Pedagogical Research
2026, 11(4), em0304
e-ISSN: 2468-4929
https://www.pedagogicalresearch.com

MODESTUM

Review Article

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Bridging the intention–practice gap in higher education faculty's use of generative AI: A systematic literature review

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Citation: Xuting, W., Abdul Hanid, M. F., & Lee, H. Y. (2026). Bridging the intention–practice gap in higher education faculty's use of generative AI: A systematic literature review. *Pedagogical Research, 11*(4), em0304. https://doi.org/10.29333/pr/19963

ARTICLE INFO

Received: 10 May 2026

Accepted: 15 Sep. 2026

ABSTRACT

Generative artificial intelligence has rapidly entered higher education teaching. A growing body of empirical research examines faculty attitudes and intention to adopt tools such as ChatGPT. However, emerging evidence suggests that intention does not consistently translate into sustained pedagogical integration. Unlike previous syntheses of AI in higher education, which have focused on applications, perceptions, or acceptance, this study addresses this discrepancy through a systematic review of empirical research published between 2023 and 2026. Following the PRISMA protocol, the review identified 150 methodologically adequate studies indexed in Scopus and Web of Science. A focused explanatory synthesis was conducted on 33 core investigations that included both intention-related constructs and indicators of pedagogical use. The analysis mapped publication trends, research designs, theoretical orientations, and predictors of behavioral intention, and examined mechanisms underlying the intention–practice gap. The findings indicate that technology acceptance models dominate the literature and consistently explain intention formation through perceived usefulness, performance expectancy, effort expectancy, and social influence. Nevertheless, only one-third of the core studies explicitly identified a discrepancy between intention and enacted pedagogical practice, whereas the majority did not directly examine or report this relationship. The evidence suggests that pedagogical capability, particularly TPACK-related competence and instructional design knowledge, mediates the translation of intention into structured classroom integration. Institutional support, governance clarity, professional development, and identity-related factors moderate the strength of this process. The review proposes a conditional intention–practice translation model integrating UTAUT and TPACK. The findings suggest that the central challenge in higher education lies not in faculty willingness, but in developing pedagogical capability within supportive institutional environments that enable sustained instructional transformation.

Keywords: generative artificial intelligence, higher education faculty, technology acceptance, UTAUT, TPACK, pedagogical capability, intention–practice gap

INTRODUCTION

Generative artificial intelligence has rapidly entered higher education. Large language models such as ChatGPT can generate teaching materials, draft assessments, provide feedback, and simulate real-time dialogue (Alm & Ohashi, 2024; Singerin et al., 2025). Faculty members across disciplines began experimenting with these tools soon after their public release (Singh & Strzelecki, 2025; Sobaih Abu Elnasr et al., 2025). Instructors report using generative AI for lesson planning, assessment design, and research support (Iqbal et al., 2025; Song et al., 2025).

At the same time, faculty members report new tensions. Instructors express concerns about academic integrity and overreliance on automated systems (Alhur et al., 2025; Sobaih Abu Elnasr et al., 2025). Qualitative evidence shows that generative Artificial Intelligence (AI) challenges traditional views of teacher expertise and professional identity (Ellis et al., 2025). Institutional conditions also shape implementation. Jiang et al. (2025) find that unclear policy guidelines increase hesitation. Joseph and Areepattamannil (2025) show that governance framing influences faculty engagement. These findings suggest that generative AI adoption involves more than technical use. Faculty adoption reflects changes in instructional practice and professional identity.

Empirical research on faculty adoption has expanded quickly since 2024. Many studies examine attitudes, perceived usefulness, and behavioral intention (Nevárez Montes & Elizondo-García, 2025; Singh & Strzelecki, 2025). Technology acceptance frameworks dominate this research. Zaim et al. (2024) show that performance expectancy and effort expectancy predict intention. Singerin et al. (2025) and Jamshed et al. (2025) show that perceived usefulness predicts intention.

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Table 1. SPIDER model

No.	SPIDER Model Element	Content in the Study
1.	S: Sample	Higher education faculty members
2.	PI: Phenomenon of Interest	Adoption and pedagogical use of generative AI in higher education teaching
3.	D: Design	Empirical quantitative, qualitative, or mixed-methods studies; theory-driven empirical studies
4.	E: Evaluation	Technology acceptance (e.g., intention, attitudes) and pedagogical integration (e.g., instructional use, teaching practice), including evidence of an intention–practice gap
5.	R: Research Type	Empirical research grounded in UTAUT, TPACK, or related frameworks

These studies explain why faculty members intend to adopt generative AI. Nonetheless, several studies show that intention does not always lead to sustained classroom integration. Abdelhalim et al. (2025) report significant relationships between intention and reported use, yet classroom transformation remains moderate. Alm and Ohashi (2024) observe widespread curiosity but limited structural embedding. Alhur et al. (2025) describe instructors who express positive attitudes but hesitate to integrate AI deeply due to professional identity concerns. This pattern suggests a gap between intention and practice. Faculty members often express willingness, but meaningful instructional change remains uneven and context-dependent.

Existing systematic reviews of AI in higher education have predominantly examined applications rather than faculty decision-making. Zawacki-Richter et al. (2019), in a systematic review of 146 studies published between 2007 and 2018, mapped the field into four areas—profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems—and noted that most included publications originated in computer science and STEM and that the field remained weakly connected to theoretical pedagogical perspectives, thereby raising the question of whether educators were adequately represented in the research agenda. Crompton and Burke (2023) provided an up-to-date state of the field between 2016 and 2022, and Bond et al. (2024), in a review of reviews, synthesized 66 publications (predominantly systematic reviews) and called for greater ethical, methodological, and contextual rigor as well as interdisciplinary approaches. More recent syntheses have begun to center faculty perspectives: Marchena Sekli et al. (2024) reviewed generative AI solutions for faculty and students and proposed a research roadmap, Qian (2025) systematically reviewed pedagogical applications of generative AI in higher education, and Nikolic et al. (2024) synthesized teaching academics' attitudes, intentions, and behaviors toward AI and generative AI through a UTAUT lens, concluding that institutional support and training shape behaviors. Taken together, however, these reviews examine applications, perceptions, acceptance, or general use as outcomes; none systematically investigates whether and how faculty intention translates into sustained, deep pedagogical integration, and none integrates technology acceptance with pedagogical capability frameworks such as TPACK. Even the closest comparator, Nikolic et al. (2024), remains centered on attitudes, intentions, and the conditions that shape general use rather than on the mechanisms through which intention becomes enacted instructional redesign. The present review fills this gap by examining the mechanisms that enable or constrain the translation of intention into enacted pedagogical practice.

The current literature reveals three structural imbalances. First, researchers focus more on technology acceptance models than on pedagogical competence frameworks. Ríos Gonzales et al. (2025) and Song et al. (2025) show that TPACK competence predicts meaningful integration. Nevertheless, few studies combine acceptance constructs with pedagogical knowledge. Second, many studies rely on cross-sectional surveys rather than longitudinal designs (Wattanakasiwich et al., 2025). Third, few studies examine how institutional conditions shape translation over time. However, Jiang et al. (2025) and Iqbal et al. (2025) highlight the importance of governance clarity and professional development. These imbalances raise a central question: How does faculty intention to adopt generative AI translate into sustained pedagogical practice?

This study addresses this question through a systematic review of empirical research published between 2023 and 2026. The review synthesizes 150 methodologically adequate studies and conducts a focused analysis of 33 mechanism-oriented investigations. These 33 core studies receive particular attention because they include both intention-related constructs and indicators of pedagogical use, allowing examination of potential intention–practice relationships.

This review contributes to the literature in three ways. First, it synthesizes the rapidly growing body of empirical research on higher education faculty's use of generative AI. Second, it examines how prior studies conceptualize and measure the relationship between adoption intention and pedagogical integration. Third, it develops an explanatory perspective that integrates technology acceptance and pedagogical capability frameworks to understand how intention becomes enacted instructional practice.

This review pursues three research questions:

RQ1: What are the main structural characteristics of empirical studies on higher education faculty's use of generative AI?

RQ2: How have prior studies conceptualized and measured faculty intention and pedagogical integration?

RQ3: What mechanisms explain the gap between intention and enacted pedagogical practice?

This review integrates technology acceptance theory and pedagogical knowledge theory. The analysis draws on UTAUT to understand intention formation (Zaim et al., 2024). The analysis draws on TPACK to understand instructional integration (Ríos Gonzales et al., 2025). The analysis also considers institutional and identity factors that shape translation (Jiang et al., 2025).

The research questions were developed using the SPIDER framework (Sample, Phenomenon of Interest, Design, Evaluation, and Research type), which supports systematic reviews that examine educational experiences and practice (Cooke et al., 2012). **Table 1** presents the SPIDER elements that guided the search strategy and inclusion criteria. Overall, this review aims to clarify how intention becomes practice in generative AI contexts and to support institutions seeking to integrate generative AI sustainably into teaching.

LITERATURE REVIEW

Generative AI and Teaching in Higher Education

Generative artificial intelligence has rapidly entered higher education teaching following the release of tools such as ChatGPT. These systems can generate text, images, and other forms of educational content, which makes them adaptable to a wide range of instructional activities (Qian, 2025). Recent studies indicate that generative AI is increasingly used in teaching preparation and instructional design: Marchena Sekli et al. (2024) report that AI tools can assist educators in generating course materials, designing learning activities, and supporting instructional planning. These functions help reduce preparation time and allow instructors to experiment with new teaching approaches.

In addition, evidence from discipline-specific studies further illustrates these applications. Zaiarna et al. (2024) find that language instructors use ChatGPT to design vocabulary exercises, grammar tasks, and writing prompts. In this context, generative AI often serves as a teaching assistant, supporting content generation and task development.

Generative AI is also increasingly used in assessment and feedback processes. Prompiengchai et al. (2025) explain that large language models can generate practice questions and support formative feedback. These tools help instructors provide more timely and individualized responses to student work. Similarly, Pham (2025) shows that generative AI can support learning activities such as practice exercises, inquiry tasks, and case-based simulations in health professional education.

Despite these emerging applications, faculty engagement with generative AI remains exploratory. Zaiarna et al. (2024) note that many instructors are still experimenting with these tools while evaluating their pedagogical value. At the same time, researchers highlight concerns about academic integrity, overreliance on AI-generated content, and the need for institutional guidelines to regulate responsible use (Ravichandran & Sasikala, 2025). Overall, generative AI has begun to reshape everyday instructional practices in higher education, yet its integration into structured pedagogical practice remains uneven and continues to evolve.

Faculty Adoption and Technology Acceptance Models

The previous section described the rapid emergence of generative AI in higher education teaching. Nonetheless, the presence of a technology does not guarantee its use in practice. The impact of educational technologies largely depends on whether faculty members choose to adopt them in their teaching.

Educational technology research has long emphasized the importance of teachers' adoption of technology. Digital tools such as ICT systems and learning platforms can support new teaching approaches; however, their educational value ultimately depends on whether instructors integrate them into everyday instructional activities. Lawrence and Tar (2018) show that even when institutions invest heavily in technological infrastructure, classroom adoption often remains uneven. Because of this gap between technological availability and actual use, many studies focus on explaining why individuals accept or reject new technologies, and Granić and Marangunić (2019) review this research area as central to understanding how users decide to adopt digital learning tools.

Several theoretical models have been used to explain these adoption decisions. The Technology Acceptance Model (TAM) proposes that perceived usefulness and perceived ease of use shape attitudes toward technology and influence adoption intentions (Granić & Marangunić, 2019). Later research expanded this perspective through the UTAUT, which highlights the roles of performance expectancy, effort expectancy, social influence, and facilitating conditions in shaping technology use (Ilham & Apriliyanti, 2025).

Empirical studies confirm the importance of these factors in higher education. For example, Zhang et al. (2023) find that performance expectancy and effort expectancy strongly influence faculty adoption of online teaching technologies, and Diffusion of Innovations theory suggests that individuals evaluate technologies based on characteristics such as relative advantage and compatibility (Lawrence & Tar, 2018). Overall, technology acceptance models provide a useful framework for understanding how higher education faculty form intentions to adopt emerging technologies, including generative AI.

Limits of Intention-Based Explanations

Although technology acceptance models have been widely used to explain educational technology adoption, their explanatory scope remains limited. A central limitation is that many studies focus primarily on behavioral intention rather than actual instructional change. Research based on models such as Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) typically treats intention as the primary outcome variable and assumes that stronger intention leads to technology use (Granić & Marangunić, 2019; Zhang et al., 2023).

Nevertheless, empirical evidence suggests that this assumption does not always hold. Tzeng et al. (2022) note that many studies assume a direct relationship between intention and behavior, yet empirical findings do not consistently support this relationship. In practice, intention does not always translate into actual technology use, especially in educational contexts where teaching practices are complex.

A second limitation concerns how technology use is measured. Many survey-based studies rely on self-reported usage as a proxy for actual behavior. As a result, adoption is often measured through questionnaire responses rather than observable changes in instructional design or classroom practice (Tzeng et al., 2022). This approach makes it difficult to determine whether technologies meaningfully reshape teaching activities.

Finally, intention-based models rarely address the pedagogical dimensions of technology integration. Research on teachers' professional practice suggests that adopting new technologies often requires changes in pedagogical routines, epistemic practices, and professional identity (Geertshuis & Liu, 2022; Liu & Geertshuis, 2016). Similarly, Mor and Abdu (2018) argue that teachers may recognize the potential value of educational technologies yet struggle to design learning activities that fully leverage them. These findings suggest that intention does not necessarily translate into meaningful instructional change.

Pedagogical Capability and Instructional Integration

The limitations of intention-based explanations highlight the need to examine how teachers actually integrate technology into teaching practice, with particular attention to teachers' pedagogical capability and their ability to design instruction with technology. Research on the TPACK framework shows that effective technology use depends not only on technical skills but also on pedagogical knowledge: the TPACK model posits that teachers must integrate content, pedagogical, and technological knowledge when using digital tools in instruction (Priyanda et al., 2025). Studies show that teachers draw on this integrated knowledge when designing technology-enhanced lessons and selecting appropriate instructional strategies.

Recent research also indicates that pedagogical capability shapes how teachers adopt educational AI tools. Oved and Alt (2025) report that teachers' TPACK profiles are closely related to their intention to use educational AI tools, while pedagogical–technological knowledge plays a stronger role in explaining their actual instructional use. In other words, understanding how technology supports teaching practice influences whether AI tools are integrated into classroom activities.

In the context of generative AI, integration often requires changes in teaching design rather than simple tool adoption. Studies on AI-supported pedagogy argue that educators need to reconsider lesson structures, learning activities, and assessment approaches when introducing generative AI into classrooms (Dewi, 2025; Wegerif & Casebourne, 2025). These adjustments often involve redesigning instructional tasks, guiding student interaction with AI, and aligning AI use with learning objectives.

Pedagogical capability also influences the depth of technology integration. Specifically, teachers with stronger pedagogical and technological knowledge are more likely to redesign learning activities, integrate digital tools into curriculum planning, and develop new forms of assessment (Burneo-Arteaga et al., 2025; Fahadi & Khan, 2022). Consequently, these capabilities enable educators to move beyond surface-level adoption toward deeper instructional integration. These studies suggest that pedagogical capability may influence whether intention leads to meaningful instructional integration.

Conceptualizing the Intention–Practice Gap

The previous sections highlight an important tension in research on educational technology adoption. Studies based on technology acceptance models explain how teachers form intentions to use new technologies. These studies identify factors such as perceived usefulness, effort expectancy, and social influence as predictors of adoption intention (Granić & Marangunić, 2019; Ilham & Apriliyanti, 2025; Zhang et al., 2023).

Nonetheless, intention does not always translate into actual instructional change. Empirical studies show that intention and behavior are not always aligned, particularly in complex educational settings (Tzeng et al., 2022). Many studies, therefore, measure technology adoption through self-reported usage rather than examining how teaching practices are redesigned.

Research on pedagogical capability offers an alternative perspective. Studies drawing on the TPACK framework suggest that teachers' pedagogical knowledge influences how technologies are integrated into lesson design, curriculum planning, and assessment practices (Oved & Alt, 2025; Priyanda et al., 2025), and these capabilities shape the depth and quality of instructional integration. Taken together, these findings point to a potential intention–practice gap in faculty adoption of generative AI. Understanding how intention translates into instructional practice is, therefore, an important research question in higher education contexts.

METHODOLOGY

Research Design and Review Protocol

This study used a systematic literature review design. The review followed the PRISMA framework to ensure a clear and well-structured process. PRISMA supports transparency, consistency, and repeatability in systematic reviews. It also helps readers understand how studies were identified, selected, and analyzed.

The PRISMA protocol guided each stage of the review. It guided the formulation of research questions, the development of the search strategy, and the multi-stage selection process. It also informed the quality review and reporting process. By following PRISMA, the study allows readers to judge the strength of the review process and the reliability of the findings. **Figure 1** summarizes the study identification, screening, eligibility assessment, and final selection process.

Data Sources and Search Strategy

The authors searched the literature using Scopus and Web of Science. Notably, these databases include a wide range of peer-reviewed journals in education and the social sciences. They are excellent sources for finding research on higher education teachers and their use of generative artificial intelligence. The search strategy followed the SPIDER framework. This framework helped match the search terms with the research goals. Accordingly, the search focused on four main areas. The first area was generative artificial intelligence. The second area was the higher education context. The third area was faculty members. The fourth area was technology acceptance and teaching outcomes. Furthermore, **Table 2** shows the full search words used in Scopus

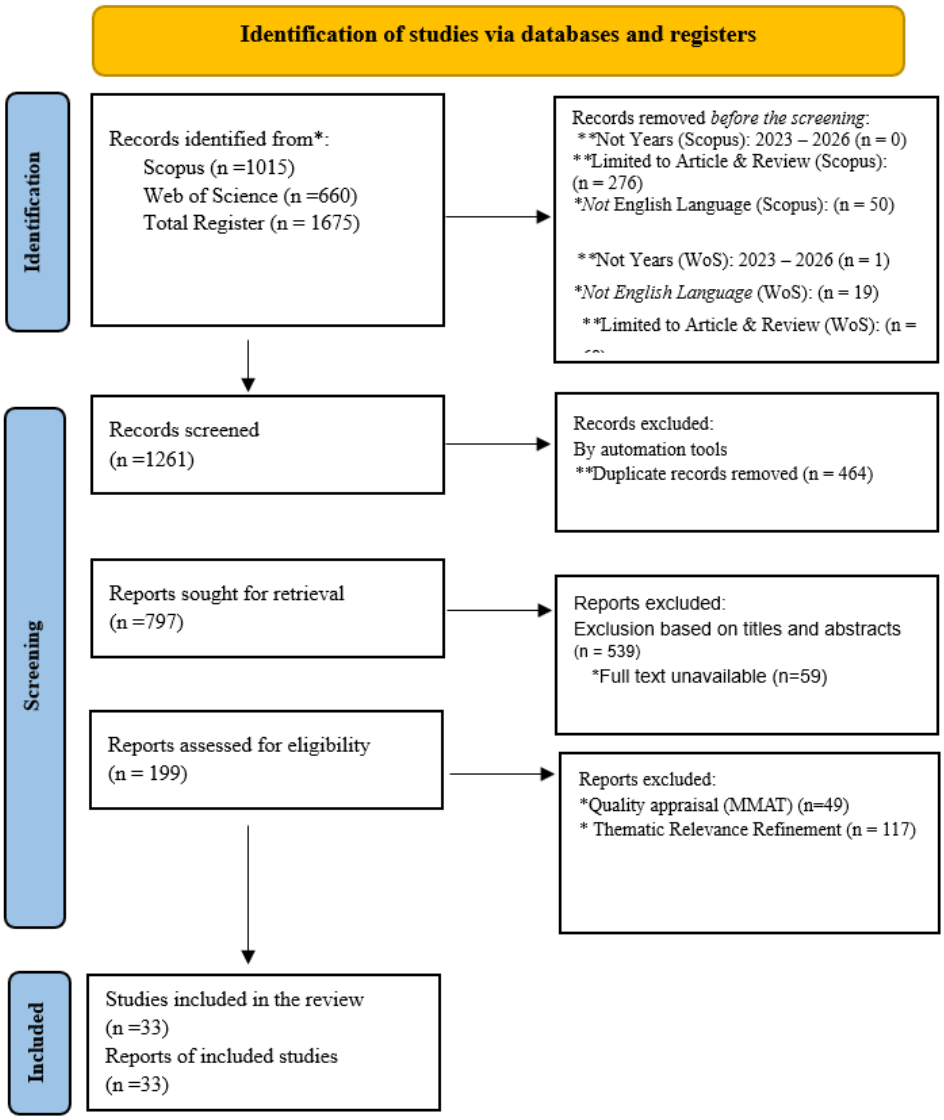


Figure 1. The flow diagram of the study (Adapted from Page et al., 2021)

Table 2. Search strategies for Scopus and Web of Science

Database	Boolean Operator Used
Scopus	TITLE-ABS-KEY ((“generative AI” OR “generative artificial intelligence” OR ChatGPT OR “large language model*” OR LLM*) AND (“higher education” OR university OR “tertiary education”) AND (faculty OR instructor* OR academic* OR lecturer* OR teacher*) AND (intention OR acceptance OR adoption OR “technology acceptance” OR UTAUT OR TAM OR TPACK OR “pedagogical integration” OR “instructional use” OR “teaching practice*”))
Web of Science	TS = ((“generative AI” OR “generative artificial intelligence” OR ChatGPT OR “large language model*” OR LLM*) AND (“higher education” OR university OR “tertiary education”) AND (faculty OR instructor* OR academic* OR lecturer* OR teacher*) AND (intention OR acceptance OR adoption OR “technology acceptance” OR UTAUT OR TAM OR TPACK OR “pedagogical integration” OR “instructional use” OR “teaching practice*”))

and Web of Science. The search applied several filters to ensure quality. The search included peer-reviewed journal articles and review papers. However, only empirical studies were retained for descriptive mapping and explanatory synthesis. All studies were written in English. The publication period was limited to 2023-2026. This period reflects the rapid growth of generative AI use in higher education teaching.

Identification

The initial search across Scopus and Web of Science yielded 1,675 hits. Filters for publication year (2023–2026) (Literature search was last performed on January 30, 2026), document type (peer-reviewed articles), and language (English) were applied directly within the database search engines, refining the initial pool to 1,261 records for export.

Data Management and Deduplication

The 1,261 exported records were imported into Zotero. Prior to the screening phase, automated deduplication combined with manual verification was conducted, removing 464 duplicate records and resulting in a set of 797 unique records.

Table 3. Assessment results of full-text studies (n = 199)

Quality Level	Number of Studies
High (5/5)	42
Moderate (3–4/5)	108
Low (≤2/5)	36
Screening fail	13

Screening

Subsequently, two independent reviewers screened the titles and abstracts of 797 records against predefined inclusion and exclusion criteria. Any discrepancies between reviewers were resolved through discussion. If consensus could not be reached, a third senior reviewer adjudicated the decision.

Studies not related to higher education, not focusing on faculty members as primary participants, or not addressing generative AI in teaching contexts were excluded. This process resulted in the exclusion of 539 records. After title and abstract screening, 258 reports were sought for full-text retrieval. Among these, 59 reports were excluded because their full texts were unavailable. The remaining 199 full-text articles proceeded to quality appraisal.

Inclusion and Exclusion Criteria

Studies were included in the review if they met all of the following criteria:

(1) The study is conducted in a higher education context (e.g., university, college, tertiary education).

(2) The study focuses on faculty members, instructors, lecturers, academics, or teachers as the primary participants.

(3) The study examines generative artificial intelligence (e.g., ChatGPT, generative AI, large language models).

(4) The study addresses teaching-related use, such as instructional design, teaching practice, pedagogical integration, assessment, or feedback.

(5) The study is a peer-reviewed journal article or review article.

The exclusion criteria were as follows:

(1) The study focuses primarily on students, learners, or pre-service teachers.

(2) The educational context is K–12, primary, or secondary education.

(3) The study examines non-generative AI technologies (e.g., learning analytics, robotics, rule-based AI) without generative functions.

(4) The study focuses solely on technical system development, algorithm design, or computational performance.

(5) The publication is a conference paper, editorial, commentary, book chapter, or non-peer-reviewed source.

(6) The study does not relate to teaching or pedagogical practice.

Quality Appraisal

The methodological quality of the 199 full-text studies was assessed using the Mixed Methods Appraisal Tool (MMAT), version 2018 (Hong et al., 2018). Two independent reviewers evaluated each study against the relevant MMAT criteria, based on its research design. Disagreements were resolved through discussion, and when consensus could not be reached, a third senior reviewer adjudicated the final decision to ensure reliability and transparency.

Thirteen studies did not meet the MMAT screening questions (S1 or S2) and were excluded from further analysis, and thirty-six studies met only two MMAT criteria and were considered to demonstrate limited methodological robustness. After quality appraisal, 150 studies met at least three MMAT criteria and were retained for subsequent descriptive and explanatory analysis. Among these, 42 studies met all five MMAT criteria and were classified as high-quality, while 108 studies met three or four criteria and were classified as moderate-quality. **Table 3** summarizes the methodological quality appraisal results for the 199 full-text studies.

Consistent with MMAT guidelines, no overall numerical score was calculated. Instead, studies were stratified based on the number of methodological criteria satisfied. This stratified approach ensured methodological rigor while maintaining sufficient coverage of the evidence base.

Thematic Relevance Refinement

Following quality appraisal, the 150 methodologically adequate studies were subjected to a two-stage thematic relevance refinement process, designed to ensure conceptual alignment with the central objective of the review—explaining the intention–practice gap in higher education faculty's use of generative AI through insights drawn from technology acceptance and pedagogical knowledge perspectives. Two reviewers checked all studies independently using clear and fixed criteria, coding each criterion as either satisfied or not satisfied. Disagreements were resolved through discussion, with a third reviewer joining when needed.

Stage 1: Thematic Relevance (TR)

The first stage assessed general thematic alignment using three criteria: (1. Does the study examine faculty intention, acceptance, or adoption of generative AI? 2. Does the study examine faculty pedagogical use or instructional integration of generative AI?). 3. Is the reported use explicitly teaching-related (e.g., instructional design, assessment, feedback, classroom practice) rather than administrative or general productivity use? Studies that demonstrated sufficient thematic relevance were retained. Following this stage, 55 studies met the thematic alignment criteria and proceeded to the next stage of refinement.

Stage 2: Explanatory Value (EV)

The second stage focused on identifying studies with explanatory value relevant to the intention–practice transition. Three additional criteria were applied to the 55 thematically aligned studies: (1. Does the study explore relationships, mechanisms, or influencing factors related to faculty use of generative AI? 2. Does the study provide empirical or analytical evidence relevant to the transition from intention to actual pedagogical practice? 3. Can the study's findings be meaningfully interpreted within a UTAUT (intention-focused) and/or TPACK (pedagogical integration-focused) framework?). Following this second-stage refinement, 33 studies met the explanatory criteria and were included in the final review.

Reason for this step

This topic refinement served a different purpose from the quality check. The MMAT ensured good research methods. The two-stage topic screening ensured theoretical alignment with the research goals. This extra step gave the review much deeper explanatory power.

Data Analysis

Following study selection and eligibility screening, data analysis proceeded in two stages aligned with the three research questions. In the first stage, descriptive mapping was conducted using all 150 methodologically adequate empirical studies to characterize the structural features of the evidence base; review articles identified during the search were excluded from quantitative mapping and mechanism analysis because they did not provide primary empirical data. For each study, publication year, country or regional context, research design, and theoretical framework were extracted and synthesized to identify publication trends, geographical distribution, methodological patterns, and dominant theoretical orientations, thereby addressing RQ1.

The second stage involved conceptual and explanatory synthesis to address RQ2 and RQ3. Although all 150 studies contributed to descriptive mapping, only a subset examined both intention-related constructs and pedagogical integration indicators. Therefore, in-depth analysis focused on 33 core studies selected through the thematic relevance and explanatory value refinement process described in Section *Thematic Relevance Refinement*.

Within this subset, a structured coding procedure was applied. Intention-related constructs were identified and categorized based on their operationalizations. Indicators of pedagogical integration were coded, including instructional redesign, AI-supported lesson planning, assessment transformation, TPACK-related competence, and reported classroom implementation depth. The alignment between intention and enacted practice was then examined to identify potential discrepancies.

Explanatory variables reported in the selected studies were further classified according to functional role. Variables modeled statistically as mediators or moderators, or described qualitatively as barriers and enablers, were categorized as either mediating mechanisms (e.g., pedagogical competence) or moderating conditions (e.g., institutional support, governance clarity, prior experience, or professional identity). This two-stage design ensured both comprehensive mapping of the evidence base and focused examination of mechanisms shaping intention–practice translation.

Inter-Rater Reliability

To quantify the reliability of the study selection and coding decisions, percentage agreement and Cohen's kappa were computed from the two reviewers' independent assessments before any discussion. During title and abstract screening, both reviewers independently assessed all 797 records against each of the five predefined inclusion criteria, yielding 3,985 criterion-level ratings with an overall percentage agreement of 99.12% ($\kappa = 0.975$); criterion-level agreement ranged from 96.49% ($\kappa = 0.930$) to 100.00% ($\kappa = 1.000$). At the full-text stage, the eligibility of the 199 retrieved full texts was verified by the two reviewers, and no disagreements were recorded, yielding 100.00% percentage agreement; because all eligibility decisions were unanimous, Cohen's kappa was not calculated for this stage. For the methodological quality appraisal, the two reviewers independently appraised all 199 full-text studies against the MMAT criteria applicable to each study's research design; overall percentage agreement was 95.15% with a Cohen's κ of 0.881, indicating almost perfect overall agreement, and criterion-level agreement ranged from 88.89% to 100.00%. For the two-stage thematic relevance and explanatory value refinement, inter-rater agreement was assessed separately for each stage's criteria: in Stage 1 (150 studies), criterion-level agreement ranged from 97.33% to 98.00% ($\kappa = 0.924$–0.948), and the overall percentage agreement across 450 judgments was 97.56% ($\kappa = 0.943$); in Stage 2 (55 studies), criterion-level agreement ranged from 96.36% to 100.00% ($\kappa = 0.732$–1.000), and the overall percentage agreement across 165 judgments was 97.58% ($\kappa = 0.906$). Following resolution of disagreements, both reviewers independently identified the same 33 studies for final inclusion (100.00% agreement; $\kappa = 1.000$). Some criterion-level κ values were lower than their corresponding percentage agreements (e.g., MMAT Criteria 1.5, 4.2, 4.4, and 5.4; Stage 2 Criterion 3); this pattern reflects the highly skewed distribution of ratings on those criteria, for which the chance-corrected κ statistic is attenuated by category prevalence, so criterion-level κ values were interpreted alongside percentage agreement rather than in isolation. Overall, these statistics indicate almost perfect inter-

Table 4. Inter-rater agreement across review stages

Review stage		Records	Agreement (%)	Cohen's κ	Interpretation
Title & Abstract screening		797	99.12%	0.975	almost perfect
Full-text screening		199	100%		almost perfect
MMAT appraisal		199	95.15%	0.881	almost perfect
Thematic Relevance Refinement	Stage 1: Thematic Relevance (TR)	150	97.56%	0.943	almost perfect
	Stage 2: Explanatory Value (EV)	55	97.58%	0.906	almost perfect

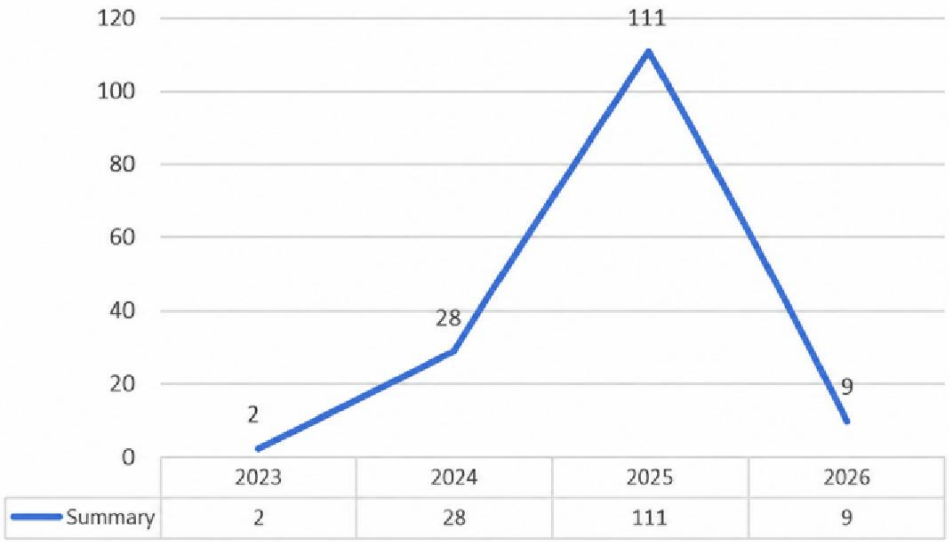


Figure 2. Annual publication trend of empirical studies (2023–2026) (Source: Authors' own elaboration)

rater agreement at each stage. Disagreements were resolved through discussion, and cases on which consensus could not be reached were adjudicated by the third senior reviewer. **Table 4** summarizes the agreement statistics for each review stage.

RESULTS

Main Characteristics of the Empirical Evidence Base (RQ1)

Publication trends and research context

A total of 150 empirical studies met the inclusion criteria and were included in the descriptive analysis. The publication pattern shows a rapid increase in research after the public release of generative AI tools: **Figure 2** shows that only two empirical studies appeared in 2023, increasing to 28 in 2024 and rising sharply to 111 in 2025. The smaller number recorded for 2026 (n = 9) reflects incomplete database indexing rather than reduced research interest, indicating that the field is still expanding.

This growth followed the rapid diffusion of ChatGPT and related tools in academic settings. Alm and Ohashi (2024) document early, sometimes polarized faculty reactions. Abdelhalim et al. (2025) report cross-cultural differences in engagement patterns. The sharp rise in 2025 suggests that exploratory interest developed into broader empirical investigation.

The geographical distribution is uneven. **Figure 3** shows that the United States (n = 11) and China (n = 11) contribute the most studies, followed by Australia (n = 6). Ríos Gonzales et al. (2025) represent emerging research from Latin America. Nevertheless, Africa, Southeast Asia, and parts of the Middle East remain underrepresented. This concentration suggests that current findings mainly reflect conditions in well-resourced higher education systems.

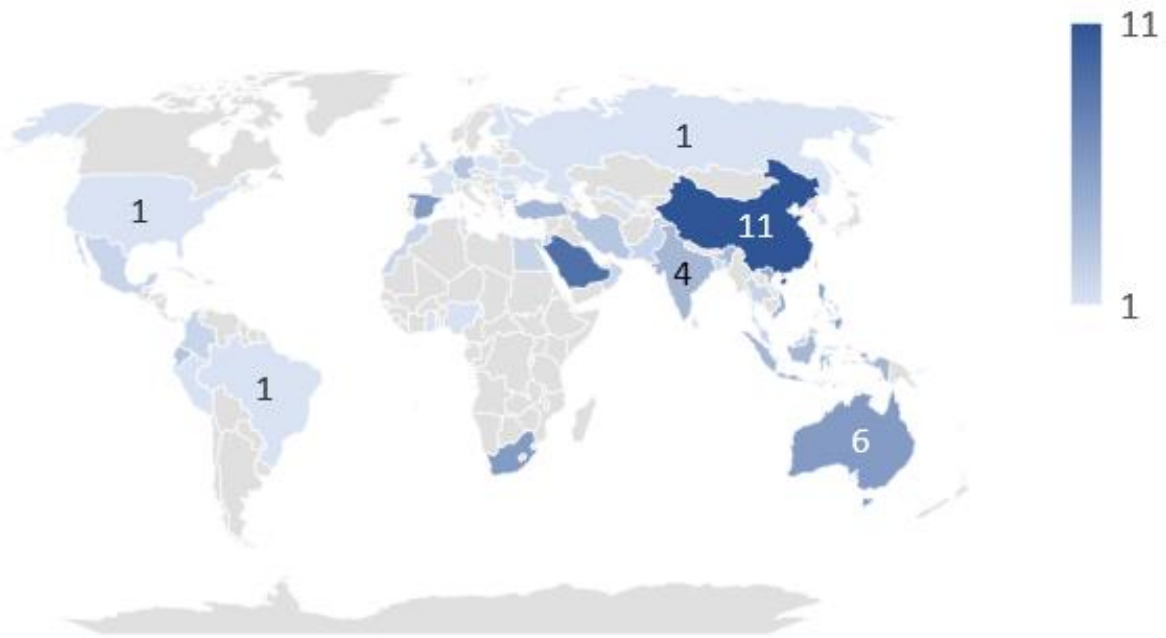


Figure 3. The top contributing countries in the reviewed studies (Source: Authors' own elaboration)

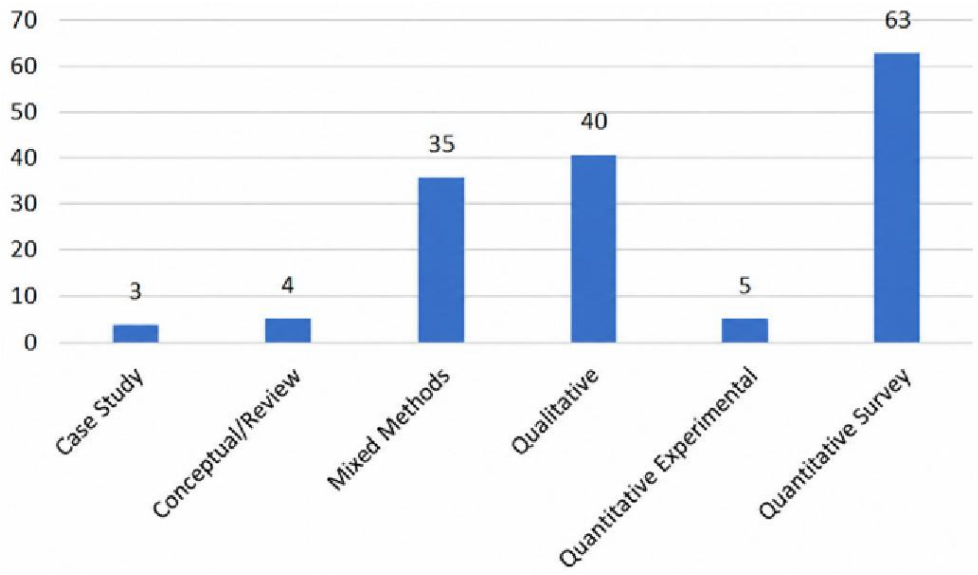


Figure 4. Distribution of research designs (Source: Authors' own elaboration)

Research designs and methodological patterns

The methodological landscape is dominated by survey-based quantitative research. As depicted in **Figure 4**, quantitative survey designs account for the largest proportion of studies (n = 63, 42%), followed by qualitative approaches (n = 40, 27%) and mixed-methods designs (n = 35, 23%). Experimental studies remain comparatively rare (n = 5), suggesting that causal evaluations of instructional impact remain limited.

The prevalence of quantitative designs reflects the field's strong reliance on technology acceptance frameworks. Many studies employ structural equation modeling to examine predictors of behavioral intention. For example, UTAUT-based models are frequently applied to explain faculty intention across disciplinary contexts (Zaim et al., 2024). These studies provide robust evidence regarding motivational formation but typically rely on self-reported measures of use rather than direct observation of pedagogical redesign.

In contrast, qualitative investigations offer richer insight into how generative AI is enacted within teaching practice. Ellis et al. (2025) identified qualitatively distinct orientations toward AI-supported teaching, while Joseph and Areepattamannil (2025) described a shift in faculty roles from policing academic integrity to redesigning learning experiences. Despite their interpretive depth, such studies remain numerically outnumbered by perception-focused surveys. Overall, the methodological pattern

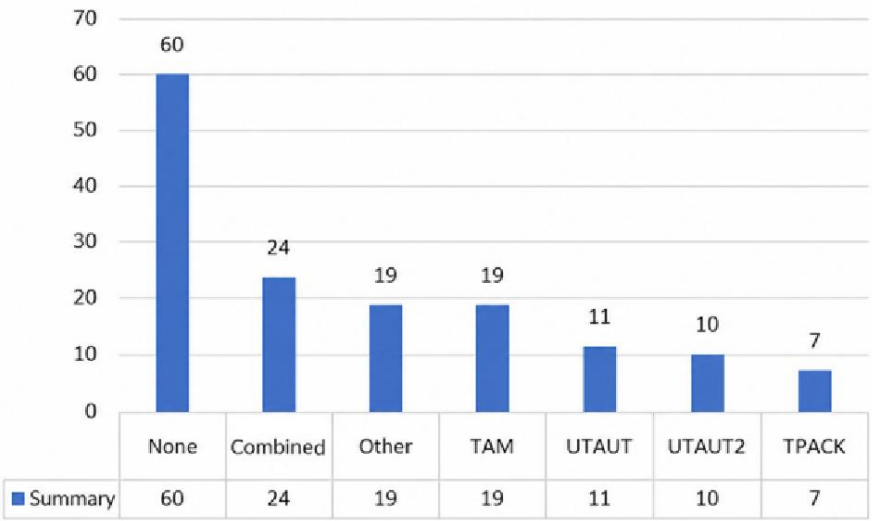


Figure 5. Theoretical frameworks (Source: Authors' own elaboration)

suggests a field that has prioritized understanding willingness and perception over longitudinal or intervention-based examination of sustained instructional transformation.

Theoretical orientation

The theoretical orientation of the reviewed studies reveals further structural imbalance. As shown in **Figure 5**, a substantial proportion of investigations (n = 60, 40%) do not explicitly adopt a formal theoretical framework. These studies typically describe attitudes, perceptions, or usage patterns without situating findings within established explanatory models.

Among theory-driven research, technology acceptance models dominate. TAM, UTAUT, and related extensions collectively account for the majority of explicitly grounded studies. For instance, diffusion-based perspectives have been used to conceptualize academics as adopters of innovation (Singh & Strzelecki, 2025), while acceptance-oriented constructs have been applied to model expectancy beliefs and behavioral intention (Nevárez Montes & Elizondo-García, 2025). This theoretical concentration reinforces the field's strong focus on intention formation.

In contrast, pedagogically grounded frameworks such as TPACK are less frequently employed (n = 7); when adopted, however, they provide stronger explanatory leverage regarding instructional integration. Ríos Gonzales et al. (2025) demonstrated that TPACK competence significantly predicts adoption behavior beyond attitudinal constructs, and Song et al. (2025) linked AI-generated lesson design effectiveness to instructors' pedagogical knowledge structures. Hybrid models (n = 24) indicate emerging efforts to bridge motivational and pedagogical perspectives, although systematic integration between acceptance and instructional competence frameworks remains limited. Taken together, this imbalance—strong emphasis on motivational readiness but comparatively weaker grounding in pedagogical theory—anticipates the intention–practice translation gap examined in Section *Explaining the Intention–Practice Gap (RQ3)*.

Examination of Faculty Intention Toward Generative AI (RQ2)

The descriptive mapping of 150 studies reveals structural patterns. Sections *Examination of Faculty Intention Toward Generative AI (RQ2)* and *Explaining the Intention–Practice Gap (RQ3)* will move beyond structural descriptions to focus on 33 core interpretive studies. These studies included measures of intention-related constructs and instructional integration indicators, enabling analysis of their potential alignment, which was determined through a two-stage data analysis procedure. This research enables us to investigate further the theoretical framework, operationalization, and empirical testing process of intention-building in mechanism-oriented studies.

Theoretical frameworks used to examine intention

Table 5 shows that intention-focused research is largely grounded in technology acceptance theory. Seven studies apply the original TAM. Singerin et al. (2025) examine how perceived usefulness and perceived ease of use shape faculty intention. Similarly, Jamshed et al. (2025) report similar modeling results in the Saudi higher education context. These studies treat intention as the central outcome variable.

Three studies extend TAM with additional contextual or affective elements. Shata and Hartley (2025) incorporate communication-related factors into a TAM-based structure. Consequently, these extensions retain the core acceptance logic while broadening the model.

Furthermore, four studies apply UTAUT or UTAUT2. Zaim et al. (2024) test performance expectancy and effort expectancy among English as a Foreign Language (EFL) instructors. Wattanakasiwich et al. (2025) report comparable results in physics education. These studies position behavioral intention as the primary dependent variable.

Table 5. Distribution of theoretical frameworks in intention-focused studies

Category	Frequency
Technology Acceptance Model	7
Technology Acceptance Model Extended	3
Unified Theory of Acceptance and Use of Technology	2
Unified Theory of Acceptance and Use of Technology 2	2
Hybrid Models	4
Other Theoretical Perspectives	9
Not Reported	6
Total	**33**

Table 6. Operationalization of intention constructs across studies

Intention Construct Category	Number of Studies
Behavioral Intention	14
Use Intention	6
Adoption Willingness	3
Attitude Toward Use	2
Continued Intention	1
Multiple	2
Not Reported	5
Total	**33**

Moreover, four studies adopt hybrid frameworks. Ríos Gonzales et al. (2025) combine TPACK competence with acceptance constructs to explain adoption behavior. Singh and Strzelecki (2025) integrate diffusion theory with intention models. These approaches move beyond single-model explanations but still center on motivational constructs.

Nine studies draw on other perspectives. Joseph and Areepattamannil (2025) use a governance framing lens. Ellis et al. (2025) apply a phenomenographic approach to examine teaching orientations. These studies situate intention within broader institutional or professional contexts.

Six studies do not report a clearly defined theoretical framework. Alm and Ohashi (2024) describe faculty responses descriptively rather than through a formal model. Overall, intention research remains closely tied to acceptance-based theories. Fewer studies embed intention within pedagogical or organizational frameworks.

Operationalization of intention constructs

Table 6 shows variation in how intention is defined and measured. In particular, fourteen studies use behavioral intention as the primary construct. Zaim et al. (2024) define behavioral intention as the likelihood that instructors will integrate generative AI into their teaching preparation. Wattanakasiwich et al. (2025) used survey items adapted from UTAUT to measure intention to use the classroom. In addition, six studies use the term use intention. Nguyen et al. (2025) ask lecturers about their stated intention to use ChatGPT in writing instruction. These measures focus on planned future behavior rather than observed practice. Three studies frame intention as adoption willingness. Singh and Strzelecki (2025) define willingness as the readiness to adopt an innovation within diffusion theory.

Furthermore, two studies combine intention with attitude constructs. Stan et al. (2025) measure teachers' attitudes toward ChatGPT and link it to readiness for integration. In these cases, intention is not clearly separated from evaluative belief. One study examines continued intention, focusing on sustained willingness rather than initial adoption. Five studies do not report a clearly operationalized intention variable. Alm and Ohashi (2024) describe faculty willingness narratively rather than through a structured scale. Across studies, intention is most often treated as a survey-based outcome. Fewer studies connect intention directly to observable instructional redesign.

Predictors of behavioral intention

Table 7 shows that perceived usefulness and perceived ease of use are the most frequently examined predictors. Specifically, fourteen studies test perceived usefulness. Singerin et al. (2025) report that perceived usefulness strongly predicts behavioral intention. Jamshed et al. (2025) find similar results. Nevárez Montes and Elizondo-García (2025) show that perceived usefulness predicts both intention and reported use. Singerin et al. (2025) also show that perceived ease of use strengthens perceived usefulness.

Moreover, performance expectancy and effort expectancy appear in five studies each. Zaim et al. (2024) and Wattanakasiwich et al. (2025) report that performance expectancy predicts intention. Evidence for effort expectancy is less consistent, although Zaim et al. (2024) identify indirect effects through perceived ease.

Social influence and facilitating conditions are examined in six studies. Zaim et al. (2024) show that peer and institutional norms shape intention. Wattanakasiwich et al. (2025) include facilitating conditions as contextual predictors of use. Furthermore, nine studies include attitude toward technology. Singerin et al. (2025) show that attitudes directly predict intentions. Stan et al. (2025) report similar findings in language education.

Self-efficacy, institutional support, and trust appear less frequently but are generally associated with stronger intention or reported use. Technological anxiety is examined in only two studies, and the findings remain limited. Overall, the literature

Table 7. Frequently examined predictors of behavioral intention

Predictor	Number of Studies
Performance Expectancy	5
Effort Expectancy	5
Social Influence	6
Attitude Toward Technology	9
Self-Efficacy	4
Institutional Support	5
Facilitating Conditions	6
Perceived Usefulness	14
Perceived Ease of Use	14
Trust in Technology	3
Technological Anxiety	2

Table 8. Distribution of intention–practice gap across core studies (n = 33)

Gap Category	Frequency	Percentage (%)
Gap explicitly identified (Yes)	11	33.3
Gap not identified (No)	2	6.1
Not reported (NR)	20	60.6

emphasizes usefulness, ease, and expectancy beliefs. Emotional and contextual variables appear less central within intention models.

Explaining the Intention–Practice Gap (RQ3)

Prevalence of the intention–practice gap

Table 8 summarizes the distribution of intention–practice gap classifications across the 33 core studies. Among the 33 core explanatory studies, 11 (33.3%) explicitly identified a discrepancy between intention and enacted pedagogical integration, whereas the majority (60.6%) did not directly examine or report this relationship despite measuring both intention and usage-related constructs. This absence does not necessarily imply that no gap exists; rather, it reflects a structural orientation in the literature toward modeling intention formation without systematically tracing its behavioral realization. Many survey-based investigations treat reported use as a direct outcome of intention without interrogating the quality or depth of pedagogical integration.

For example, Alhur et al. (2025) describe a paradoxical dynamic in which educators express positive attitudes yet hesitate to implement AI tools due to professional identity concerns. Similarly, Abdelhalim et al. (2025) report statistically significant intention–use relationships, but qualitative accounts reveal only moderate instructional transformation. This pattern suggests that the intention–practice gap may be underreported rather than absent, pointing to a methodological blind spot within the current evidence base.

Mechanisms underlying the intention–practice translation gap

Table 9 summarizes three groups of mechanisms that shape the translation from intention to practice: motivational factors, pedagogical capability factors, and contextual or identity conditions. Studies show that motivational variables mainly explain intention formation. Singerin et al. (2025) report that perceived usefulness strongly predicts behavioral intention. Similarly, Jamshed et al. (2025) and Nevárez Montes and Elizondo-García (2025) report similar findings. Singerin et al. (2025) also show that perceived ease of use strengthens perceived usefulness. In addition, Zaim et al. (2024) and Wattanakasiwich et al. (2025) find that performance expectancy predicts intention. Zaim et al. (2024) show that effort expectancy has weaker or inconsistent effects. Meanwhile, Stan et al. (2025) report that social influence shapes willingness to integrate ChatGPT. Singerin et al. (2025) show that attitudes directly predict intentions. Abdelhalim et al. (2025) find that behavioral intention predicts reported use frequency. Singh and Strzelecki (2025) and Arroyo-Machado et al. (2025) show that relative advantage and compatibility explain adoption decisions. However, most of these studies measure frequency of use rather than instructional redesign.

Studies also show that pedagogical capability supports the translation of knowledge into practice. Ríos Gonzales et al. (2025) find that TPACK competence predicts higher levels of instructional integration beyond attitudinal variables. Song et al. (2025) show that AI-generated lesson plans become pedagogically aligned only when instructors apply instructional design knowledge. Moreover, Pargmann et al. (2025) report that structured AI feedback improves the quality of lesson planning over time. Xavier et al. (2025) find that AI-supported feedback leads instructors to adjust teaching strategies. Iqbal et al. (2025) show that AI literacy training increases confidence and reported depth of integration. Finally, Ellis et al. (2025) show that instructors with reflective pedagogical grounding move toward deeper redesign. These studies indicate that capability enables instructors to translate intention into structured teaching practice.

Studies further show that contextual and identity factors regulate this process. For instance, Singerin et al. (2025) report that institutional support strengthens the link between intention and use. Iqbal et al. (2025) find that professional development increases the depth of implementation. den Hollander et al. (2025) report that unclear policies weaken structured integration. In contrast, Joseph and Areepattamannil (2025) show that supportive governance framing promotes innovation. Alhur et al. (2025) find that professional identity concerns create hesitation despite positive attitudes. Likewise, Sobaih Abu Elnasr et al. (2025) report

Table 9. Categorized mechanisms in the intention–practice translation process

Mechanism Category	Specific Mechanism	Translational Role	Empirical Status	Effect on Intention–Practice Translation	Representative Core Studies
Motivational Mechanisms	Perceived usefulness	Predictor of intention	SEM tested	Predicts behavioral intention; practice depth is not measured	Singerin et al. (2025); Jamshed et al. (2025); Nevárez Montes and Elizondo-García (2025)
	Perceived ease of use	Predictor of intention	SEM tested	Predicts intention indirectly via attitude; no redesign measurement	Singerin et al. (2025); Jamshed et al. (2025)
	Performance expectancy	Strong predictor of intention	SEM tested	Significant positive effect on BI; instructional transformation not measured	Zaim et al. (2024); Wattanakasiwich et al. (2025); Ríos Gonzales et al. (2025)
	Effort expectancy	Predictor of intention (inconsistent)	SEM tested	Weak or non-significant effect on BI in some models	Zaim et al. (2024); Wattanakasiwich et al. (2025)
	Social influence	Predictor of intention	SEM tested	Positive effect on BI; limited direct evidence on curriculum restructuring	Zaim et al. (2024); Stan et al. (2025)
	Attitude toward AI use	Direct predictor of intention	Regression / SEM tested	Strengthens intention formation; mediating role not consistently tested	Singerin et al. (2025); Jamshed et al. (2025)
	Behavioral intention	Direct predictor of use behavior	SEM tested	Strong positive effect on reported use behavior	Abdelhalim et al. (2025); Wattanakasiwich et al. (2025); Zaim et al. (2024)
	DOI attributes (relative advantage, compatibility)	Adoption intention predictor	Regression tested	Explains adoption decision; sustained instructional transformation is not measured	Singh and Strzelecki (2025); Arroyo-Machado et al. (2025)
Pedagogical Capability Mechanisms	TPACK competence	Capability predictor associated with adoption	SEM tested	Associated with higher instructional integration levels	Ríos Gonzales et al. (2025)
	Instructional design competence	Pedagogical alignment enabler	Experimental comparison	Enables pedagogically aligned lesson design; mediation not tested	Song et al. (2025)
	Structured AI feedback intervention	Capability-strengthening intervention	Longitudinal intervention	Improves lesson planning quality and implementation refinement	Pargmann et al. (2025); Xavier et al. (2025)
	AI literacy & pedagogical training	Capability predictor	Survey / qualitative evidence	Increases confidence and reported integration depth	Iqbal et al. (2025); Basty et al. (2025)
	Reflective pedagogical orientation	Reflective capability factor	Qualitative evidence	Supports deeper instructional transformation processes	Ellis et al. (2025); Pargmann et al. (2025)
Contextual & Identity Mechanisms	Institutional support	Contextual predictor of enactment	Regression / SEM	Strengthens translation from intention to reported use	Singerin et al. (2025); Iqbal et al. (2025)
	Institutional ambiguity/policy uncertainty	Contextual constraint	Qualitative evidence	Weakens enactment; increases hesitation	den Hollander et al. (2025)
	Governance framing	Institutional orientation factor	Qualitative evidence	Supportive framing promotes innovation; policing framing constrains adoption	Joseph and Areepattamannil (2025)
	Facilitating conditions	Contextual determinant (direct path)	SEM tested	Direct effect on BI; moderation not tested	Zaim et al. (2024); Ríos Gonzales et al. (2025)
	Professional identity concerns	Identity-based inhibitor	Qualitative evidence	Produces hesitation despite positive intention	Alhur et al. (2025)
	Ethical & academic integrity concerns	Restrictive contextual concern	Qualitative evidence	Limits deep adoption; promotes cautious engagement	Sobaih Abu Elnasr et al. (2025)
	Personality traits (e.g., openness)	Individual difference predictor	Regression tested	Shapes experimentation, orientation, and risk tolerance	Kılavuz and Mede (2025)
	Self-efficacy	Individual capability predictor	Regression tested	Higher confidence is associated with stronger use behavior	Nevárez Montes and Elizondo-García (2025)
	Prior AI experience	Experience-based strengthening factor	Survey evidence	Increases integration confidence and implementation depth	Alm and Ohashi (2024); Kohnke and Ulla (2024)

that ethical concerns limit the deep adoption of technology. Nevárez Montes and Elizondo-García (2025) show that higher self-efficacy is associated with greater use. Alm and Ohashi (2024) and Kohnke and Ulla (2024) report that prior AI experience increases confidence and depth of integration. These findings suggest that contextual and identity conditions shape how intention becomes enacted practice. Overall, motivational factors explain why faculty form intention. Pedagogical capability explains whether intention leads to meaningful redesign. Contextual and identity conditions influence the strength of this translation.

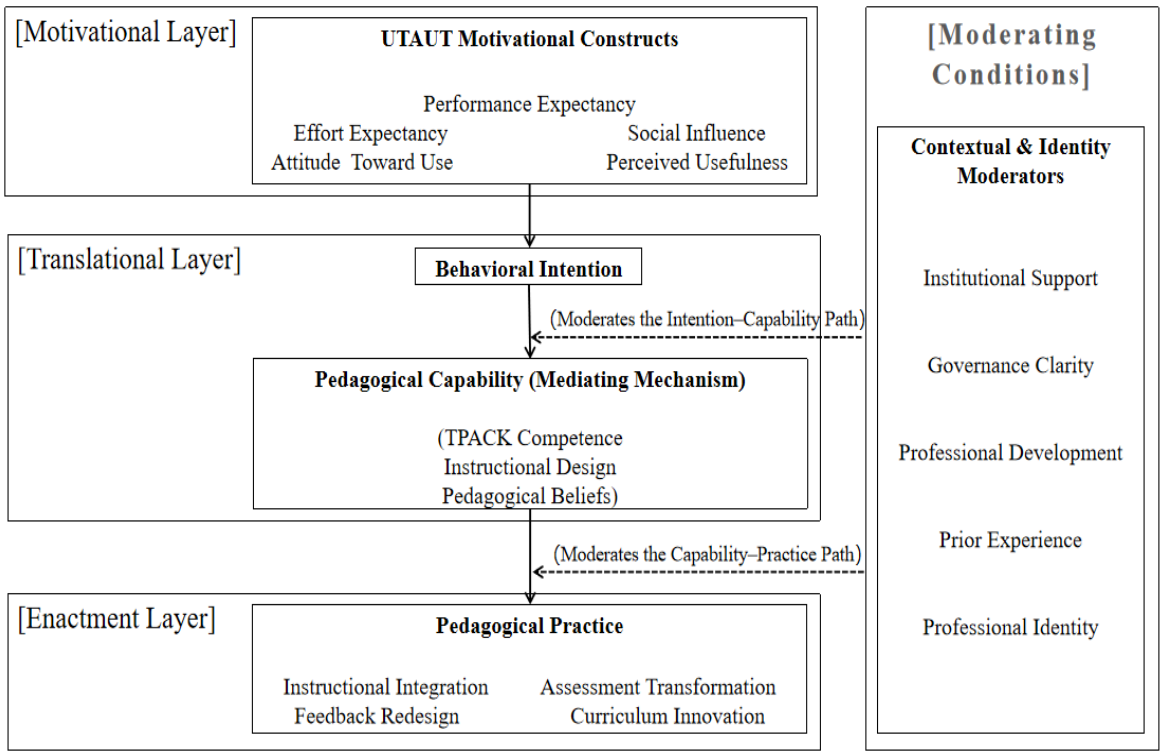


Figure 6. Conditional intention–practice translation model integrating UTAUT and TPACK (Source: Authors' own elaboration)

Integrative interpretation through a conditional intention–practice model

Figure 6 presents the proposed conditional intention–practice translation model integrating UTAUT and TPACK. The 33 core studies show that the link between intention and practice is conditional. Abdelhalim et al. (2025) report a strong intention; however, only a moderate classroom transformation. Alm and Ohashi (2024) observe positive orientation with limited structural embedding. These findings show that intention does not guarantee instructional change.

Studies at the motivational level explain the formation of intentions. Notably, Zaim et al. (2024) show that performance expectancy predicts behavioral intention. Wattanakasiwich et al. (2025) report similar results. Singh and Strzelecki (2025) find that relative advantage and compatibility shape intention. These variables predict willingness rather than redesign depth.

Studies at the translational level highlight pedagogical capability. Ríos Gonzales et al. (2025) show that TPACK competence predicts instructional integration beyond attitudinal factors. Similarly, Song et al. (2025) find that AI-generated lesson design becomes effective only when instructors apply instructional design knowledge. Iqbal et al. (2025) report that AI literacy training enhances readiness for curriculum redesign. These studies position capability as the mechanism that links intention to practice.

Studies at the contextual level show that institutional and identity conditions regulate implementation. Jiang et al. (2025) report that governance clarity reduces uncertainty. den Hollander et al. (2025) show that policy ambiguity constrains integration. Additionally, Alhur et al. (2025) find that concerns about professional identity create hesitation. Kılavuz and Mede (2025) show that personality traits influence openness to experimentation.

The evidence supports a layered explanation. Motivational factors generate intention. Pedagogical capability enables translation. Contextual and identity conditions shape the strength of implementation. Consequently, the intention–practice gap emerges when capability or institutional support is insufficient. This model frames generative AI adoption as a conditional instructional change process rather than a linear progression from intention to use.

DISCUSSION

Rapid Growth with a Narrow Explanatory Focus

This review shows that research on generative AI in higher education has expanded rapidly since 2024. For example, Alm and Ohashi (2024) document early curiosity among language instructors. Abdelhalim et al. (2025) report cross-cultural variation in early engagement. These early studies focus mainly on perception and attitude.

Moreover, most empirical studies rely on survey designs. Zaim et al. (2024) apply UTAUT to model behavioral intention. Wattanakasiwich et al. (2025) confirm that performance expectancy predicts intention. Nevárez Montes and Elizondo-García (2025) show that perceived usefulness predicts intention and reported use. These studies provide strong statistical support for the formation of intentions.

Nonetheless, few studies examine sustained instructional change. Xavier et al. (2025) conducted an intervention study; such designs remain rare. Abdelhalim et al. (2025) find significant links between intention and use frequency, yet they observe only moderate classroom transformation. This pattern suggests that the field explains willingness more clearly than it explains pedagogical change.

Acceptance Models Clarify Motivation but Not Instructional Depth

The evidence shows that technology acceptance models dominate this field. Specifically, Zaim et al. (2024) and Wattanakasiwich et al. (2025) show that performance expectancy and effort expectancy predict intention. Singh and Strzelecki (2025) show that relative advantage and compatibility shape adoption willingness. Singerin et al. (2025) confirm that attitude predicts intention and reported use.

These findings indicate that faculty members form intention when they perceive usefulness and manageable effort. Acceptance models provide strong explanations of motivational readiness. However, most studies treat reported use as sufficient evidence of adoption. Few studies examine the depth or structure of instructional redesign. Abdelhalim et al. (2025) report moderate classroom transformation despite strong intention scores. Alm and Ohashi (2024) observe positive orientation without structural embedding. Taken together, these findings suggest that acceptance models clarify why faculty adopt generative AI. Nevertheless, they offer limited insight into how teaching practice evolves.

Pedagogical Capability Enables Instructional Translation

The explanatory studies indicate that pedagogical capability plays a central role in translation. Ríos Gonzales et al. (2025) show that TPACK competence predicts instructional integration beyond attitudinal factors. Song et al. (2025) show that AI-generated lesson plans become effective only when instructors apply instructional design knowledge. In addition, Iqbal et al. (2025) show that AI literacy training enhances readiness for curriculum redesign.

Intervention studies further support this pattern. Pargmann et al. (2025) show that structured AI feedback improves the quality of lesson planning over time. Xavier et al. (2025) show that AI-supported feedback leads instructors to adjust teaching strategies. Moreover, Ellis et al. (2025) show that instructors with stronger pedagogical grounding move toward deeper redesign.

These findings position pedagogical capability as the mechanism that connects intention to structured practice. In other words, faculty willingness alone does not produce transformation. Instructional knowledge and design competence enable sustained integration.

Context and Identity Shape Implementation Conditions

The evidence also shows that translation depends on institutional and professional conditions. For instance, Iqbal et al. (2025) show that professional development strengthens implementation depth. Jiang et al. (2025) show that governance clarity reduces uncertainty. den Hollander et al. (2025) show that policy ambiguity constrains structured integration.

Identity factors further influence enactment. Alhur et al. (2025) show that concerns about professional identity create hesitation. Kılavuz and Mede (2025) show that personality traits influence openness to experimentation. Furthermore, Alm and Ohashi (2024) and Kohnke and Ulla (2024) show that prior AI experience increases confidence and depth of integration. These findings indicate that instructional change unfolds within organizational and identity contexts. Institutional clarity and professional positioning shape how intention becomes enacted practice.

A Conditional and Layered Explanation

The 33 core studies collectively suggest a layered explanation rather than a linear adoption path: motivational constructs generate intention, pedagogical capability enables translation, and institutional and identity conditions regulate implementation strength. The intention–practice gap thus emerges when intention is not matched by sufficient capability or contextual alignment. Generative AI adoption, therefore, reflects a conditional instructional change process rather than a simple progression from intention to use.

This conditional account is further supported by the Mediated Message Model (MMM) proposed by Banas and Beyda-Lorie (2025), which conceptualizes faculty GenAI adoption as the joint product of perceived efficacy and perceived value rather than the outcome of any single psychological factor. The model distinguishes four cognitive–behavioral outcomes—engaged adoption, impassive acceptance, discouraged hesitation, and aversive rejection—that arise from specific combinations of these two perceptions. For example, faculty may comply with institutional expectations without developing a personal commitment (impassive acceptance), or recognize a technology's value yet remain inactive because they do not feel able to implement it (discouraged hesitation). This typology offers a more nuanced lens for interpreting the patterns identified in the present review, helping to explain why positive attitudes and strong intentions do not always translate into deep instructional change. The MMM further suggests that meaningful adoption is unlikely to result from any single stimulus; instead, faculty development should integrate complementary experiences, including personal experiences, peer demonstrations, and authoritative readings. This recommendation is consistent with our finding that professional development and pedagogical capability facilitate the conversion of adoption intentions into meaningful instructional redesign.

CONCLUSIONS AND LIMITATIONS

Conclusions

This review synthesized 150 empirical studies and conducted focused analysis on 33 explanatory investigations. The evidence consistently indicates that technology acceptance constructs such as performance expectancy and perceived usefulness predict behavioral intention, as shown by Zaim et al. (2024), Wattanakasiwich et al. (2025), Singerin et al. (2025), and Nevárez Montes and Elizondo-García (2025).

Nonetheless, the synthesis shows that intention alone does not ensure deep pedagogical integration. Abdelhalim et al. (2025) report moderate transformation despite strong intention. Alhur et al. (2025) show that identity concerns limit implementation. The review identifies pedagogical capability as the central mechanism linking intention to instructional redesign. Ríos Gonzales et al. (2025) and Song et al. (2025) suggest that instructional knowledge predicts structured integration. Intervention studies further show that training and feedback strengthen redesign capacity.

The review also shows that institutional clarity and professional development regulate implementation strength. Jiang et al. (2025) indicate the importance of governance clarity. Iqbal et al. (2025) provide evidence on the role of professional development. Taken together, the findings support a conditional intention–practice model. Faculty willingness alone is insufficient. Sustained transformation depends on pedagogical capability within supportive institutional environments.

The present review was motivated by two gaps in the existing literature. Previous syntheses of AI in higher education have predominantly examined applications, perceptions, acceptance, or general use as outcomes, and none has systematically investigated whether and how faculty intention translates into sustained pedagogical integration; technology acceptance and pedagogical capability have also typically been studied in isolation. By synthesizing 150 empirical studies and focusing on 33 core investigations that included both intention-related constructs and indicators of pedagogical use, the review addresses these gaps and contributes to the field in three ways. First, it shows that intention alone does not ensure deep integration: only 11 of the 33 core studies explicitly identified a discrepancy between intention and enacted pedagogical practice, and the majority did not directly examine or report this relationship, suggesting that the intention–practice gap is likely underreported. Across the reviewed evidence, pedagogical capability, particularly TPACK-related competence and instructional design knowledge, emerges as the central mechanism through which intention becomes structured classroom integration. Second, the review specifies the conditions that strengthen or weaken this translation, including institutional support, governance clarity, professional development, and identity-related factors. Third, it proposes a conditional intention–practice translation model that integrates UTAUT and TPACK, which can be tested in future primary research and used to guide institutional strategy. In contrast to the closest comparator, Nikolic et al. (2024), which centered on attitudes and intentions within a single acceptance framework, the present review focuses on the mechanisms through which intention is realized in enacted instructional redesign, redirecting attention from faculty willingness toward the pedagogical and institutional conditions that enable sustained instructional transformation.

Limitations and Future Directions

This review includes peer-reviewed English-language journal articles published between 2023 and 2026. This scope ensures comparability but may exclude regional or non-English studies. Notably, most included studies rely on cross-sectional surveys. Many studies measure self-reported use rather than observed redesign. Longitudinal and experimental research remains limited, although Pargmann et al. (2025) and Xavier et al. (2025) provide early examples.

Accordingly, future research should address these gaps through more specific designs. In primary studies, researchers should move beyond self-reported use toward direct indicators of instructional redesign, such as lesson planning, curriculum design, and assessment transformation, and should track faculty cohorts longitudinally across at least one academic year to determine whether intention stabilizes, decays, or translates into practice over time. Intervention studies should test professional development programs that combine complementary experiences, such as personal experimentation, peer demonstration, and authoritative readings (Banas & Beyda-Lorie, 2025), and should measure intention and enacted practice before and after the intervention. Studies should also test moderation explicitly, rather than only prediction, by comparing institutions that differ in policy clarity, professional development availability, and governance arrangements, and by sampling across disciplines, institution types, and geographic contexts beyond those currently represented, given the uneven geographical distribution of the evidence.

Future systematic reviews should complement this primary research. Given the rapid growth of the literature since 2024, the present review should be updated at regular intervals, for example through a living systematic review or a formal update every three to five years. Subsequent syntheses should broaden their inclusion criteria to non-English databases, regional journals, conference proceedings, and gray literature, and should consider discipline-specific or context-specific reviews. As comparable effect sizes accumulate, future reviews should conduct meta-analysis, including meta-analytic structural equation modeling (Cheung, 2015), to test the mediating role of pedagogical capability and the moderating effects of institutional factors within the conditional intention–practice translation model. Finally, because most core studies did not directly examine the intention–practice relationship, future reviews should adopt standardized criteria for reporting how intention and enacted pedagogical use are operationalized, so that the depth of integration, rather than reported use alone, can be synthesized across studies.

Author contributions: WX: formal analysis, writing – original draft; **MFAH:** methodology, interpretation; **HYL:** supervision, validation, writing – original draft; All authors contributed to the final manuscript and approved its submission.

Funding: The authors would like to acknowledge the financial support from Universiti Teknologi Malaysia under UTM Encouragement Research Grant Scheme (UTMER) (Q.J130000.3853.42J25).

Ethical statement: The authors stated that the study did not require ethical approval as it is based solely on secondary data retrieved from the Scopus and Web of Sciences database.

AI statement: The authors stated that, during the preparation of this study, we employed AI tools, including ChatGPT 5.2, to improve the article's readability, and to ensure grammatical accuracy. Additionally, we utilized AI tools to ensure the integrity and proofreading of the data. Following the use of these tools, we carefully reviewed and validated the final version of the manuscript. As the authors, we assume full responsibility for the content of the published work.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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