

Faculty Members' Attitudes Toward Using Generative Artificial Intelligence in University Teaching and Barriers to Adoption: An Integrative Review and Research Framework

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Abstract

Generative artificial intelligence (GenAI) has moved rapidly from a peripheral innovation to a consequential feature of higher education. Yet institutional decisions about its educational use depend substantially on faculty members, whose attitudes influence whether GenAI is ignored, prohibited, adopted instrumentally, or integrated into pedagogy in responsible and learning-centered ways. This article critically integrates recent peer-reviewed evidence on university faculty attitudes toward GenAI, their perceived benefits, and the barriers that constrain adoption. Twenty-two DOI-verified sources were examined, including direct faculty surveys and interviews, systematic reviews, policy analyses, conceptual studies, and the foundational Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology. The synthesis indicates that faculty attitudes are best described as **conditionally positive and risk-sensitive**. Perceived usefulness, performance expectancy, ease of use, technology readiness, personal innovativeness, social influence, enjoyment, and facilitating conditions support adoption. However, accuracy concerns, academic-integrity risks, privacy and intellectual-property issues, anxiety, reduced human interaction, student overreliance, ambiguous policy, inadequate professional development, unequal access, and weak technical support inhibit responsible use. An integrated model is proposed in which attitudes and behavioral intention mediate the effects of positive drivers and perceived risks on instructional use, while institutional

support both enables adoption and buffers risk. The article also presents a multilevel taxonomy of barriers, ten testable hypotheses, and a sequential explanatory mixed-methods design for future empirical validation. The analysis implies that universities should move beyond polarized “ban or embrace” responses toward coherent governance, assessment redesign, sustained faculty development, secure infrastructure, and discipline-sensitive communities of practice.

Keywords: generative artificial intelligence; ChatGPT; faculty attitudes; higher education; technology adoption; barriers; UTAUT; TAM; university teaching

Introduction

The public release of widely accessible generative artificial intelligence systems, particularly large language models such as ChatGPT, has changed the conditions under which teaching, learning, assessment, and academic work occur. GenAI can generate explanations, examples, questions, feedback, summaries, code, images, and drafts at a speed and scale that make it attractive for educational use. For university faculty, these capabilities create opportunities to reduce repetitive work, diversify learning materials, provide formative support, and experiment with new forms of human–AI collaboration. At the same time, the probabilistic and opaque nature of many GenAI systems introduces problems of fabrication, bias, privacy, authorship, accountability, and academic integrity (Dwivedi et al., 2023; Farrokhnia et al., 2024; Kasneci et al., 2023).

Faculty attitudes are therefore strategically important. University teachers make day-to-day decisions about whether GenAI may be used, how its use should be disclosed, which learning activities remain educationally meaningful, and what evidence counts as valid assessment. They are also expected to explain institutional policies, model responsible practices, and respond to student use even when their own training or access is limited. This position

makes faculty members both potential change agents and potential bottlenecks. Their adoption cannot be understood solely as a matter of technical willingness; it is embedded in professional identity, disciplinary norms, pedagogical judgment, institutional governance, and perceptions of student learning.

Early literature often framed GenAI through a binary opposition between promise and threat. More recent empirical evidence reveals a more complex pattern. Faculty may appreciate the efficiency of GenAI while doubting the quality of its output; support limited classroom use while fearing overreliance; or express willingness to experiment only when institutional policies and secure tools are available. Systematic literature also shows that there are positive perceptions regarding instruction improvement, but reliability, academic integrity, skills development, and insufficient organizational support remain issues (Nikolic et al., 2024; Wu et al., 2025). The relevant question is therefore not whether faculty are simply “for” or “against” GenAI, but **under what pedagogical, ethical, technological, and organizational conditions favorable attitudes become responsible instructional practice.**

This article provides an integrative review of DOI-verified scholarly literature on faculty attitudes toward the use of GenAI in university teaching and the barriers to adoption. It makes four contributions. First, it distinguishes the cognitive, affective, ethical, and behavioral components of faculty attitudes. Second, it synthesizes barriers at individual, pedagogical, ethical/legal, and organizational/technical levels. Third, it integrates the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with trust, risk, anxiety, and institutional support. Fourth, it proposes testable hypotheses and a mixed-methods design for empirical validation, with particular relevance to universities seeking evidence-based policy and professional-development strategies.

Purpose and Review Questions

The purpose of this article is to explain how faculty members evaluate the use of GenAI in university teaching, identify the conditions that encourage or inhibit adoption, and translate the evidence into a coherent research and institutional-action framework. The review addresses five questions:

1. How are faculty attitudes toward GenAI in university teaching characterized in the recent literature?
2. What are the advantages that faculty members see in GenAI?
3. What constraints affect the implementation of GenAI?
4. Which theoretical constructs and contextual factors explain faculty behavioral intention and instructional use?
5. What methodological and institutional priorities follow from the available evidence?

Review Approach

A structured integrative-review approach was used because the relevant literature includes heterogeneous evidence: cross-sectional surveys, structural-equation models, qualitative interviews, mixed-methods studies, systematic reviews, policy analyses, and conceptual articles. The goal was interpretive integration rather than statistical meta-analysis. Scholarly searches conducted in August–September 2026 used combinations of terms referring to *faculty*, *University instructors*, *teachers*, *generative AI*, *ChatGPT*, *perceptions*, *acceptance*, *adoption*, *hindrances*, *higher education*, *TAM*, and *UTAUT*. More emphasis was laid on peer-reviewed research articles published starting from 2023, whereas theory was kept intact wherever necessary.

Sources were included when they addressed at least one of four domains: faculty attitudes or behavioral intention; reported instructional use; perceived benefits and barriers; or higher-education governance relevant to faculty practice. Student-only studies were generally excluded unless they directly compared student and faculty perceptions or supplied context essential to faculty decision making. Every reference in the final corpus was checked against a publisher or DOI landing page, and all retained sources have a DOI. The resulting evidence base comprised 22 publications: direct empirical studies of faculty, systematic and integrative reviews, policy/document analyses, conceptual papers on educational implications, and the foundational TAM and UTAUT articles. Because this was an integrative review rather than a registered systematic review, the synthesis should be interpreted as analytically comprehensive rather than exhaustive.

Conceptual Foundations

Technology Acceptance Model

The Technology Acceptance Model proposes that perceived usefulness and perceived ease of use are central determinants of technology acceptance (Davis, 1989). In the context of GenAI, **perceived usefulness** concerns whether faculty believe that a tool improves the quality, efficiency, or effectiveness of teaching-related work. **Perceived ease of use** concerns the effort required to learn, prompt, evaluate, and incorporate the tool. The model remains useful because GenAI adoption often begins with highly practical questions: Does the tool save time? Does it improve a task? Can the instructor use it without excessive cognitive or technical cost?

However, TAM alone is not sufficient for GenAI. A lecturer might view a tool as being helpful and easy to use, but reject it due to issues of privacy, integrity, accuracy, or professional reasons. In other words, the model needs to include trust, risk perception, anxiety, ethical

judgment, and context. Current research on lecturers indeed does this through incorporating enjoyment, technology readiness, social influence, perceived risk, or well-being (Barakat et al., 2025; Cambra-Fierro et al., 2025).

Unified Theory of Acceptance and Use of Technology

UTAUT models the process of adoption based on performance expectancy, effort expectancy, social influence, and facilitating conditions with demographic and experiential moderators (Venkatesh et al., 2003). It is quite relevant to apply the UTAUT model to the process of faculty GenAI adoption since this process is seldom individual and separate from the rest of the environment. Departmental expectations, colleague's actions, student demand, officially supported platforms, support, and policy affect the decision to experiment. Studies have confirmed that in the case of teaching academics, institution training and policy is never irrelevant; it affects whether intention becomes action (Nikolic et al., 2024)..

The UTAUT2-related literature also underscores the importance of personal innovativeness, hedonic motivation, habit, and price value. For educators in the Arab region within the higher education setting, personal innovativeness, social influence, hedonic motivation, effort expectancy, and habit have been found to influence intention, while price value can limit usage because of limited access to sophisticated technology (Ayyoub et al., 2025). Thus, such evidence supports the idea of considering adoption a situational phenomenon rather than extrapolating from resource-rich settings.

Trust, Risk, Anxiety, and Professional Judgment

GenAI differs from many earlier educational technologies because it produces fluent content that may be inaccurate, biased, or fabricated. Faculty must therefore evaluate not only usability but also the trustworthiness and educational consequences of machine-generated

outputs. Perceived risk includes concern about reliability, privacy, intellectual property, accountability, and reputational harm. Anxiety includes uncertainty about using the technology correctly, concern about student misuse, and apprehension about effects on learning or academic work. A validated educator-focused instrument identified effectiveness, anxiety, technology readiness, perceived usefulness, social influence, and perceived risk as distinct dimensions of university educators' attitudes (Barakat et al., 2025).

Theoretical constructs used in this article are summarized in Table 1.

Table 1

Core Constructs for Explaining Faculty Adoption of Generative AI

Construct	Working definition	Expected role	Primary theoretical basis
Performance expectancy / perceived usefulness	Belief that GenAI improves teaching quality, productivity, feedback, or task completion	Positive predictor of attitude and intention	TAM; UTAUT
Effort expectancy / perceived ease of use	Perceived cognitive and technical effort required to learn and use GenAI	Positive predictor of attitude and intention	TAM; UTAUT
Social influence	Perception that colleagues, leaders, students, or the profession expect or value use	Positive predictor of intention	UTAUT/UTAUT2
Facilitating conditions	Availability of infrastructure, approved tools, time, guidance, and technical support	Positive predictor of intention and use	UTAUT
Technology readiness / personal innovativeness	General preparedness and willingness to experiment with emerging technology	Positive predictor of attitude and intention	Extended TAM/UTAUT2
Pedagogical self-efficacy	Confidence in designing, supervising, and evaluating educational uses of GenAI	Positive predictor of attitude and responsible use	Social-cognitive extension
Trust in output	Willingness to rely on GenAI after appropriate verification	Positive but conditional predictor	Trust-risk perspective
Perceived risk	Expected harm involving accuracy, privacy, ethics, integrity, or accountability	Negative predictor of attitude and intention	Risk perspective
GenAI-related anxiety	Unease concerning use, student misuse, or consequences for learning and work	Negative predictor of intention	Technology-anxiety research
Faculty attitude	Overall favorable or unfavorable evaluation of GenAI for teaching	Mediator of beliefs and intention	TAM
Behavioral intention	Stated likelihood of future instructional use	Proximal predictor of use	TAM; UTAUT
Responsible instructional use	Purposeful use aligned with outcomes, disclosure rules, verification, privacy, and human oversight	Main behavioral outcome	Integrated framework

Note. TAM = Technology Acceptance Model; UTAUT = Unified Theory of Acceptance and Use of Technology.

Faculty Attitudes Toward Generative AI

Conditionally Positive and Risk-Sensitive Attitudes

What seems the most reasonable approach to synthesizing attitudes of faculty towards AI is to conclude that these attitudes are not consistently supportive or generally resistant. Rather, their position regarding the implementation of GenAI is conditional and positive only if GenAI helps to perform valued work and the associated risks can be managed; otherwise, their attitude will be cautious. For instance, Nikolic et al. (2024) discovered that teachers acknowledged the efficiency of AI for education and its ability to improve teaching while raising concerns about academic integrity, precision, reliability, and skill-building.

Further empirical evidence supports this trend. Kim et al. (2025) at a major public university in the United States conducted a survey among 982 students and 76 faculty members. Faculty and students were alike in many perceptions about the technology; both considered that GenAI could increase academic cheating as well as that the technology should be part of university curriculum. The utilization was not yet prevalent. The combination of inevitability, educational value, and concern about possible negative learning consequences reveals the reason why a single attitude measure is insufficient.

The qualitative analysis adds more dimensions to the issue. Time-saving, personalized teaching and learning, professional development, and experimenting with new educational technology were cited as motivators by interviews of higher education teachers from Oman. These people were worried about reliability and accuracy, security and privacy, lack of human interaction, institutional support, and dependency (Al-Mughairi & Bhaskar, 2025). In addition, interviews of teachers from India also found out that the teachers were motivated due to time-

saving, enhanced student-learning, research support, educational advantages, problem-solving and usability, although they faced technical issues, less creativity, lack of personal touch, and ethics issues (Bhaskar & Rana, 2024).

Positive Drivers of Adoption

Utility perception is a consistently positive theme. GenAI can help with lesson planning, development of curricula, generation of questions, illustrations, explanations at various levels, formative assessment, rubrics, translation, refinement of written texts, coding, and initial data analysis. These works stress the potential for customization and time-saving in routine production activities, which can allow instructors to focus more on mentoring and pedagogical decision-making (Baig & Yadegaridehkordi, 2024; Kasneci et al., 2023; Wu et al., 2025).

Ease of use is important since conversational interfaces provide lower entry barriers than specialized programs. However, seemingly easy interface design does not mean that there is no need for a certain level of skill when creating prompt, verifying output, securing information, and using it in line with educational purposes. Ease of access is thus accompanied by the need for evaluation skills. It is crucial not just to know how to get an answer, but how to make sure that it is correct, properly cited, unbiased, and acceptable.

Adoption is affected by technology readiness, innovativeness, social influence, enjoyment, and habit. According to a study done in Spain on 401 faculty members using TAM approach, usefulness, ease of use, and enjoyment were predictors of adoption of ChatGPT, and the adoption was correlated positively with happiness and energy and negatively with stress (Cambra-Fierro et al., 2025). In a multinational Arab sample consisting of 307 early adopters of education, intention was influenced positively by personal innovativeness, social influence,

hedonic motivation, effort expectancy, and habit, while price value was negatively influential due to financial constraint (Ayyoub et al., 2025).

Differences Between Attitude, Intention, and Use

Positive attitude does not necessarily translate to adoption. While faculty may see value in some tool or technology, they may choose not to adopt because of lacking approval, lack of time, lack of training, or policies. On the other hand, intentions do not guarantee quality adoption. For example, a teacher may decide to adopt the technology for administrative preparation but not use it with students or may adopt it frequently, but without any verification and pedagogical alignment. The research needs to make a distinction between at least four possible outcomes

. This distinction helps reconcile apparently inconsistent findings. A faculty member can be positive about the technology in principle, cautious about student use, and selective in actual teaching practice. Another may be skeptical but use GenAI because of social or administrative pressure. Measurement instruments should therefore avoid treating adoption as a binary variable and should assess the purposes, visibility, governance, and pedagogical sophistication of use.

Perceived Pedagogical and Professional Benefits

Efficiency and Workload Management

Time-saving emerges as another common motivation behind the usage of AI systems. GenAI can help generate first versions of outlines for lessons, examples, questions for discussions, quiz questions, case studies, rubrics, feedback forms, and alternative explanations. When teachers remain in charge of verification and editing, such capabilities may help alleviate teachers' routine work. Time-saving is considered one of the major motivators in qualitative research in Oman and India (Al-Mughairi & Bhaskar, 2025; Bhaskar & Rana, 2024), while

general reviews highlight efficiency as an ongoing advantage (Nikolic et al., 2024; Wu et al., 2025).

The connection between efficiency and educational quality cannot be established without any grounds. It becomes useful only if it is consistent with professional standards and results. Otherwise, it will simply transfer the efforts from writing itself to editing. The actual usefulness of it, therefore, will depend on the ability of the faculty member to elicit and analyze the output.

Personalization and Accessibility

GenAI can give examples of varying degrees of difficulty, translate or explain text, converse, and instantly explain something. Such capabilities could facilitate differentiation and accessibility in education. Educators may employ GenAI to foresee possible misconceptions, make several interpretations of one concept, or give practice exercises. Large language models may even play the role of temporary conversation partners, especially when educators do not have enough time for discussion (Kasneci et al., 2023; Tlili et al., 2023).

Nevertheless, the use of personalization based on sensitive student data poses privacy issues, while the use of automated systems could lead to biases. Instructors thus require appropriate platforms, data minimization strategies, and also the definition of limitations regarding the kind of information that can be inputted. Personalization should also complement rather than substitute for personal guidance.

Curriculum, Assessment, and Feedback Design

GenAI can be utilized by lecturers to think up authentic tasks, to make up alternative questions, to develop practice cases, and also to give examples of feedback. Moreover, GenAI can reveal flaws in traditional assessments because if a task could be performed effectively by any generic chatbot, then such a task depends on reproduction rather than on situated thinking.

Thus, GenAI puts pressure on assessment redesigning in terms of oral defense, iterations, process documentation, reflections, locally-based evidences, lab/studio performances, collaborative reasoning, and critical evaluation of GenAI work (Cotton et al., 2024).

On the contrary, this technology could pose risks when not used in accordance with clear guidelines. It is up to faculty to determine what is forbidden, permitted, mandatory, or acceptable under certain circumstances, and the students need to know about the expectations regarding disclosure and citation. The policies that tell faculty to develop guidelines without proper training may lead to inconsistency and unfairness to students (An et al., 2025).

Professional Learning and Well-Being

GenAI can act as an aid to professional learning through brainstorming, technical problem-solving, language polishing, and exploring new methodologies. The relationship between GenAI adoption and increased teacher happiness and vigor as found by Cambra-Fierro et al. (2025) implies that there could be additional gains besides improved task performance. However, any such relationship is derived from cross-sectional data, which cannot be construed as causation. Additional gains in well-being may come about if GenAI alleviates burdens, or if it creates them..

Barriers to Faculty Adoption

Individual-Level Barriers

The first set of barriers includes knowledge, confidence, preparedness, and emotions. The faculty may not be fully aware of the capabilities of GenAI technology, feel uncertain about prompt creation, or be unsure of how to evaluate the output. One example is a mixed methods study conducted on 184 university professors and administrative staff in which only a small

portion felt confident in recognizing AI-created content, even though they saw benefits for productivity and writing (Cordero et al., 2025).

Anxiety and risk perception are different yet related variables. In a study carried out by Barakat et al. (2025), these were separately recognized as constructs within an acceptance tool developed for educators. A study conducted on 249 academics in Spanish public universities demonstrated how anxiety about the learning and abuse of technology decreased behavioral intention, part of which was through performance and effort expectancy. Anxiety about the future of the profession did not emerge as a significant predictor (Verano-Tacoronte et al., 2025). The distinction is relevant for designing interventions that may be more effective because generic assurances of job security would not alleviate anxiety regarding learning and abuse.

Pedagogical Barriers

The problem of accuracy and reliability persists. GenAI tools can generate accurate-looking yet fake information, invented citations, simplified answers, bias, and contradictory information. This is especially problematic in fields where even small mistakes can lead to significant misunderstandings. The time spent on validation may outweigh any possible benefits from using GenAI tools (Farrokhnia et al., 2024; Kasneci et al., 2023).

Another issue related to pedagogy is over-dependency. In case students delegate the job of idea generation, reasoning, writing, coding, and problem-solving to GenAI without having gained adequate proficiency, GenAI will help the students finish their tasks but fail to aid them in learning. There are fears among faculty members that engaging frequently with automatic systems will lead to the diminution of communication, creativity, disciplinary identity, and the personal component of teaching. However, the answer is not in banning it but in task design.

Ethical and Legal Barriers

Academic integrity is the primary obstacle, but it must be considered part of an overall ethical framework. Unsanctioned help, undisclosed use of language generation software, fabrication of sources, and plagiarism may all contravene course policies. However, unreliable language-detection technology raises the possibility of a false charge. Institutional policy increasingly cautions against the use of detection scores as final evidence and promotes the establishment of clear expectations (An et al., 2025; Cotton et al., 2024).

Privacy and data security are other aspects worth considering. The faculty and learners may upload data such as unpublished research results, assessment material, personal data, and confidential institutional data to third-party systems. There are uncertainties on issues related to data retention, model training, data processing across borders, and contract terms, which makes it difficult to be sure about some aspects. There are copyright and intellectual property issues related not only to the data used to train models but also to the output generated by them.

Organizational and Technological Barriers

The lack of clarity of the institution in such situations will transform potential risks into barriers to adoption. While professors can get general statements on innovation, there is no information about the acceptable technologies, protection of data, disclosures, evaluation, accessibility, and liability for mistakes. In an analysis of 214 documents providing GenAI guidelines from top U.S. higher education institutions, professors had to set their course-related policies and share them via syllabus (An et al., 2025).

Training is often generic, optional, or focused on tools. The development process must take disciplinary differences into account and integrate technological knowledge with assessment design, validation, ethics, accessibility, and communication in class. A single demonstration will

not lead to lasting expertise. Time, peer interaction, models, and acknowledgment are also needed for redesign.

Infrastructure and access lead to further disparities. Free products may offer reduced functionality or less effective data protection; more sophisticated options may be subscription-based; and licensing may be inconsistent across institutions. Network bandwidth, language, accessibility, compatibility with learning platforms, and dependability are also relevant factors. Thus, cost is not just a personal matter but a matter of equity and governance as well (Ayyoub et al., 2025).

Table 2*Selected Empirical Evidence on Faculty Attitudes and Adoption*

Study	Context and sample	Design / framework	Main positive findings	Main barriers or cautions
Al-Mughairi and Bhaskar (2025)	Oman; 34 teachers across 10 university branches	Interviews; interpretative phenomenological analysis	Time saving, personalization, innovation, professional development	Accuracy, privacy, security, reduced interaction, overreliance, weak institutional support
Ayyoub et al. (2025)	Arab countries; 307 early-adopter educators	Survey; extended UTAUT2; PLS-SEM	Innovativeness, social influence, enjoyment, effort expectancy, and habit supported intention	Price value constrained adoption; effects varied by experience and gender
Barakat et al. (2025)	Jordan; 236 university educators	Survey; TAM-based instrument development; EFA	Effectiveness, readiness, usefulness, and social influence supported favorable attitudes	Anxiety and perceived risk emerged as distinct barriers
Bhaskar and Rana (2024)	India; 48 higher-education teachers	Interviews; interpretative phenomenological analysis	Time saving, student-learning support, research facilitation, ease of use	Technical difficulty, reduced creativity, lack of personal touch, ethical issues
Cambra-Fierro et al. (2025)	Spain; 401 university professors	Survey; extended TAM; CB-SEM	Usefulness, ease, and enjoyment predicted adoption; adoption correlated with happiness and energy	Cross-sectional design limits causal interpretation
Cordero et al. (2025)	Ecuador; 184 university teachers and administrators	Mixed methods; professional-development context	Resource creation, lesson planning, productivity, writing support	Veracity, misinformation, privacy, intellectual property, low detection confidence
Kim et al. (2025)	United States; 76 faculty and 982 students	Survey; modified UTAUT; CFA	Both groups saw a role for GenAI in courses	Academic dishonesty and possible negative effects on learning; regular use remained low
Verano-Tacoronte et al. (2025)	Spain; 249 public-university faculty	Survey; UTAUT; PLS-SEM	Clarified pathways linking expectancy and intention	Anxiety about student learning and misuse reduced intention

Note. CB-SEM = covariance-based structural equation modeling; CFA = confirmatory factor analysis; EFA = exploratory factor analysis; PLS-SEM = partial least squares structural equation modeling.

Table 3*Multilevel Taxonomy of Barriers and Institutional Responses*

Level	Barrier domains	Likely consequences	Priority responses
Individual	Low AI literacy; low pedagogical self-efficacy; anxiety; perceived risk; resistance; low readiness	Avoidance, superficial use, uncritical reliance, or inconsistent decisions	Scaffolded professional development; mentoring; practice with verification; recognition of redesign work
Pedagogical	Hallucinations; weak alignment; overreliance; shallow learning; reduced human interaction; assessment validity	Lower-quality materials, compromised learning, uncertain grading, loss of trust	Learning-outcome alignment; human review; authentic assessment; process evidence; AI critique activities
Ethical/legal	Integrity; privacy; bias; transparency; copyright; accountability	Misconduct, data exposure, inequity, disputed authorship, reputational risk	Clear disclosure rules; approved secure tools; data minimization; due process; human

Level	Barrier domains	Likely consequences	Priority responses
			accountability
Organizational	Ambiguous policy; insufficient training; inconsistent departmental practice; limited leadership coordination	Uneven adoption, faculty hesitation, student confusion, policy noncompliance	Coherent governance; model syllabi; help desk; communities of practice; periodic policy review
Technological/economic	Cost; unequal access; infrastructure; language limitations; accessibility; vendor reliability	Digital inequality, interrupted use, exclusion, dependence on unapproved tools	Institutional licensing; accessibility review; procurement standards; contingency plans; equitable access

Integrated Conceptual Framework

Figure 1 integrates positive adoption drivers, risk and anxiety factors, attitudes, intention, and responsible instructional use. Performance expectancy, effort expectancy, technology readiness, and pedagogical self-efficacy are expected to shape faculty attitudes. Social influence may operate more directly on intention, particularly when peers, leaders, professional bodies, or students normalize use. Ethical/integrity risk, accuracy/bias concern, privacy concern, and GenAI-related anxiety are expected to weaken attitudes. Facilitating conditions and institutional support are represented as both direct enablers and buffers that reduce the practical effect of risk.

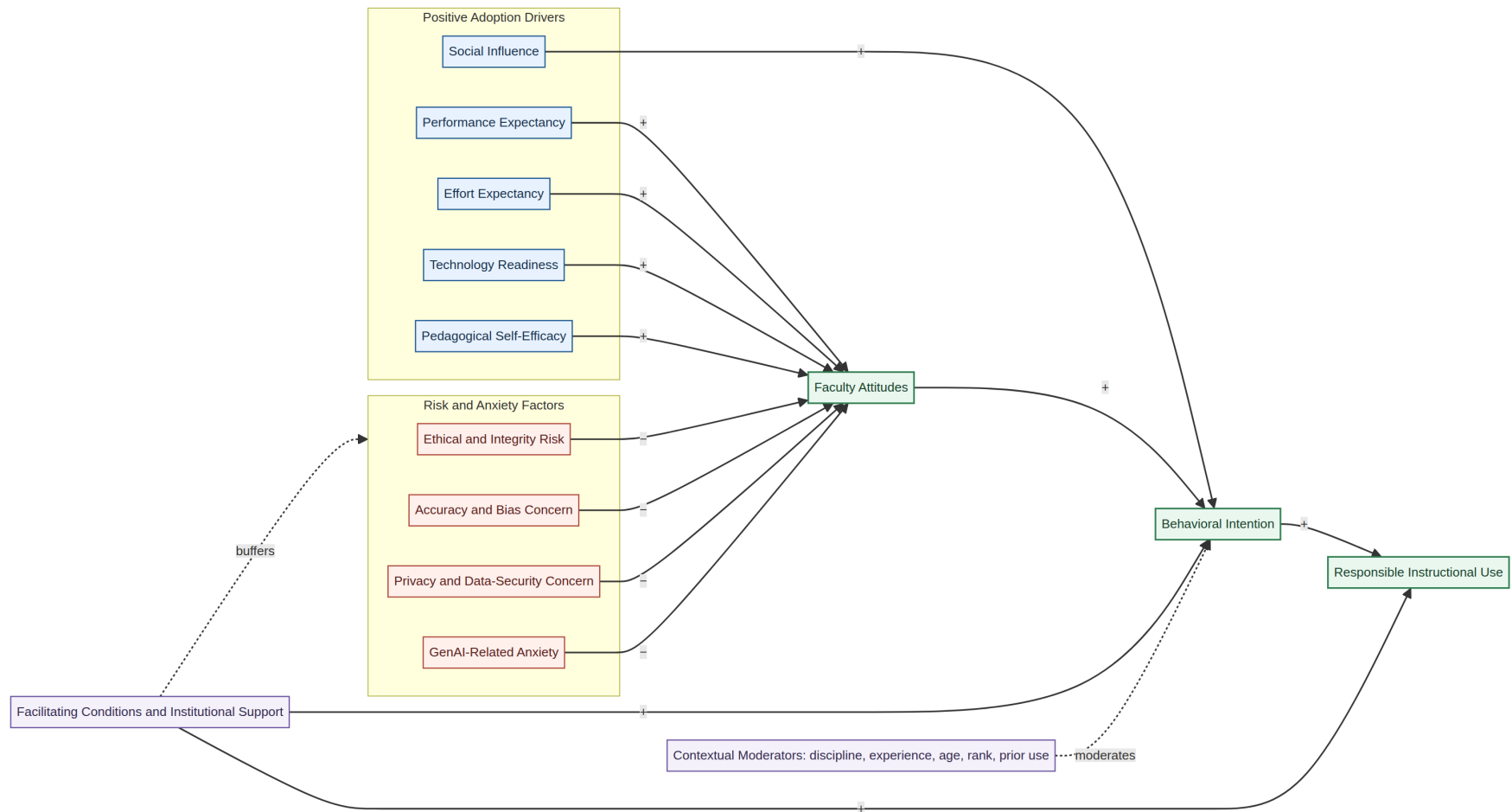


Figure 1. *Integrated conceptual model of faculty adoption of generative AI.* Solid arrows indicate direct predictive paths; dotted arrows indicate moderation or buffering.

The framework treats responsible instructional use as more than frequency. Responsible use requires alignment with learning outcomes, disclosure, verification, protection of data, equitable access, and human accountability. This outcome is deliberately stricter than general technology use because frequent but uncritical adoption may increase rather than reduce educational risk.

Hypotheses

- H1:** Performance expectancy positively predicts faculty attitudes toward using GenAI in university teaching.
- H2:** Effort expectancy positively predicts faculty attitudes toward using GenAI in university teaching.
- H3:** Technology readiness and GenAI pedagogical self-efficacy positively predict faculty attitudes.
- H 4:** Social influence positively predicts behavioral intention to use GenAI.
- H5:** Facilitating conditions and institutional support positively predict behavioral intention and responsible instruction.
- H 6:** Perceived ethical, privacy, accuracy, and academic integrity risks negatively predict faculty attitude and behavioral intention.
- H7:** GenAI anxiety negatively predicts behavioral intention, mediated by reduced performance and effort expectancy..
- H8:** Faculty attitudes positively predict behavioral intention, which in turn predicts responsible instructional use.
- H9:** Institutional support weakens the negative relationship between perceived risk and behavioral intention.
- H10:** Prior GenAI experience, discipline, academic rank, age, teaching experience, gender, and institutional context moderate selected relationships in the model.

Proposed Empirical Methodology

Research Design

A **sequential explanatory mixed-methods design** is recommended to test and refine the framework. The first phase would use a cross-sectional survey to estimate attitudes, intentions, reported instructional use, barriers, and their relationships. The second phase would use semi-structured interviews to explain patterns that the survey alone cannot resolve, such as why faculty with high perceived usefulness nevertheless avoid student-facing use, or how disciplinary norms alter the meaning of academic integrity.

Population and Sampling

The target population should include full-time and part-time faculty who taught at least one university course during the preceding academic year. A stratified sampling approach should represent major disciplinary clusters, academic rank, gender, institutional type, and campus or geographical region. A target of approximately 400–600 valid survey responses would ordinarily provide a reasonable basis for confirmatory factor analysis, structural-equation modeling, and selected subgroup comparisons, but the final requirement should be determined by an a priori power analysis based on model complexity and anticipated effect sizes. For the qualitative phase, approximately 20–30 participants could be purposively selected across contrasting profiles, subject to information power and thematic saturation.

Instrument Development

The questionnaire should adapt validated items from TAM, UTAUT, UTAUT2, and educator-specific acceptance measures. It should separate general attitude from behavioral intention and actual use. It should also distinguish use for behind-the-scenes preparation from student-facing integration. The Ed-TAME-ChatGPT domains reported by Barakat et al. (2025)—effectiveness, anxiety, technology readiness, usefulness, social influence, and perceived risk—offer a particularly relevant starting point, while UTAUT provides performance expectancy, effort expectancy, social influence, and facilitating conditions.

Table 4

Proposed Survey Constructs and Illustrative Indicators

Construct	Operational definition	Illustrative indicator	Suggested source basis
Performance expectancy	Degree to which GenAI is believed to improve teaching performance	“Using GenAI would improve the efficiency of my teaching-related tasks.”	Davis (1989); Venkatesh et al. (2003)
Effort expectancy	Perceived ease of learning and using GenAI	“Learning to use GenAI effectively for teaching would be easy for me.”	Davis (1989); Venkatesh et al. (2003)
Social influence	Perceived approval or expectation from relevant others	“Colleagues whose opinions I value support responsible GenAI use.”	Venkatesh et al. (2003); Ayyoub et al. (2025)
Facilitating conditions	Availability of resources, approved tools, time, and support	“My institution provides the technical support needed for responsible use.”	Venkatesh et al. (2003); Nikolic et al. (2024)

Construct	Operational definition	Illustrative indicator	Suggested source basis
Technology readiness	Willingness and preparedness to use emerging technology	"I feel prepared to experiment with new AI-supported teaching practices."	Barakat et al. (2025)
Pedagogical self-efficacy	Confidence in designing and evaluating educational GenAI use	"I can design a learning activity in which GenAI use supports the intended outcome."	Integrated extension
Trust in output	Conditional confidence in output after verification	"With appropriate checking, GenAI can provide dependable support for selected teaching tasks."	Integrated trust extension
Ethical/integrity risk	Concern about misconduct, authorship, fairness, and accountability	"GenAI use makes it more difficult to ensure that assessed work represents students' own learning."	Cotton et al. (2024); Nikolic et al. (2024)
Accuracy/bias concern	Concern that output may be false, fabricated, or discriminatory	"GenAI may provide convincing content that is factually incorrect."	Farrokhnia et al. (2024); Kasneci et al. (2023)
Privacy/data-security concern	Concern about exposure or misuse of data entered into GenAI tools	"Using public GenAI tools may expose confidential institutional or student information."	Al-Mughairi and Bhaskar (2025); An et al. (2025)
GenAI-related anxiety	Unease about use, student misuse, or learning consequences	"I feel anxious about the effect of student GenAI use on genuine learning."	Barakat et al. (2025); Verano-Tacoronte et al. (2025)
Attitude	Overall positive or negative evaluation	"Using GenAI appropriately in university teaching is a good idea."	Davis (1989)
Behavioral intention	Likelihood of future use	"I intend to use GenAI in at least one teaching activity during the next academic term."	Venkatesh et al. (2003)
Responsible instructional use	Frequency and depth of verified, disclosed, outcome-aligned use	Multi-item index covering preparation, feedback, assessment, student-facing use, verification, and disclosure	Integrated outcome measure

All illustrative items should be subjected to expert review and pilot testing; they should not be treated as a validated scale in their present form.

Validity, Reliability, and Bias Control

Content validity should be assessed by experts in educational technology, psychometrics, university pedagogy, discipline-based education, information security, and AI ethics. Cognitive interviews should identify ambiguity and determine whether faculty interpret terms such as “use,” “responsible,” “risk,” and “institutional support” consistently. A pilot study should assess completion time, missingness, distributional properties, and preliminary reliability.

For the main survey, confirmatory factor analysis should test the measurement structure. Internal consistency should be reported using McDonald’s omega and Cronbach’s alpha. Convergent validity can be evaluated through factor loadings and average variance extracted, and discriminant validity through the heterotrait–monotrait ratio. Where the model contains higher-order or formative constructs, specification should be theoretically justified. Procedural remedies for common-method bias should include clear anonymity, separation of predictor and outcome sections, balanced wording, and psychologically neutral instructions. Statistical diagnostics may supplement but should not replace these design protections.

Quantitative Analysis

The analysis should begin with missing-data assessment, descriptive statistics, distributions, and item correlations. Attitude and barrier profiles should be summarized overall and by discipline, rank, prior use, and institutional context. Group differences may be examined using parametric or robust alternatives according to assumptions. The hypothesized model can be evaluated with covariance-based structural equation modeling when distributional assumptions and sample size are adequate. Prediction-oriented or formative extensions may justify partial least squares SEM, but the choice should be made before analysis and defended theoretically.

Mediation analysis should test whether attitudes transmit the effects of usefulness, ease, readiness, and perceived risk to behavioral intention. Moderation analysis should examine whether institutional support buffers the negative effect of perceived risk and whether experience or discipline changes selected paths. Because cross-sectional data cannot establish temporal causality, future studies should incorporate longitudinal measurement, professional-development interventions, or course-level implementation data.

Qualitative Phase and Integration

Interview participants should be selected from contrasting survey profiles, such as high-use/positive, low-use/positive, low-use/negative, and high-use/high-risk groups. Interviews should explore concrete teaching decisions, incidents that changed attitudes, verification practices, policy interpretation, disciplinary norms, and unmet support needs. Reflexive thematic analysis can identify mechanisms and contextual conditions. Integration should use joint displays that align quantitative patterns with qualitative explanations, thereby showing not only which factors matter but how and why they operate.

Ethical Considerations

Participation should be voluntary and based on informed consent. The study should avoid collecting identifiable prompts, student records, confidential assessment content, or proprietary research material. Because attitudes toward GenAI may be professionally sensitive, reports should prevent identification of individuals, small departments, or institutions. Participants should understand that the study evaluates perceptions and practice rather than compliance or competence. Researchers should disclose any use of GenAI in instrument development, coding support, translation, or writing and retain human responsibility for all methodological and interpretive decisions.

Discussion

From Acceptance to Responsible Integration

The evidence suggests that universities should not treat adoption as the final objective. The more meaningful outcome is responsible, pedagogically aligned integration. A narrow acceptance model may interpret increased frequency as success even when use is poorly verified, inaccessible to some students, or misaligned with outcomes. The proposed framework therefore retains the explanatory strengths of TAM and UTAUT while defining responsible use through human oversight, transparency, privacy, equity, and learning-outcome alignment.

It would be wrong to view faculty skepticism as a manifestation of reluctance towards innovation. Accuracy, pedagogical value, integrity, and confidentiality are just some of the many issues related to professional judgment. On the other hand, an innovative spirit does not necessarily mean being competent. There is a need for a strategy that can accommodate both innovation and prudence.

Institutional Support as Enabler and Risk Buffer

Institutional support is not merely another predictor in an adoption equation. It changes the meaning and consequences of other predictors. A faculty member who worries about privacy may be willing to use an institutionally licensed system with contractual safeguards but unwilling to use a public tool. A teacher concerned about academic integrity may adopt GenAI after assessment redesign support and clear disclosure rules. A novice may gain confidence through discipline-specific workshops and peer mentoring. Support therefore operates both directly and as a buffer between risk and intention.

Figure 2 presents a multilevel model of barriers and mitigation. It emphasizes that individual training alone cannot solve structural problems such as ambiguous policy, inequitable

access, or unreliable infrastructure. Likewise, policy alone cannot create pedagogical competence.

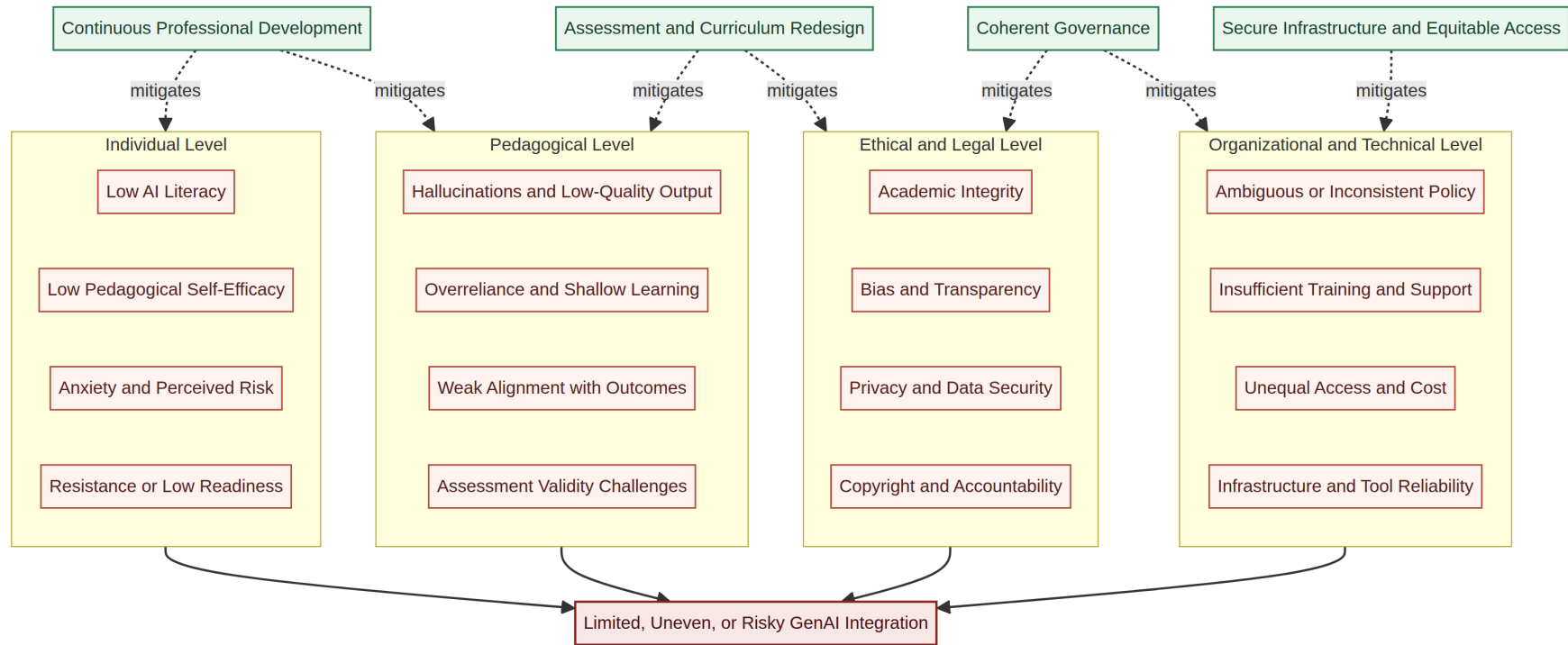


Figure 2. Multilevel barriers to responsible GenAI integration and corresponding mitigation strategies.

Assessment as the Critical Site of Change

Assessment brings together a number of faculty concerns since it encompasses issues of learning, fairness, integrity, and institution credibility. The use of AI detection scores to counter the problem of plagiarism is an insufficient response since AI detection scores may produce false results and could be easily bypassed. Effective ways of tackling this issue involve assessment sequences, evidence-based assessments, oral assessments, critique of AI outputs, and clarification of acceptable help.

This does not mean that all assessments must utilize GenAI. The courses must retain their non-AI components if they are essential for building basic skills or demonstrating self-reliance. The key point is the alignment between the goal of learning and AI: permitted usage should be based on the learning goal, while restrictions should be justified, explainable, and enforceable.

Implications for Arab Universities

Studies carried out in Oman, Jordan, as well as wider Arab higher education institutions, reveal not only great interest but also context-related barriers (Al-Mughairi & Bhaskar, 2025; Ayyoub et al., 2025; Barakat et al., 2025). The following aspects need to be considered at Arab universities: language, culture, and discipline related factors, data sovereignty, availability of high-level systems, and institutional capacities. Bilingual prompts and their verification, where applicable, should be an integral part of professional training.

Comparison at Arab universities is another avenue for useful comparative research. The region has universities that are funded differently, have varying technology infrastructure, use diverse languages in teaching, and have different histories of governance. Comparative studies of multiple universities can determine whether the proposed relationships in Figure 1 hold in all settings or whether certain factors carry more weight in specific settings.

Institutional Recommendations

Universities should adopt a coordinated strategy rather than isolated workshops or prohibition-focused rules. The strategy should begin with a governance framework that defines approved platforms, data classifications, disclosure expectations, human responsibility, accessibility, and review mechanisms. Faculty should receive model syllabus language that can be adapted by discipline without producing contradictory student experiences.

Professional development must be ongoing and practical. Introduction sessions must be followed by workshops related to assessment reform, output validation, bias, privacy issues, copyright and application to the discipline. Communities of practice would allow faculty members to exchange questions, assignments, failures, and evaluation criteria. Participation needs to be rewarded with workload consideration or professional development credits rather than being invisible work.

Equitable access to secure tools must also be provided by institutions. Purchasing should consider the following: privacy, accessibility, language skills, retention policy, interoperability, transparency, and stability of vendor. It should be noted that students should not have to pay for premium access, unless cost and alternatives have been considered. Finally, evaluation needs to go beyond use statistics and look at learning outcomes.

Limitations and Future Research

The evidence base is rapidly changing and remains dominated by cross-sectional self-report studies. Attitudes measured soon after ChatGPT's release may differ from attitudes after faculty gain experience or institutions introduce formal policies. Many studies use convenience samples from a single institution or discipline, limiting generalizability. Some examine ChatGPT specifically, whereas the relevant ecosystem now includes multiple text, image, audio, coding, and multimodal systems with different capabilities and governance arrangements.

Behavioral intention is generally considered a substitute for adoption, while reported use is not typically associated with instructional quality or student outcomes measured through observation. Longitudinal research should explore the changes in attitude following training, policy change, institutional accreditation, and classroom implementation. Experimental and quasi-experimental research should assess whether certain models of professional development enhance self-efficacy, verification behavior, quality assessment, and responsible use.

Comparative research should assess the cross-language, cross-disciplinary, cross-country, and cross-institutional measurement invariance of the measures.

Future studies should also identify different kinds of anxieties and risks, assess professional identity, and explore the allocation of new labor. GenAI could help speed up the writing process, yet it could require more effort to verify, redesign, explain, and deal with any abuses. The amount of net work that GenAI saves should be assessed rather than the presumed gains in efficiency. It should be determined how faculty navigate the limits between assistance and substitution across different disciplines.

Conclusion

Faculty members' attitudes toward GenAI in university teaching are best understood as conditionally positive, multidimensional, and sensitive to risk. Academics recognize opportunities for efficiency, personalization, resource creation, feedback, professional learning, and innovation. Their willingness to adopt is strengthened by usefulness, ease of use, readiness, innovativeness, social influence, enjoyment, habit, and supportive conditions. At the same time, adoption is constrained by concerns about accuracy, bias, academic integrity, privacy, intellectual property, student overreliance, weakened interaction, assessment validity, cost, policy ambiguity, and insufficient training.

The implication is that universities should neither assume adoption will occur automatically nor reduce the issue to individual faculty resistance. Responsible integration is a sociotechnical and pedagogical achievement. It requires coherent governance, secure and equitable access, discipline-sensitive professional development, assessment redesign, transparent communication, and ongoing evaluation. The framework and methodology proposed in this article offer a basis for testing how these conditions shape faculty attitudes, intentions, and practice and for moving institutional debate from polarized reactions toward evidence-informed educational design.

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