT self-efficacy |

**4.7 FOCUS ON TECHNOLOGY IN REVIEW STUDIES**

The reviewed studies demonstrate a wide range of applications of AI in education, spanning from the use of AI technologies in general to the use of specific tools like:

*AI Chatbots and Virtual Assistants*: Studies focused on Academic Advising Chatbots, Teacher-bots for learning, and Voice Assistants. Chatbot-focused studies focus on the usability of chatbots, intelligence perception, and automation of academic functions, but lack technical descriptions of the bots, reflecting only on the educational aspect (Bilquise et al., 2024; Pillai et al., 2024).

*AI-Driven Learning Platforms*: Platforms like Blackboard, Moodle, Edmodo, Coursera, and edX, which are not inherently AI-based, also find applications in Learning analytics dashboards and adaptive and personalised learning (Salas, 2022).

*Advanced features of AI*: Some studies focused on more advanced features of AI, such as AI-based robots and AI speech evaluation tools (Zou et al., 2023). These tools allow users to interact with technology more lifelike or engagingly. For example, robots can move or speak, and speech tools can give real-time feedback. These technologies draw attention to new factors like robot-related anxiety, trust, and the overall experience of interacting with AI in a more human-like way. However, such studies are still very limited in number, showing that AI tools with physical or interactive features are underexplored in higher education research. This suggests a need for more studies examining how students and teachers respond to these newer, more immersive AI tools.

*AI for Academic Writing and Creativity*: Few studies focused on AI-assisted writing (Cui, 2025), idea generation (Chergarova et al., 2023), and co-creation capabilities (Wen et al., 2024), emphasising creative and exploratory use of AI in higher education.

*Generative AI Tools (e.g., ChatGPT)*: Among all the applications of AI in education, generative AI, especially ChatGPT, appears in 7 studies and receives the maximum scholarly attention. Use of ChatGPT has been explored from different angles like acceptance, satisfaction, continued use (Yu et al., 2024; Saif et al., 2024), faculty well-being (Cambra-Fierro et al., 2024), Metacognitive self-regulated learning support (Dahri et al., 2024), trust and personalisation (Zhao et al., 2024). Importantly, all the studies treat it as the primary technological focus, not just one of several AI tools. This highlights the growing use of ChatGPT as a content generator and a cognitive partner that can enhance well-being and serve as an excellent pedagogical tool.

**4.8 SYNTHESIS OF CORE INSIGHTS**

A synthesis of findings reveals that cognitive factors- Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the most significant predictors of Behavioural Intention (BI) to adopt AI in higher education. These constructs have been validated in all the reviewed studies. Researchers have sometimes renamed them as Performance Expectancy or Effort Expectancy, suggesting flexibility of TAM. Actual use has been rarely measured, indicating a recurring intention-actual use gap.

Researchers have also investigated the effect of affective constructs like perceived enjoyment (PE), anxiety, satisfaction, and cognitive factors. PE was found to enhance intrinsic motivation in adopting AI and was found to be a stronger predictor of BI than PU. Reviewed studies also included social and normative factors, such as subjective norms, social influence, and perceived organisational support (Zhao et al., 2024; Roy et al., 2024). These factors significantly impacted BI's adoption of AI in higher education. On the contrary, subjective norms and security were reported to exert insignificant influence on BI in the study conducted by Shamsi et al. (2024) on university students studying in the UAE. Different cultural contexts or specific AI applications may explain the variation in findings. This SLR also highlights AI-specific factors like AI literacy, AI explainability, personalisation, co-creation intention, and AI anxiety. These factors were found to influence BI. AI literacy significantly mediated the relationship between the TR trait optimism and AI cocreation behaviour. It was also found that AI explainability and personalization enhance trust resulting in enhanced willingness to engage in co-creation activities (Wang et al., 2024). Analysis of reviewed studies also highlighted the importance of self-belief in shaping teachers’ AI adoption behavior digital literacy (Ma & Lei, 2024) and self-efficacy (Yao & Wang, 2024). These findings indicate that incorporating AI-specific constructs in future studies is crucial because they enhance TAM's explanatory power and help explain how users understand, trust, and adapt to AI tools.

Lastly, TRAM-based studies combine personality with cognitive, affective, and social traits to offer a holistic understanding of AI adoption. Few studies explore post-adoption perceptions of users through self-reported measures like continued use intention, user satisfaction, and technology-induced well-being. For instance, Cambra-Fierro et al. (2024) highlighted that ChatGPT adoption was associated with higher faculty satisfaction, reduced stress, and improved well-being, while Zhao et al. (2024) and Roy et al. (2024) demonstrated how optimism and perceived control facilitated AI acceptance. However, these outcomes are based on survey findings, not objective and observable behaviour. Thus, the inferences drawn from these studies lack depth and strength. Not all TRI traits are of equal importance. For example, while optimism has consistently been found to predict post-adoption outcomes, discomfort and insecurity were inconsistent or non-significant in several models (Zhao et al., 2024; Roy et al., 2024). Innovativeness, another TRI trait, positively affected AI literacy, co-creation behaviour, and early-stage adoption (Chergarova et al., 2023). Users ranking high on innovativeness are more inclined to engage with AI tools. Also, innovativeness has been studied less frequently, highlighting the need for integration in future studies.

In summary, PU and PEOU remain the most important predictors of AI adoption in higher education. Integrating affective, social and AI-specific constructs provided a more holistic understanding. The lack of longitudinal studies that measure actual use and satisfaction remains a persistent methodological gap, as do the comparative studies that measure the cultural and contextual impact. Integrating TAM with TRI shows promise in capturing the complex interplay between cognitive, emotional, and readiness-based variables, especially in diverse educational contexts. Including TRI variables enhances the explanatory power of TAM, and future studies must consider implementing TRI along with TAM.

**5. IDENTIFIED RESEARCH GAPS AND FUTURE DIRECTIONS**

1. Methodological gaps: Using self-reported measures to capture post-adoption behaviours in all studies suggests the dominance of cross-sectional design studies in AI adoption in higher education. However, longitudinal studies must address the intention-behaviour gap by tracking actual usage patterns to adequately capture post-adoption behaviours. Also, the absence of experimental or quasi-experimental methods is a methodological gap that needs to be addressed in future studies. Actual use was measured through self-reported measures instead of objective behavioural metrics (e.g., usage logs, clickstream data), weakening conclusions about actual use behaviour.

2. Theoretical Gaps: Only a few studies employ TRI or integrate TAM and TRI models. This limits the holistic understanding of users’ technology adoption dynamics. Readiness traits are significant predictors of technology adoption; they determine people’s mental map to use the latest technology (Kaushik & Agrawal, 2020). Hence, their inclusion alongside TAM will enhance understanding of technology adoption. Despite their demonstrated relevance, attitude and PE are still understudied constructs, so future studies should include them in their investigation. Future research should also consider integrating models like sRAM better to capture user trust, anthropomorphism, and socio-emotional responses, particularly as educational institutions increasingly deploy AI agents with human-like features.

3. Population Gap: There is an underrepresentation of inclusive education professionals in AI adoption research in higher education. AI technologies have the potential to enhance the learning experience for all sections of users; hence, more studies focusing on the inclusive aspect of AI must be undertaken in the future. Additionally, only two studies included the perspective of education leaders and management staff, while studies that incorporate views or perceptions of curriculum designers and IT staff are absent. The exclusion of these key stakeholders from the study population limits the generalizability of findings across the broader educational sector. Moreover, none of the reviewed studies adopted a cross-cultural or comparative design, which is crucial in understanding cultural differences. Therefore, future research should include diverse educational stakeholders’ perspectives and comparative analysis to support the development of a more holistic and representative adoption framework.

**6. CONCLUSION**

This systematic literature review synthesises findings from 25 studies on AI adoption in higher education using TAM, TRI, and TRAM frameworks. The results emphasise the importance of cognitive factors- perceived usefulness and ease of use in predicting behavioural intention, reinforcing the dominance of TAM in technology adoption studies. Integrating affective, social, and AI-specific constructs, such as enjoyment, trust, and explainability, also plays an important role in shaping user acceptance models. Despite the use of diverse information systems (IS) theories to understand adoption, crucial methodological gaps persist, such as the underutilization of qualitative and comparative studies that could provide a more in-depth understanding of the subject. The underrepresentation of viewpoints of diverse educational stakeholders and longitudinal analyses is another gap observed. Therefore, to enhance the scope and generalizability of the findings, future studies must prioritise longitudinal, comparative, and experimental studies. This review maps the evolving landscape of AI adoption research in higher education and provides a clear agenda for more robust, inclusive, and theoretically grounded future studies.

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