Faculty Acceptance of Generative AI in Higher Education: A Meta-Analysis of TAM and UTAUT Studies (2021-2025)

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Abstract

This meta-analysis synthesizes evidence from 10 empirical studies (2021–2025) on faculty acceptance of generative AI in higher education. Following PRISMA 2020 procedures, 523 records were screened, and 10 studies met the inclusion criteria for quantitative synthesis. Using random-effects models (REML), we estimated pooled associations between perceived usefulness (PU), perceived ease of use (PEOU), and social influence (SI) with attitudes (ATT) and behavioral intention (BI). All included studies employed cross-sectional survey designs (total N = 3,006), noting that the cumulative N varies across pathways because not all studies reported all relationships. Pooled effects indicated the most significant associations for PU with ATT ($r = 0.40$) and BI ($r = 0.26$), with more minor pooled associations for PEOU and SI. Heterogeneity was substantial across pathways ($I^2 = 71–94\%$). Publication bias diagnostics did not indicate systematic bias for most pathways; interpretation of SI → ATT remains cautious due to $k = 3$. Overall, the synthesis suggests that perceptions of usefulness and ease of use are correlates of faculty attitudes and intentions to adopt generative AI, while highlighting substantial contextual variability.

Keywords: artificial intelligence, higher education; meta-analysis, TAM, UTAUT, faculty

1. Introduction

Over the past decade, artificial intelligence (AI) has attracted increasing attention in higher education, particularly in teaching, learning, and academic decision-making. This domain, commonly referred to as Artificial Intelligence in Education (AIEd), includes intelligent tutoring systems (ITS), educational robots, recommender systems, automated assessment tools, and, more recently, generative technologies such as ChatGPT (Alateyyat & Soltan, 2024; Crompton & Burke, 2023). These applications can be broadly categorized into student-oriented tools (e.g., adaptive learning and instant feedback), faculty-oriented tools (e.g., automated grading and workload reduction), and institutional tools for decision-making support (Leong et al., 2025). To explain the adoption or rejection of such technologies, many studies have relied on well-established theoretical frameworks. The Technology Acceptance Model (TAM), introduced by Davis (1989), emphasizes two key determinants: perceived usefulness (PU) and perceived ease of use (PEOU). In contrast, the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), expanded this explanatory scope by integrating multiple prior models and adding performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Owing to their explanatory capacity, TAM and UTAUT are among the most frequently applied frameworks in digital learning research (Granić, 2023; O'Dea, 2025).

Despite extensive research on AI adoption in education, there remains a notable gap regarding faculty members, with much of the existing literature focusing on students or mixed samples and relatively limited attention to instructors' perspectives and adoption behaviors. Prior reviews have also tended to examine AI applications broadly, without tailoring the focus to a specific group of end users.

Against this backdrop, the present study conducts a meta-analysis of 10 empirical studies published between 2021 and 2025 to estimate the effect sizes of TAM and UTAUT determinants in explaining faculty acceptance of generative AI (GenAI) technologies in higher education. By focusing on faculty samples and synthesizing recent findings, this work provides quantitative evidence on instructors' acceptance of generative AI tools such as ChatGPT, thereby addressing a critical gap in the literature and offering both theoretical and practical insights for higher education institutions.

1.1 Research Question

This study seeks to quantitatively estimate the effect sizes of key relationships within the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Specifically, it examines how perceived usefulness (PU), perceived ease of use (PEOU), and social influence (SI) relate to faculty members' attitudes (ATT) and behavioral intentions (BI) toward adopting artificial intelligence (AI) applications in higher education from 2021 to 2025.

2. Theoretical Background

The study of technology acceptance in educational contexts has been profoundly shaped by two foundational theoretical models: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models serve as the primary frameworks for understanding why individuals adopt—or reject—emerging technologies, including those in higher education.

2.1 Technology Acceptance Model (TAM)

Developed by Davis (1989), the Technology Acceptance Model (TAM) explains users' acceptance of computer systems through two core cognitive beliefs: perceived usefulness (PU)—the extent to which an individual believes that using a technology will enhance job performance—and perceived ease of use (PEOU)—the extent to which the system is believed to be free of effort. PU and PEOU influence users' attitudes (ATT) toward the technology and their behavioral intention (BI) to use it. Owing to its conceptual simplicity and strong predictive power, TAM has been extensively applied in educational technology research, spanning domains such as e-learning, mobile applications, and, more recently, artificial intelligence (AI) tools.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Proposed by Venkatesh et al. (2003), UTAUT integrates eight prior acceptance models and comprises four main determinants: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These factors predict both behavioral intention (BI) and actual use (UB) of new technologies. UTAUT has been widely applied in educational contexts, including mobile learning and AI-based systems, providing a more comprehensive view by accounting for both individual cognition and social/institutional influences.

2.3 Comparing TAM and UTAUT in Education

Meta-analytic and review evidence suggest that TAM remains among the most widely used models in educational research, whereas UTAUT serves as a complementary framework with substantial acceptance (Granić, 2023). TAM's appeal stems from its simplicity and effectiveness in predicting educators' and students' perceptions of usefulness and ease of use (Zawacki-Richter & Jung, 2023). Conversely, UTAUT expands the analytical lens to include organizational and social factors, which are critical in academic environments where institutional policies and peer influences significantly affect adoption (Ali et al., 2025).

2.4 Implications for AI Adoption in Higher Education

The rapid growth of generative AI tools such as ChatGPT underscores the need for integrative theoretical frameworks that combine cognitive and social/institutional determinants. TAM offers insight into perceived usefulness and ease of use, while UTAUT adds depth by capturing academic norms, infrastructure, and institutional support as influential factors shaping adoption intentions. Thus, synthesizing TAM and UTAUT provides a robust foundation for understanding faculty adoption of generative AI in university settings Al-Kfairy, 2024; Nasni Naseri & Abdullah, 2024). Recent reviews confirm that such models are essential for explaining the acceptance and implementation of emerging technologies in educational contexts (Cambra-Fierro et al., 2025).

3. Related Literature

In recent years, research on the adoption of artificial intelligence (AI) in higher education has accelerated across application domains, including chatbots, intelligent tutoring systems, AI-driven assessment, personalized learning, and generative tools such as ChatGPT. A substantial proportion of recent empirical studies on AI adoption in higher education have operationalized acceptance using TAM- or UTAUT-based constructs, particularly when examining faculty attitudes and intentions.

Across the literature, perceived usefulness (PU) frequently emerges as a strong predictor of attitudes (ATT) and behavioral intentions (BI) toward the adoption of AI technologies (Cortez et al., 2024; Osman et al., 2023). Several studies also demonstrate a positive link between perceived ease of use (PEOU) and both BI and ATT; however, sporadic nonsignificant findings suggest that this relationship may be context-dependent or moderated by other factors (Keji, 2024; Purwandari et al., 2024; Wijaya et al., 2024). Such mixed evidence highlights the need for meta-analytic approaches that can synthesize and clarify these discrepancies.

Social influence (SI) similarly contributes to shaping BI and ATT, especially in academic contexts where organizational culture, policies, and peer norms can either facilitate or hinder faculty adoption of new technologies (Abubakar & Al-Mamary, 2025; Benard et al., 2024). By contrast, evidence regarding facilitating conditions (FC) remains inconsistent: some studies report no significant impact, whereas others identify FC as critical, perhaps reflecting differences in institutional infrastructure and support (Abubakar & Al-Mamary, 2025; Hassan et al., 2020). Despite the growing research base, existing literature predominantly focuses on students or mixed samples, with limited attention to faculty perspectives and experiences. To address this gap, the present study centers on the core determinants of TAM and UTAUT—PU, PEOU, and SI—and provides a meta-analytic estimate of their effect sizes on faculty acceptance of AI technologies in higher education. By synthesizing findings from 2021 to 2025, this work aims to clarify the predictive strength of these factors and inform future research, policy, and practice.

3.1 Hypotheses

Based on the theoretical background and literature review, the present study tests the following hypotheses:

H1: Perceived usefulness (PU) will have a positive and significant effect on behavioral intention (BI) to adopt and use generative AI applications in higher education.

H2: Perceived ease of use (PEOU) will have a positive and significant effect on behavioral intention (BI) to adopt and use generative AI applications in higher education.

H3: Perceived usefulness (PU) will have a positive and significant effect on attitudes (ATT) toward adopting generative AI applications in higher education.

H4: Perceived ease of use (PEOU) will have a positive and significant effect on attitudes (ATT) toward adopting generative AI applications in higher education.

H5: Social influence (SI) will have a positive and significant effect on behavioral intention (BI) to adopt and use generative AI applications in higher education.

H6: Social influence (SI) will have a positive and significant effect on attitudes (ATT) toward adopting generative AI applications in higher education.

4. Method

This meta-analysis was conducted in accordance with the PRISMA 2020 guidelines for systematic reviews and meta-analyses (Page et al., 2021). The PRISMA framework is intended to enhance transparency and rigor in reporting and is widely adopted in educational and information technology research (Ali et al., 2025; Hew et al., 2021; Jiao et al., 2024; Jongsma et al., 2023; Khan et al., 2022).

4.1 Literature Search

A comprehensive search was performed in the Web of Science (WoS) database using the following query string:

TS = ("technology acceptance" OR "technology adoption")

AND TS = ("artificial intelligence" OR "AI-based" OR "chatbot" OR "intelligent tutoring" OR "generative AI"

OR "ChatGPT" OR "AI-based learning")

AND TS = ("higher education" OR "university" OR "college")

AND TS = ("faculty" OR "instructor" OR "professor" OR "academic staff")

To maximize coverage, additional strategies were employed, including backward and forward citation tracking and snowball sampling. Studies were included if published in English between January 2021 and September 2025 and reported quantitative TAM or UTAUT findings related to faculty in higher education. Only cross-sectional or survey-based studies with extractable statistics were considered.

4.2 Inclusion and Exclusion Criteria

To ensure the quality and relevance of the included studies, the inclusion and exclusion criteria were applied to the selected studies for this meta-analysis as shown in Table 1.

4.3 Study Selection and Data Extraction

The initial database search retrieved 523 records. After removing duplicates, screening titles/abstracts, and full-text assessment, 10 studies met the inclusion criteria. Data extraction was conducted using structured forms that captured:

(1) bibliographic details (author, year, country, journal/conference).

(2) methodological characteristics (field, discipline, sample size and type, AI application, study design, theoretical model),

(3) and statistical outcomes (correlations, standardized β coefficients, t-values, Fisher's Z transformations, confidence intervals, p-values).

4.4 Variable Harmonization and Effect Size Coding

To address variations in construct naming across the included studies:

(1) Adoption Intention and Intention to Use were standardized as Behavioral Intention (BI).

(2) Effort Expectancy (EE) was merged with Perceived Ease of Use (PEOU).

(3) Performance Expectancy (PE) was aligned with Perceived Usefulness (PU).

Table 1. Inclusion and Exclusion Criteria Applied for This Meta-Analysis

Category	Inclusion Criteria	Exclusion Criteria
Educational scope	Higher education only (universities/colleges/institutes)	Studies in K-12 education or vocational training
Participants	Faculty members (lecturers, professors, teaching assistants); mixed samples accepted if faculty results are reported separately	Student-only samples or general samples without separate reporting for faculty
Theoretical model	Studies that quantitatively test TAM or UTAUT constructs	Studies not adopting TAM/UTAUT frameworks or not providing quantitative results
Time frame	Studies published between 2021 and 2025	Studies published before 2021
Study design	Cross-sectional designs or quantitative surveys with extractable statistics	Theoretical papers, literature reviews, opinion pieces, or studies without extractable coefficients (r/β)
Language	English	Any other languages

4.5 Effect Sizes were Standardized Following Meta-analytic Conventions

(1) Reported Pearson's r was directly used and converted to Fisher's Z.

(2) Spearman's ρ was treated as equivalent to r (Peterson & Brown, 2005).

(3) Standardized β coefficients from SEM-based studies were treated, where applicable, as approximate r values, following established meta-analytic practice, while recognizing that this transformation introduces additional uncertainty.

4.6 Data Analysis Procedures

All analyses were performed using R (metafor package) and JASP. The analytic procedures included:

(1) Descriptive summaries of study characteristics (country, discipline, sample size, framework).

(2) Heterogeneity testing using Q, I^2, and τ^2 statistics.

(3) Application of the random-effects model (REML) for all meta-analytic paths due to the presence of substantial heterogeneity, consistent with methodological recommendations (DerSimonian & Laird, 1986; Higgins et al., 2003).

(4) Publication bias assessment using funnel plots, Egger's regression test, and the Fail-safe N approach.

(5) Estimation of pooled effect sizes for the hypothesized relationships among TAM/UTAUT constructs (PU, PEOU,

SI), attitudes (ATT), and behavioral intentions (BI).

The PRISMA 2020 Flow Diagram (Haddaway et al., 2022) was used to represent the study selection process visually.

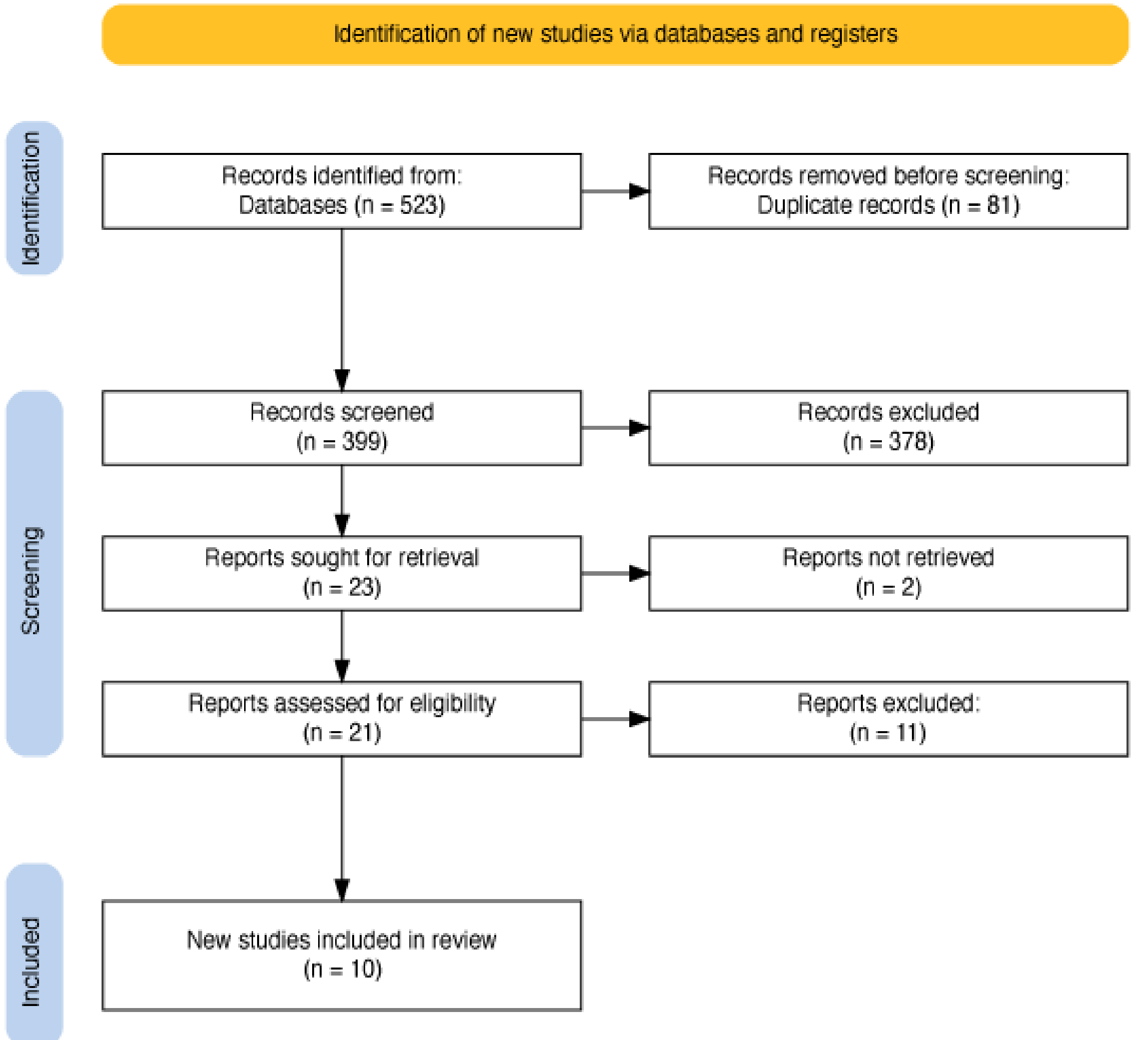

Figure 1. PRISMA 2020 Flow Diagram illustrating the study selection process

4.7 Standardization of Variables

The included studies differed in how core TAM and UTAUT constructs were labeled and operationalized. For example, constructs such as Adoption Intention and Intention to Use were frequently used interchangeably with the standard variable Behavioral Intention (BI). Similarly, Effort Expectancy (EE) was considered conceptually equivalent to Perceived Ease of Use (PEOU), and Performance Expectancy (PE) was treated as analogous to Perceived Usefulness (PU). In accordance with prior meta-analytic research practice (Ali et al., 2025; Khan et al., 2022), these variable names were standardized across all included studies to ensure consistency and comparability before conducting the meta-analysis. This harmonization allowed for meaningful quantitative synthesis of effect sizes and robust interpretation of the relationships between constructs.

4.8 Selection of Paths for Meta-Analysis

Six core paths were identified based on the TAM and UTAUT frameworks. Following a review of the included studies, only relationships for which there were sufficient independent estimates (≥3 studies) were eligible for quantitative synthesis: PU → BI, PEOU → BI, PU → ATT, PEOU → ATT, SI → BI, and SI → ATT.

As shown in Table 2, the frequency of each path across the included studies was summarized along with the decision regarding their inclusion in the quantitative synthesis.

This decision aligns with meta-analytic methodological recommendations, which emphasize that a minimum of three independent studies per path is necessary to produce stable estimates of heterogeneity and pooled effect sizes (Borenstein et al., 2009; Valentine et al., 2010).

Table 2. Frequency of each path across the included studies and the decision regarding its inclusion in the quantitative synthesis

Path	Frequency	Inclusion decision
PU → BI	9	Included in meta-analysis
PEOU → BI	9	Included in meta-analysis
PU → ATT	5	Included in meta-analysis
PEOU → ATT	5	Included in meta-analysis
SI → BI	4	Included in meta-analysis
SI → ATT	3	Included in meta-analysis

Note 2. Only relationships supported by at least three independent studies were eligible for quantitative synthesis.

5. Results

5.1 Descriptive Analysis

This meta-analysis synthesized data from 10 primary studies conducted between 2021 and 2025, each investigating faculty acceptance and use of generative AI—primarily ChatGPT and similar tools—in higher education settings. All included studies employed non-experimental, cross-sectional quantitative survey designs without experimental manipulation or random assignment, reflecting prevailing methodological conventions in technology acceptance research. Because not all studies reported all hypothesized relationships, the adequate sample size (N) varied across meta-analytic paths.

The studies encompassed a wide range of geographic and cultural contexts, spanning the United States, Mexico, Ecuador, Spain, Pakistan, China, India, Saudi Arabia, and the United Kingdom. Academic samples in these papers ranged from approximately 32 to 425 faculty members per study, collectively totaling 3,006 faculty participants and representing a variety of higher education institutions, both public and private.

Disciplines covered included social sciences, humanities, pedagogy, business, management, engineering, and multidisciplinary domains. The studies applied technology acceptance frameworks—primarily TAM or UTAUT and their variants—and several integrated extended constructs such as trust, self-efficacy, AI literacy, TPACK, and perceived privacy. The most frequently analyzed variables were Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Social Influence (SI), with Behavioral Intention (BI) and Attitudes (ATT) as primary outcomes. All studies focused specifically on faculty populations, either exclusively or as an analyzed subsample.

Most surveys assessed AI acceptance in relation to real-world educational applications, including content generation, automated grading, personalized learning support, and academic assessment. Although the overarching subject was the acceptance of generative AI, operationalizations of AI tools and models varied across institutional settings and national contexts. This methodological and contextual diversity enhances the generalizability of the meta-analytic findings. It highlights the global landscape of faculty attitudes and intentions regarding the adoption of generative AI tools in higher education.

A complete summary table of study characteristics is provided in Appendix A.

5.2 Meta-Analysis

A random-effects model (REM) was employed for all eligible effect paths, given substantial heterogeneity across studies, as indicated by high I^2 values. This approach follows the classic methodological foundations of meta-analysis (DerSimonian & Laird, 1986; Higgins et al., 2003) and adheres to contemporary recommendations that emphasize evaluating heterogeneity using the Q statistic and the I^2 index when selecting the statistical model (Yang et al., 2020). Substantial between-study heterogeneity is well documented in multidisciplinary meta-analyses. For instance, Senior et al. (2016) found that the mean I^2 across nearly 700 published meta-analyses ranged from 85% to 92%, indicating that high heterogeneity is common and should be expected rather than treated as exceptional.

5.3 Heterogeneity Tests and Pooled Effect Sizes

Heterogeneity tests were conducted for all meta-analytic paths included in the quantitative synthesis ($k \geq 3$), in line with the predefined inclusion criteria. The I^2 statistic ranged from 71.1% to 94.0% across most relationships, indicating substantial heterogeneity among study findings. Q-tests were statistically significant for all paths except SI → ATT ($p = .062$, $k = 3$). Given the small number of contributing studies, the heterogeneity estimate for SI → ATT should therefore be interpreted with caution.

The pooled estimates revealed that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Social Influence (SI) exerted statistically significant positive effects on both Attitudes (ATT) and Behavioral Intentions (BI) toward the adoption of generative AI among faculty in higher education. PU showed a moderate positive effect on both Behavioral Intention (PU → BI: r = 0.26, 95% CI [0.20, 0.33]) and Attitude (PU → ATT: r = 0.40, 95% CI [0.16, 0.59]); PEOU displayed a weaker but consistent effect (PEOU → BI: r = 0.17, 95% CI [0.05, 0.29]; PEOU → ATT: r = 0.30, 95% CI [0.18, 0.41]); and SI showed a moderate effect on BI (SI → BI: r = 0.26, 95% CI [0.14, 0.37]) but a smaller and less robust effect on ATT (SI → ATT: r = 0.23, 95% CI [0.01, 0.43]). These estimates are summarized in Table 3.

Table 3. Pooled effect sizes (r) for all meta-analytic pathways (random-effects, REML)

Path	k	Effect size (r)	95% CI
PU → BI	9	0.26	[0.20, 0.33]
PEOU → BI	9	0.17	[0.05, 0.29]
PU → ATT	5	0.40	[0.16, 0.59]
PEOU → ATT	5	0.30	[0.18, 0.41]
SI → BI	4	0.26	[0.14, 0.37]
SI → ATT	3	0.23	[0.01, 0.43]

5.4 Publication Bias Analysis

To examine potential publication bias, several established tools have been employed in the literature, most notably funnel plots, Egger’s regression test, and the Fail-safe N test. Lin and Chu (2018) described the funnel plot as a simple and visual tool for detecting publication bias. In educational research, Ali et al. (2025) applied both funnel plots and the Fail-safe N test in a meta-analysis on the adoption of artificial intelligence applications, while Lara-Alvarez et al. (2023) and Susanti et al. (2024) combined funnel plots with Egger’s regression test, consistently reporting no substantial evidence of bias. Similarly, Feng et al. (2021) relied exclusively on the Fail-safe N test, whereas Peterson and Brown (2005) provided a broader methodological discussion of its importance and applications.

Forest plots (Figure 2; see also Table 3) present the pooled effect sizes and between-study heterogeneity for all core TAM/UTAUT pathways. Most relationships—including PU → BI, PU → ATT, PEOU → ATT, and SI → BI—show moderate-to-positive pooled estimates, with effect sizes well-centered within their confidence intervals and no evidence of significant outliers. Pathways like PEOU → BI and SI → ATT demonstrated weaker yet still positive effects.

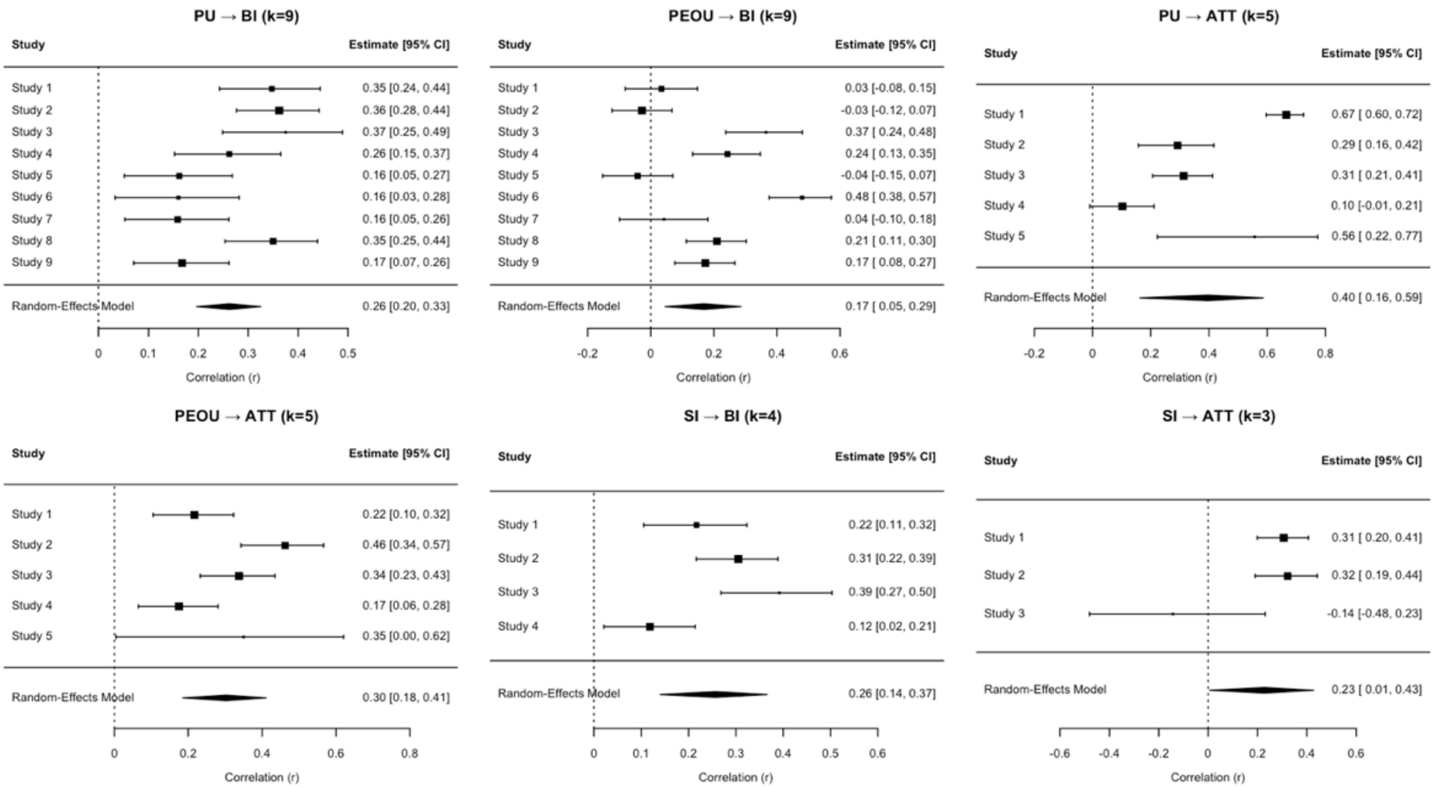

Figure 2. Forest plots of pooled effect sizes for each hypothesis pathway

Squares represent study-level effect size estimates, horizontal lines indicate the 95% confidence intervals, and the diamond at the bottom shows the pooled random-effects estimate.

Funnel plots (Figure 3) visually assess publication bias by examining the symmetry of effect-size distributions across standard errors. The pathways PU → BI, PEOU → ATT, SI → BI, and PU → ATT appear well-centered and symmetrical, indicating minimal risk of publication bias. While some mild skewness was noted for PEOU → BI and PU → ATT, neither visual inspection nor formal tests suggests substantial bias.

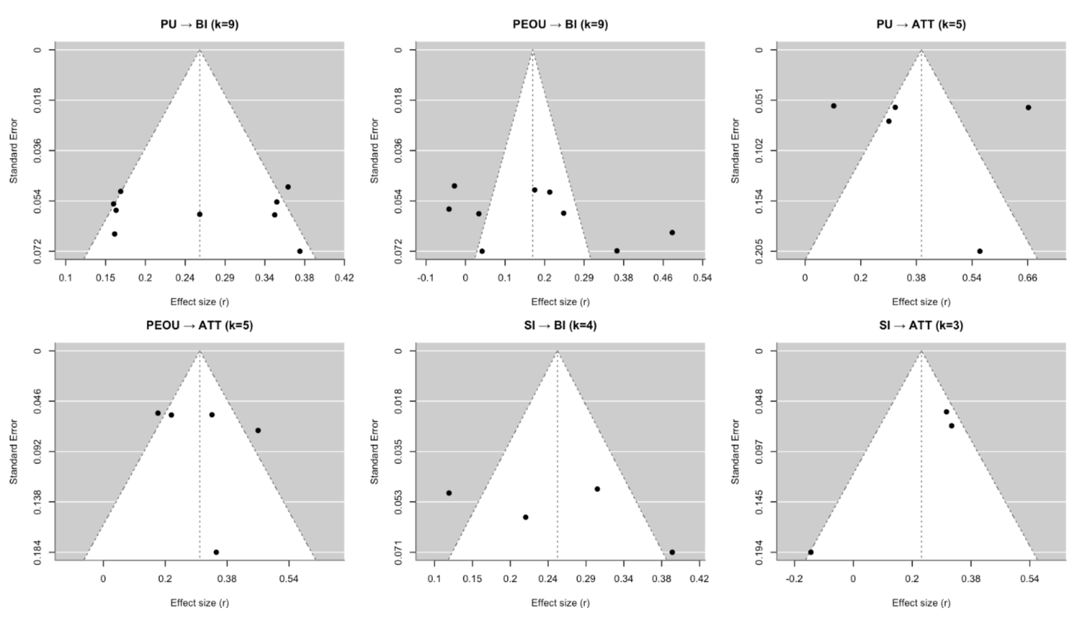

Figure 3. Funnel plots of effect size versus standard error for each pathway

Symmetry in the distributions indicates no evidence of substantial publication bias. Statistical tests corroborate the visual evidence: Egger's regression was not statistically significant for five of six pathways ($p > .05$), indicating no major small-study or reporting bias. For SI → ATT, Egger's test was statistically significant ($p = .024$, $k = 3$); however, this pathway is supported by only three studies, which limits the reliability of the bias estimate in this case. Fail-safe N values (see Table 4) further support the robustness of the main pathways, indicating that substantially more null-effect studies would be needed to challenge the results.

5.5 Effect Sizes and Hypothesis Testing

The meta-analysis assessed six hypothesized pathways (H1–H6), revealing consistently positive associations between core TAM/UTAUT constructs—Perceived Usefulness (PU), Perceived Ease Of Use (PEOU), and Social Influence (SI)—and outcome variables of Attitude (ATT) and Behavioral Intention (BI) toward adopting AI tools in higher education. However, the magnitude, statistical certainty, and robustness of these relationships varied.

H1 (PU → BI): Across nine studies (N ≈ 2,868), this pathway showed a statistically significant medium effect ($r = 0.262$, 95% CI [0.20, 0.33], $z = 7.59$, $p < .001$). Heterogeneity was moderate-to-high ($I^2 = 71.1\%$). The Fail-safe N was 75, indicating moderate robustness but some vulnerability to additional null-effect studies.

H2 (PEOU → BI): Based on nine studies (N ≈ 2,868), Perceived Ease Of Use predicted BI with a weaker effect ($r = 0.168$, 95% CI [0.05, 0.29], $z = 2.65$, $p = .029$). Heterogeneity was extremely high ($I^2 = 90.8\%$), and the Fail-safe N was low (7), suggesting this finding is fragile.

H3 (PU → ATT): From five studies (N ≈ 1,143), PU to Attitude showed a medium to strong effect ($r = 0.395$, 95% CI [0.16, 0.59], $z = 3.32$, $p = .029$), with very high heterogeneity ($I^2 = 94.0\%$). Fail-safe N was 5, indicating limited robustness.

H4 (PEOU → ATT): Also with five studies (N ≈ 1,143), PEOU on Attitude was a significant medium effect ($r = 0.302$, 95% CI [0.18, 0.41], $z = 5.20$, $p < .001$), high heterogeneity ($I^2 = 74.4\%$), and moderate Fail-safe N (10).

H5 (SI → BI): Across four studies (N ≈ 1,329), Social Influence on BI was moderate and significant ($r = 0.256$, 95% CI [0.14, 0.37], $z = 4.19$, $p < .001$), but with high heterogeneity ($I^2 = 79.5\%$) and low robustness (Fail-safe N = 6).

H6 (SI → ATT): For three studies (N ≈ 536), SI on Attitude yielded a weak-to-medium effect ($r = 0.228$, 95% CI [0.01, 0.43], $z = 2.19$, $p = .024$), with high heterogeneity ($I^2 = 79.4\%$) and lowest robustness (Fail-safe N = 1).

Overall, these results are consistent with key assumptions of TAM and UTAUT, indicating that PU, PEOU, and SI are positively associated with ATT and BI in faculty adoption of AI tools in higher education. However, the strength and robustness of these associations vary across pathways, and the high heterogeneity across studies and the relatively low Fail-safe N values, particularly for attitude pathways, underscore the need for cautious interpretation and highlight the importance of future rigorous research to strengthen the evidence base (see Table 4).

Table 4. Pooled effect sizes, heterogeneity, and publication bias statistics for all pathways

Path	k	Effect size (r)	95% CI	I^2(%)	τ^2	Egger's p	Fail-safe N
PU → BI	9	0.262	[0.20, 0.33]	71.1	0.0079	0.791	75
PEOU → BI	9	0.168	[0.05, 0.29]	90.8	0.0328	0.248	7
PU → ATT	5	0.395	[0.16, 0.59]	94.0	0.0747	0.543	5
PEOU → ATT	5	0.302	[0.18, 0.41]	74.4	0.0139	0.603	10
SI → BI	4	0.256	[0.14, 0.37]	79.5	0.0121	0.246	6
SI → ATT	3	0.228	[0.01, 0.43]	79.4	0.0286	0.0242	1

Note 3. Egger's regression test: Most pathways did not show statistical significance ($p > .05$), suggesting no firm evidence of publication bias. The exception was SI → ATT ($p = .024$), which may reflect some asymmetry; given that the pathway is based on only three studies, caution is warranted, and further research is required to confirm the

robustness of this finding regarding social influence on attitudes.

6. Conclusions

This meta-analysis systematically examined the determinants of faculty acceptance and adoption of artificial intelligence (AI) tools in higher education, synthesizing evidence from 10 studies published between 2021 and 2025 in accordance with PRISMA guidelines. All included studies featured samples composed exclusively of faculty members (total N = 3,006) from diverse university contexts and covered various AI applications, with a focus on ChatGPT, generative AI (GenAI), and AI-based educational tools (AIEd).

The majority of the included studies utilized the Technology Acceptance Model (TAM) or its extensions. In contrast, four studies employed the Unified Theory of Acceptance and Use of Technology (UTAUT) or an integrated framework.

The analysis indicated that the majority of the tested hypotheses (H1–H6) were statistically significant. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) consistently emerged as the most robust determinants of both Attitudes (ATT) and Behavioral Intention (BI). Social Influence (SI) also demonstrated significant, albeit comparatively weaker, effects. It is notable that relatively low Fail-safe N values for some pathways, especially those supported by a limited number of studies (e.g., SI → ATT), underline the fragility of specific results and the need for further validation.

The current evidence base is TAM-dominant, supporting inferences about the salience of perceived usefulness and perceived ease of use in explaining faculty acceptance of AI tools in higher education. At the same time, direct comparative claims between TAM and UTAUT remain constrained by the limited number of UTAUT-based studies and the absence of model-based moderator or subgroup analyses in the present synthesis. From a practical standpoint, these patterns suggest that faculty-facing AI initiatives should foreground clear, discipline-relevant benefits and usability. At the same time, institutions continue to investigate how broader social and organizational factors—often conceptualized within UTAUT—shape adoption across diverse higher education contexts.

6.1 Theoretical and Practical Implications

This research addresses a significant gap by systematically synthesizing the determinants of faculty adoption of generative AI in higher education, informed by TAM and UTAUT. The results suggest that perceived usefulness and perceived ease of use are consistently associated with faculty acceptance of AI tools. However, their relative influence may vary across institutional and contextual settings.

From a theoretical standpoint, the substantial heterogeneity observed across most meta-analytic pathways suggests that the relationships between acceptance constructs are likely contingent on contextual moderators, including national context, type of AI application, disciplinary environment, and the stage of institutional AI integration. Although the present meta-analysis was not designed to test moderator effects, the consistently high I^2 values underscore the importance of moving beyond universal acceptance models toward more context-sensitive explanations of faculty AI adoption.

The findings also provide practical insights for university administrators, policymakers, and AI solution designers. Institutions are encouraged to implement targeted initiatives that increase faculty awareness of AI’s practical utility and reduce usability barriers, while considering how social and organizational environments shape adoption decisions. Developers should prioritize embedding functionality that enhances both perceived usefulness and perceived ease of use to support sustainable adoption and meaningful use of generative AI tools in higher education.

6.2 Limitations and Directions for Future Research

A key limitation of this meta-analysis is its reliance on a relatively small pool of eligible studies (n = 10), reflecting the emerging nature of faculty-focused research on generative AI in higher education. This restricts the generalizability of findings across all higher education contexts. Furthermore, the predominance of TAM-based studies limited the ability to compare with UTAUT directly. Several hypothesized pathways were underrepresented (≤ 3 studies), precluding robust quantitative synthesis and necessitating cautious interpretation of those results. Most existing research remains concentrated on ChatGPT and GenAI, with applications such as educational robots and intelligent agents continuing to be underexplored.

Future studies should broaden geographic and contextual diversity, systematically extend testing to more UTAUT constructs, and examine additional AI applications and pathways (e.g., BI → UB, FC → BI, SE → BI, Trust → BI). Such efforts are crucial to providing a more comprehensive, nuanced understanding of faculty adoption of AI technologies in higher education.

References

Abubakar, A. A., & Al-Mamary, Y. H. (2025). Exploring factors influencing the intention to use social media and its actual usage in higher education: A conceptual model of effectiveness, effort, communication, self-awareness, social influence, and facilitating conditions. *Interactive Learning Environments, 33*(6), 3833-3857. https://doi.org/10.1080/10494820.2025.2454435

Al-Abdullatif, A. M. (2024). Modeling teachers' acceptance of generative artificial intelligence use in higher education: The role of AI literacy, intelligent TPACK, and perceived trust. *Education Sciences, 14*(11), 1209. https://doi.org/10.3390/educsci14111209

Alateyyat, S., & Soltan, M. (2024). Utilizing artificial intelligence in higher education: A systematic review. In 2024 *ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 371-374). IEEE. https://doi.org/10.1109/ICETSIS61505.2024.10459629

Ali, I., Warraich, N. F., & Butt, K. (2025). Acceptance and use of artificial intelligence and AI-based applications in education: A meta-analysis and future direction. *Information Development, 41*(3), 859-874. https://doi.org/10.1177/02666669241257206

Al-Kfairy, M. (2024). Factors impacting the adoption and acceptance of ChatGPT in educational settings: A narrative review of empirical studies. *Applied System Innovation, 7*(6), 110. https://doi.org/10.3390/asi7060110

Benard, K., Moses, K., Arina, S., Jackson, A., & Leslie, O. A. (2024). ChatGPT usage in academia: Extending the unified theory of acceptance and use of technology with herd behavior. *International Journal of Social Science and Human Research, 7*(7), 637-646. https://doi.org/10.47191/ijsshr/v7-i07-69

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Wiley. https://doi.org/10.1002/9780470743386

Cabero-Almenara, J., Palacios-Rodr ǵuez, A., Loaiza-Aguirre, M. I., & Andrade-Abarca, P. S. (2024). The impact of pedagogical beliefs on the adoption of generative AI in higher education: Predictive model from UTAUT2. *Frontiers in Artificial Intelligence, 7*, 1497705. https://doi.org/10.3389/frai.2024.1497705

Cortez, P. M., Ong, A. K. S., Diaz, J. F. T., German, J. D., & Singh, J. S. (2024). Analyzing preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon, 10*(3), e25896. https://doi.org/10.1016/j.heliyon.2024.e25896

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, 22. https://doi.org/10.1186/s41239-023-00392-8

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

DerSimonian, R., & Laird, N. (1986). Meta-analysis in clinical trials. *Controlled Clinical Trials, 7*(3), 177-188. https://doi.org/10.1016/0197-2456(86)90046-2

Enang, E., & Christopoulou, D. (2025). Exploring academics' intentions to incorporate ChatGPT into their teaching practice. *Journal of University Teaching and Learning Practice, 21*(8). https://doi.org/10.53761/rn5y5614

Feng, G. C., Su, X., Lin, Z., He, Y., Luo, N., & Zhang, Y. (2021). Determinants of technology acceptance: Two model-based meta-analytic reviews. *Journalism & Mass Communication Quarterly, 98*(1), 83-104. https://doi.org/10.1177/1077699020952400

Granić, A. (2023). Technology acceptance and adoption in education. In O. Zawacki-Richter & I. Jung (Eds.), *Handbook of open, distance and digital education* (pp. 183-197). Springer Nature. https://doi.org/10.1007/978-981-19-2080-6_11

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and open synthesis. *Campbell Systematic Reviews, 18*(2), e1230. https://doi.org/10.1002/CL2.123

Hew, K. F., Bai, S., Huang, W., Dawson, P., Du, J., Huang, G., Jia, C., & Thankrit, K. (2021). On the use of flipped classroom across various disciplines: Insights from a second-order meta-analysis. *Australasian Journal of*

Educational Technology, 37(2), 132-151. https://doi.org/10.14742/ajet.6475

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ, 327*(7414), 557-560. https://doi.org/10.1136/bmj.327.7414.557

Jiao, Z., Chen, Y., & Lyu, C. (2024). Factors correlated with personal growth initiative among college students: A meta-analysis. *Heliyon, 10*(7), e28518. https://doi.org/10.1016/j.heliyon.2024.e28518

Jongsma, M. V., Scholten, D. J., Van Muijlwijk-Koezen, J. E., & Meeter, M. (2023). Online versus offline peer feedback in higher education: A meta-analysis. *Journal of Educational Computing Research, 61*(2), 329-354. https://doi.org/10.1177/07356331221114181

Kavitha, K., & Joshith, V. P. (2025). Artificial intelligence powered pedagogy: Unveiling higher educators' acceptance with extended TAM. *Journal of University Teaching and Learning Practice, 22*(8). https://doi.org/10.53761/s1pkk784

Keji, S. S. (2024). Relationship among perceived usefulness, ease of use, attitude and intention to use emerging technology among undergraduates in South-West Nigeria. *Journal for Lesson and Learning Studies, 7*(1), 126-132. https://doi.org/10.23887/jlls.v7i1.72043

Lara-Alvarez, C. A., Parra-González, E. F., Ortiz-Esparza, M. A., & Cardona-Reyes, H. (2023). Effectiveness of virtual reality in elementary school: A meta-analysis of controlled studies. *Contemporary Educational Technology, 15*(4), ep459. https://doi.org/10.30935/cedtech/13569

Leong, W. Y., Leong, Y. Z., & Leong, W. S. (2025). Artificial intelligence in education. *IET Conference Proceedings, 2024*(22), 183-184. https://doi.org/10.1049/icp.2024.4341

Lin, L., & Chu, H. (2018). Quantifying publication bias in meta-analysis. *Biometrics, 74*(3), 785-794. https://doi.org/10.1111/biom.12817

Nasni Naseri, R. N., & Abdullah, M. S. (2024). Understanding AI technology adoption in educational settings: A review of theoretical frameworks and their applications. *Information Management and Business Review, 16*(3(I)), 174-181. https://doi.org/10.22610/imbr.v16i3(I).3963

Nevárez Montes, J., & Elizondo-Garcia, J. (2025). Faculty acceptance and use of generative artificial intelligence in their practice. *Frontiers in Education, 10*, 1427450. https://doi.org/10.3389/feduc.2025.1427450

O'Dea, M. (2025). Editorial: Are technology acceptance models still fit for purpose?. *Journal of University Teaching and Learning Practice, 22*(8). https://doi.org/10.53761/1bdbms32

Osman, Z., Alwi, N. H., Ahmad Khan, B. N., Mohamad Jodi, K. H., & Naim Ismail, M. (2023). Deciphering academicians' usage of artificial intelligence in higher education institutions. *International Journal of Academic Research in Business and Social Sciences, 13*(10), 1385-1402. https://doi.org/10.6007/IJARBSS/v13-i10/18983

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *PLOS Medicine, 18*(3), e1003583. https://doi.org/10.1371/journal.pmed.1003583

Peterson, R. A., & Brown, S. P. (2005). On the use of beta coefficients in meta-analysis. *Journal of Applied Psychology, 90*(1), 175-181. https://doi.org/10.1037/0021-9010.90.1.175

Purwandari, D., Saparudin, M., Wulan, M., Akbari, D. A., & Kania, A. (2024). Does the lecturers' innovativeness drive online-learning adoption in higher education? A study based on extended TAM. *Jurnal Sisfokom (Sistem Informasi dan Komputer), 13*(2), 280-287. https://doi.org/10.32736/sisfokom.v13i2.2122

Saif, N., Ali, S., Rubin, A., Aljarboa, S., Almalki, N. S., Alnfiai, M. M., Khan, F., & Khan, S. U. (2025). Enabling MCQ-based assessments formulation for management science lecturers: Technology readiness acceptance model validation through ChatGPT. *Education and Information Technologies*. Advance online publication. https://doi.org/10.1007/s10639-024-13115-x

Senior, A. M., Grueber, C. E., Kamiya, T., Lagisz, M., O'Dwyer, K., Santos, E. S. A., & Nakagawa, S. (2016). Heterogeneity in ecological and evolutionary meta-analyses: Its magnitude and implications. *Ecology, 97*(12), 3293-3299. https://doi.org/10.1002/ecy.1591

Shata, A., & Hartley, K. (2025). Artificial intelligence and communication technologies in academia: Faculty perceptions and the adoption of generative AI. *International Journal of Educational Technology in Higher Education*, *22*(1), 14. https://doi.org/10.1186/s41239-025-00511-7

Susanti, D. S., Salsabilla, R., & Hidayati, R. (2024). Meta-analysis: The effect of self-regulated learning (SRL) on student ability levels. *Jurnal Pendidikan, 25*(1), 41-48. https://doi.org/10.33830/jp.v25i1.6406.2024

Valentine, J. C., Pigott, T. D., & Rothstein, H. R. (2010). How many studies do you need? A primer on statistical power for meta-analysis. *Journal of Educational and Behavioral Statistics, 35*(2), 215-247. https://doi.org/10.3102/1076998609346961

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education: An analysis of teachers' perspectives using structural equation modeling. *Educational Technology & Society, 24*(3), 116-129. https://www.jstor.org/stable/27031769

Wijaya, S. N., Japarianto, E., & Tandijaya, T. N. B. (2024). Pengaruh perceived ease of use terhadap behavior intention to use dengan perceived usefulness sebagai variabel intervening pada Google Workspace for Education. *Jurnal Manajemen Pemasaran, 18*(1), 15-24. https://doi.org/10.9744/pemasaran.18.1.15-24

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese university educators' acceptance and intention to use AI tools: An application of the UTAUT2 model. *SAGE Open, 14*(4), 21582440241290013. https://doi.org/10.1177/21582440241290013

Yang, K., Kwan, H.-Y., Yu, Z., & Tong, T. (2020). Model selection between the fixed-effects model and the random-effects model in meta-analysis. *Statistics and Its Interface, 13*(4), 501-510. https://doi.org/10.4310/SII.2020.v13.n4.a7

Zawacki-Richter, O., & Jung, I. (Eds.). (2023). *Handbook of open, distance and digital education*. Springer Nature. https://doi.org/10.1007/978-981-19-2080-6

Appendix A

Characteristics of Included Studies

Table A1. Characteristics of the studies included in the meta-analysis

No.	Study	Context	Country	Sample
1	Shata and Hartley (2025)	Higher education – Social sciences & Humanities faculty – Generative AI	United States	294
2	Cabero-Almenara et al. (2024)	Higher education – Professors' pedagogical beliefs (constructivist vs. transmissive) – Generative AI in AIEd	Ecuador	425
3	Nevárez Montes and Elizondo-Garcia (2025)	Higher education – Faculty attitudes, acceptance & use of Generative AI (ChatGPT & similar tools)	Mexico	208
4	Saif et al. (2025)	Higher education – Management Science faculty – Use of ChatGPT (3.5) to design MCQs – TRAM model	Pakistan	296
5	Wang et al. (2021)	Higher education – University teachers' adoption of AI-based applications	China & Taiwan	311
6	Enang and Christopoulou (2025)	Higher education – University of Liverpool Management School (ULMS) – Faculty attitudes toward ChatGPT	UK	32
7	Al-Abdullatif (2024)	Higher education – University teachers' acceptance of Generative AI – Focus on AI literacy	Saudi Arabia	237
8	Kavitha and Joshith (2025)	Higher education – University educators' intentions to adopt AI tools (Generative & Predictive AI)	India	400
9	Cambra-Fierro et al. (2025)	Higher education – Business & Management faculty – ChatGPT adoption and its impact on happiness, energy, stress	Spain	401
10	Xu et al. (2024)	Higher education – University educators' acceptance and intention to use AI tools – UTAUT2 framework	China	402