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BUILDING AI READINESS AMONG UNIVERSITY TEACHERS: EFFECTS OF GENERATIVE AI PROFESSIONAL DEVELOPMENT ON ADOPTION INTENTION

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Abstract
The rapid emergence of generative artificial intelligence (GenAI) has created new opportunities and challenges for higher education institutions worldwide. While GenAI tools have demonstrated potential to enhance teaching, learning, assessment, and academic support, their successful integration depends largely on educators' ability to understand, evaluate, and responsibly apply these technologies. Existing technology adoption research has primarily focused on perceived usefulness and ease of use, providing limited explanation of the knowledge, confidence, ethical awareness, and professional preparation required for effective AI integration. Therefore, this study proposes an integrated AI readiness framework to examine how generative AI professional development influences university teachers' AI literacy, AI self-efficacy, ethical AI awareness, adoption intention, and classroom AI integration. Drawing upon Social Cognitive Theory, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and emerging AI literacy frameworks, this study adopts an explanatory sequential mixed-methods design. The quantitative phase will employ structural equation modeling to test the hypothesized relationships among AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. The qualitative phase will use semi-structured interviews to explore teachers' experiences, challenges, and institutional factors influencing responsible AI adoption. The proposed framework extends traditional technology acceptance perspectives by positioning AI readiness as a central mechanism through which teacher competencies are transformed into adoption behavior. The study contributes to the AI-in-education literature by providing a comprehensive model that integrates technological knowledge, psychological confidence, ethical understanding, and institutional learning support. The findings are expected to provide practical guidance for universities seeking to design effective AI professional development initiatives and develop sustainable strategies for responsible GenAI integration in higher education.

1. Introduction

Artificial intelligence (AI) has become one of the most influential technological innovations shaping higher education, transforming teaching, learning, assessment, research, and institutional administration. Although AI has been incorporated into education for several decades through intelligent tutoring systems, adaptive learning technologies, automated assessment, and learning analytics, the emergence of generative artificial intelligence (GenAI) has fundamentally changed the educational landscape. The public release of OpenAI's ChatGPT in November 2022 accelerated the adoption of large language models (LLMs) by making sophisticated AI capabilities widely accessible to educators and students, prompting universities worldwide to reconsider traditional pedagogical practices and institutional policies (Kasneci et al., 2023; Lo, 2023).

Generative AI differs from earlier educational technologies because it can generate human-like text, summarize scientific literature, create instructional materials, produce programming code, support academic writing, provide formative feedback, and engage in interactive dialogue. These capabilities enable AI to function not merely as an automation tool but also as a cognitive partner that supports complex teaching and learning processes. Consequently, higher education institutions are increasingly integrating GenAI into curriculum design, assessment, academic support, and research activities while simultaneously addressing concerns regarding educational quality, academic integrity, and responsible AI use (Labadze et al., 2023; Dempere et al., 2023).

The rapid diffusion of ChatGPT has generated an unprecedented volume of educational research. Early studies primarily explored students' and educators' perceptions, acceptance, and initial experiences with AI-assisted learning. However, recent systematic reviews indicate that research has progressively shifted towards broader issues, including pedagogical innovation, assessment redesign, prompt literacy, AI literacy, ethical governance, faculty development, and institutional readiness for responsible AI implementation (Lo, 2023; Montenegro-Rueda et al., 2023).

Recent evidence suggests that GenAI offers considerable opportunities to improve teaching and learning in higher education. AI-powered systems can provide personalized explanations, generate differentiated learning materials, support formative assessment, assist with lesson planning, summarize scholarly literature, develop assessment rubrics, and automate routine administrative tasks. Such applications enable educators to devote greater attention to higher-order instructional activities, including mentoring, collaborative learning, critical thinking, and problem-based learning. Systematic reviews further indicate that, when integrated within sound pedagogical frameworks, AI chatbots can enhance learner engagement, promote self-regulated learning, and improve instructional efficiency (Labadze et al., 2023; Dempere et al., 2023).

Despite these educational opportunities, scholars consistently emphasize that the effectiveness of GenAI depends on responsible and pedagogically informed implementation rather than the technology itself. Large language models may generate inaccurate information, fabricated citations, biased responses, or misleading content, requiring users to critically evaluate AI-generated outputs before incorporating them into academic work. Furthermore, concerns regarding academic integrity, copyright, transparency, data privacy, accountability, and excessive dependence on AI continue to influence institutional policies and classroom practice. Accordingly, researchers advocate human-centered approaches in which educators retain responsibility for pedagogical decision-making while employing AI as a complementary tool that enhances rather than replaces professional expertise (Kasneci et al., 2023; Lo, 2023).

Within this evolving educational environment, university teachers have become central to the successful integration of GenAI. Although students have generally adopted AI technologies rapidly, faculty members often demonstrate greater caution because they must ensure instructional quality, maintain assessment validity, uphold academic integrity, and address ethical implications associated with AI-assisted learning. Consequently, successful AI integration depends not only on technological availability but also on educators' competencies, confidence, ethical awareness, and willingness to adopt AI within their teaching practice. Recent reviews consistently identify faculty preparedness as one of the most critical determinants of sustainable AI implementation in higher education (Montenegro-Rueda et al., 2023; Labadze et al., 2023).

Increasingly, these teacher-related competencies are conceptualized under the broader construct of AI readiness, which extends beyond technical proficiency to encompass AI literacy, self-efficacy, ethical AI awareness, and institutional support. Universities are therefore investing in structured professional development initiatives to equip faculty with the knowledge and skills required to integrate AI responsibly into teaching and learning. Emerging scholarship argues that professional development should move beyond technical training to cultivate critical AI literacy, pedagogical competence, ethical reasoning, and continuous reflective practice, thereby enabling educators to adapt effectively to rapidly evolving AI technologies (Dempere et al., 2023; Labadze et al., 2023).

Although previous studies have examined individual determinants of AI adoption, such as AI literacy, technology acceptance, self-efficacy, or ethical concerns, relatively few have investigated these factors within a comprehensive AI readiness framework. Moreover, empirical evidence remains limited regarding how AI professional development contributes to university teachers' AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, and subsequent adoption intention, particularly in developing higher education systems such as Pakistan. Addressing this gap, the present study proposes an explanatory sequential mixed-methods model that examines the relationships among AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. By integrating these constructs into a unified conceptual framework, this study contributes to the growing literature on artificial intelligence in higher education by developing and testing an integrated model of university teachers' AI readiness (Arshad et al., 2024). Unlike traditional technology acceptance approaches that primarily explain adoption through perceived usefulness and ease of use, the proposed framework incorporates AI professional development, AI literacy, AI self-efficacy, and ethical AI awareness as essential mechanisms shaping responsible AI adoption. By examining AI readiness as a bridge between teacher competencies and classroom AI integration, the study provides a more comprehensive explanation of how educators transition from AI awareness to meaningful educational implementation.

Accordingly, the remainder of this paper is organized as follows. Section 2 critically reviews the literature on generative AI in higher education, AI literacy, teacher self-efficacy, professional development, ethical AI awareness, technology acceptance, and institutional readiness. Section 3 presents the theoretical framework and research hypotheses. Section 4 describes the research methodology and mixed-methods design. Section 5 outlines the measurement instrument and data collection procedures. Section 6 presents the proposed data analysis strategy, while the final sections discuss the anticipated contributions, implications, limitations, and directions for future research.

Research Objectives

The study objectives are:

1. To examine the relationship between AI professional development and university teachers' AI literacy.
2. To investigate the influence of AI literacy on AI self-efficacy and ethical AI awareness.
3. To examine the effect of teacher competencies on AI readiness.
4. To analyze the relationship between AI readiness and GenAI adoption intention.
5. To explore how teachers experience and interpret AI integration within higher education contexts.

Research Questions

To strengthen alignment between objectives, hypotheses, and methodology, the manuscript may include the following research questions:

RQ1: How does AI professional development influence university teachers' AI literacy?

RQ2: How do AI literacy, AI self-efficacy, and ethical AI awareness contribute to teachers' AI readiness?

RQ3: How does AI readiness influence university teachers' intention to adopt generative AI?

RQ4: How does adoption intention translate into classroom AI integration?

RQ5: What experiences and institutional factors influence teachers' readiness for responsible AI adoption?

2. Literature Review

2.1 Evolution of Generative Artificial Intelligence in Higher Education

Artificial intelligence (AI) has evolved from a specialized computational technology into a transformative force across multiple sectors, including higher education. Early educational applications of AI primarily focused on intelligent tutoring systems, adaptive learning environments, automated assessment, and learning analytics designed to personalize instruction and improve learning outcomes (Zawacki-Richter et al., 2019). These applications were generally task-specific and operated within predefined instructional frameworks. However, the emergence of generative artificial intelligence (GenAI), particularly large language models (LLMs), has substantially expanded the capabilities of AI by enabling systems to generate human-like text, produce programming code, summarize complex information, create educational content, and engage in interactive dialogue. The release of ChatGPT by OpenAI in November 2022 marked a watershed moment, rapidly accelerating the adoption of GenAI within higher education and stimulating extensive scholarly debate regarding its educational opportunities and challenges (Kasneci et al., 2023; Lo, 2023).

Unlike earlier AI systems that primarily automated routine educational tasks, GenAI has introduced new possibilities for knowledge creation, instructional design, and academic collaboration. Educators increasingly employ AI-powered tools to generate lesson plans, prepare lecture materials, develop assessment questions, create grading rubrics, summarize research literature, and support curriculum development. Similarly, students use GenAI to obtain explanations of complex concepts, receive writing support, practice programming, brainstorm ideas, and engage in self-directed learning. Consequently, AI is increasingly viewed as a collaborative cognitive partner rather than merely an information retrieval system or administrative technology (Hasan, 2024; Kasneci et al., 2023).

The rapid expansion of GenAI has been accompanied by an equally rapid increase in scholarly research. Systematic reviews published since 2023 consistently demonstrate exponential growth in publications examining the educational implications of ChatGPT and other large language models. Lo (2023), in a systematic review of ChatGPT research in education, reported that early studies largely focused on users' perceptions, opportunities, and concerns regarding AI-assisted learning. More recent research, however, has shifted toward pedagogical integration, assessment redesign, faculty preparedness, AI literacy, prompt literacy, ethical governance, and institutional policy development. Similarly, Labadze et al. (2023) concluded that educational institutions are transitioning from exploratory discussions of AI adoption toward developing strategic frameworks for responsible implementation that integrate technological, pedagogical, and organizational considerations (Karim, 2024; James, 2023).

One of the most significant contributions of GenAI lies in its capacity to facilitate personalized and learner-centered education. Contemporary AI systems can generate customized explanations, adapt instructional content to individual learner needs, provide immediate formative feedback, and support differentiated instruction. These capabilities align with constructivist and learner-centered pedagogical approaches by enabling flexible learning experiences while reducing instructors' administrative workload. Dempere et al. (2023) argued that GenAI has considerable potential to enhance teaching efficiency through automated content generation, academic writing support, and personalized learning assistance, provided that its use is guided by sound pedagogical principles. Rather than replacing educators, AI enables instructors to devote greater attention to mentoring, collaborative learning, and higher-order cognitive activities (Lo, 2023).

Despite these opportunities, scholars consistently emphasize that the educational value of GenAI depends on responsible implementation rather than technological capability alone. Large language models may generate inaccurate information, fabricated references, algorithmic bias, or misleading explanations, making human oversight indispensable. Kasneci et al. (2023) cautioned that educators should critically evaluate AI-generated content before incorporating it into teaching or assessment, while also helping students develop the critical evaluation skills necessary to use AI responsibly. Concerns surrounding academic integrity, plagiarism, copyright, transparency, privacy, and accountability have consequently become central themes in the higher education literature (Ullah & Usman, 2023). Rather than advocating unrestricted AI use, recent studies recommend human-centered approaches in which educators retain responsibility for pedagogical decision-making while employing AI as a complementary instructional tool (Khan et al., 20226).

Institutional responses to GenAI have also evolved rapidly. Universities worldwide are developing policies governing AI use in teaching, assessment, and research while investing in faculty development initiatives that strengthen educators' AI competencies. Recent literature argues that effective AI integration requires more than access to technological tools; it depends on institutional leadership, governance structures, ethical guidelines, and continuous professional learning opportunities that enable faculty members to integrate AI confidently and responsibly (Labadze et al., 2023). These developments reflect a broader shift from technology adoption toward institutional AI readiness, in which organizational culture, policy, and professional development collectively shape sustainable implementation (Ullah et al., 2024).

Collectively, the literature indicates that higher education has entered a new phase of digital transformation driven by generative AI. While GenAI offers unprecedented opportunities to enhance teaching, learning, assessment, and research, its educational impact ultimately depends on educators' ability to understand, evaluate, and integrate AI technologies within pedagogically sound and ethically responsible practices (Amin & Imtiaz, 2025). Consequently, recent scholarship increasingly identifies teacher-related competencies—particularly AI literacy, AI self-efficacy, ethical AI awareness, and professional development—as foundational elements of successful AI adoption. This progression provides the theoretical basis for the next section, which critically examines the concept of AI literacy among university teachers and its role in promoting effective and responsible AI integration.

2.2 Generative AI and Teaching–Learning Transformation

The emergence of generative artificial intelligence (GenAI) has fundamentally transformed teaching and learning in higher education by extending the role of AI beyond automation toward knowledge generation, instructional support, and collaborative learning (Zohora et al., 2024). Unlike earlier educational technologies that primarily assisted with administrative tasks or adaptive learning, GenAI enables educators and students to engage in interactive dialogue, generate instructional content, receive personalized feedback, and co-construct knowledge through natural language interaction (Kasneci et al., 2023). These capabilities have prompted educators to reconsider conventional pedagogical approaches and explore AI-assisted teaching strategies that promote active learning, creativity, and critical thinking (Shiva et al., 2024).

One of the most significant educational contributions of GenAI is its capacity to facilitate personalized learning. Large language models can adapt explanations to learners' prior knowledge, generate examples of varying complexity, provide instant formative feedback, and recommend learning resources tailored to individual needs. Such capabilities support learner-centered pedagogies by allowing students to progress at their own pace while receiving immediate academic support. Lo (2023), in a rapid review of ChatGPT in education, concluded that GenAI has considerable potential to improve personalized learning experiences, enhance student engagement, and support self-directed learning when integrated within appropriate pedagogical frameworks. Similarly, Grassini (2023) argued that AI-powered conversational systems can complement traditional teaching by providing continuous academic assistance beyond classroom boundaries (Islam & Shiva, 2024; Kasneci et al., 2023).

Assessment practices have experienced particularly significant changes following the widespread availability of GenAI. Traditional assessments that emphasize factual recall or generic essay writing have become increasingly vulnerable to AI-assisted content generation, compelling universities to reconsider assessment validity and authenticity (Twaha, 2024). Crawford et al. (2023) argued that higher education institutions should redesign assessment practices by emphasizing authentic, process-oriented, collaborative, and higher-order learning activities that cannot easily be replicated through AI alone. Contemporary recommendations include oral examinations, project-based learning, reflective portfolios, iterative writing tasks, and authentic workplace simulations that encourage students to demonstrate critical thinking, creativity, and disciplinary understanding rather than merely producing written outputs.

Despite these opportunities, the educational transformation associated with GenAI is accompanied by substantial challenges. Large language models may generate inaccurate information, fabricated references, biased content, or oversimplified explanations, requiring both educators and students to evaluate AI-generated outputs critically (Umma & Yeasin, 2025). Furthermore, concerns regarding academic integrity, plagiarism, copyright, data privacy, transparency, and algorithmic bias have become central considerations in higher education policy. UNESCO (2023) emphasized that educational institutions should develop governance frameworks that promote ethical, transparent, and human-centered AI use while safeguarding academic values and protecting learners' rights.

Recent scholarship therefore argues that the successful educational integration of GenAI depends less on technological capability than on educators' pedagogical competence and professional judgment. AI should complement rather than replace human expertise, with instructors retaining responsibility for curriculum design, instructional decision-making, assessment, and student mentorship. Faculty members require not only technical familiarity with AI tools but also the ability to evaluate their pedagogical value, recognize their limitations, and guide students in responsible AI use. These competencies are increasingly recognized as essential components of effective AI integration within higher education (Labadze et al., 2023).

Overall, the literature indicates that GenAI is reshaping higher education by transforming instructional design, personalized learning, assessment, and collaborative knowledge construction. However, realizing these benefits requires educators who possess sufficient knowledge, confidence, and ethical awareness to integrate AI meaningfully into their teaching practice. Consequently, attention has increasingly shifted from technological innovation to teacher preparedness, with AI literacy emerging as a foundational competency for effective and responsible AI adoption. The following section therefore examines the concept of AI literacy among university teachers and its role in supporting successful classroom integration of generative AI.

2.3 AI Literacy among University Teachers

The rapid integration of generative artificial intelligence (GenAI) into higher education has elevated AI literacy from a desirable digital competency to a fundamental requirement for effective teaching and learning. As AI systems become increasingly embedded in curriculum design, instructional delivery, assessment, and academic research, university teachers are expected not only to understand how these technologies function but also to evaluate their pedagogical value, recognize their limitations, and guide students in their responsible use. Consequently, AI literacy has emerged as one of the most extensively discussed constructs in recent AI-in-education research and is widely regarded as a prerequisite for successful AI adoption in higher education (Ng et al., 2021; Long & Magerko, 2020).

Although no universally accepted definition of AI literacy exists, scholars generally conceptualize it as a multidimensional competency that integrates knowledge, skills, attitudes, and ethical awareness related to artificial intelligence. Long and Magerko (2020) defined AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies, communicate effectively about AI, and use AI as informed consumers and creators. Expanding this perspective within educational contexts, Ng et al. (2021) proposed that AI literacy encompasses three interrelated dimensions: technical understanding of AI concepts, practical competencies for interacting with AI systems, and human-centered awareness of the ethical and societal implications of AI. This broader conceptualization recognizes that effective AI use requires more than technical proficiency; educators must also understand the educational, ethical, and social consequences of AI-supported decision-making.

Within higher education, AI literacy extends beyond basic technological competence because university teachers play multiple professional roles as instructors, assessors, researchers, mentors, and curriculum developers. Educators are therefore expected to make informed decisions regarding when, how, and why AI should be incorporated into teaching practice. According to UNESCO (2024), teachers require sufficient AI literacy to critically evaluate AI-generated outputs, design learning activities that promote responsible AI use, protect students' data privacy, and foster critical thinking rather than passive dependence on AI systems. These responsibilities position AI literacy as an essential component of contemporary pedagogical competence.

Recent empirical studies indicate that AI literacy positively influences educators' confidence, perceived usefulness of AI, and willingness to integrate AI into teaching. For example, Chiu (2024) argued that teachers with stronger AI literacy are better equipped to identify appropriate educational applications of GenAI, evaluate AI-generated content critically, and redesign instructional activities that encourage higher-order learning. Similarly, systematic reviews by Crompton and Burke (2023) reported that educators possessing greater AI knowledge demonstrate more positive attitudes toward AI-supported teaching and exhibit stronger intentions to adopt emerging educational technologies. These findings suggest that AI literacy functions as both a cognitive and motivational resource that facilitates technology adoption.

Despite growing recognition of its importance, existing evidence suggests that AI literacy among university faculty remains uneven across institutions and disciplines. Several studies report that many educators possess limited knowledge of how large language models operate, their underlying capabilities, and their inherent limitations. While faculty members frequently use AI tools for lesson preparation, academic writing, and content generation, they often report uncertainty regarding prompt engineering, output verification, bias detection, copyright, and ethical classroom implementation (Lo, 2023; UNESCO, 2023). This discrepancy highlights the distinction between using AI tools and understanding them sufficiently to integrate them into pedagogy in a responsible and evidence-informed manner.

The emergence of GenAI has further expanded the scope of AI literacy by introducing competencies that were previously absent from digital literacy frameworks. One such competency is prompt literacy, which refers to the ability to formulate effective prompts, iteratively refine interactions with AI systems, and critically evaluate generated responses. Rather than accepting AI-generated outputs uncritically, educators must learn to question factual accuracy, identify hallucinated information, recognize potential biases, and verify information using authoritative academic sources. Consequently, prompt literacy is increasingly viewed as a practical extension of AI literacy that enables educators to interact effectively with conversational AI systems while maintaining academic rigor (Lo, 2023).

From a theoretical perspective, AI literacy serves as a foundational capability that influences subsequent psychological and behavioral outcomes. Individuals who possess greater knowledge and understanding of AI are more likely to develop stronger confidence in using AI technologies, perceive AI as useful for professional practice, and demonstrate greater willingness to adopt AI-supported innovations. Conversely, inadequate AI literacy may contribute to uncertainty, technology-related anxiety, resistance to innovation, and inappropriate or ineffective classroom implementation. These relationships are consistent with educational technology research demonstrating that knowledge acquisition often precedes the development of self-efficacy, positive attitudes, and behavioral intention toward new technologies (Bandura, 1997; Venkatesh et al., 2003).

Overall, the literature consistently identifies AI literacy as a cornerstone of effective and responsible AI integration in higher education. It equips university teachers with the knowledge, critical judgment, and ethical awareness necessary to evaluate AI technologies and apply them appropriately within educational contexts. However, knowledge alone does not guarantee technology adoption. Educators must also possess confidence in their ability to use AI effectively in professional practice. Therefore, the next section examines **AI self-efficacy** and its role in shaping university teachers' readiness and intention to integrate generative AI into teaching and learning.

2.4 Teacher AI Self-Efficacy and AI Adoption

While AI literacy provides university teachers with the knowledge and understanding required to engage with artificial intelligence technologies, knowledge alone does not guarantee effective adoption. A critical factor influencing whether educators integrate AI into their professional practice is their belief in their own capability to use AI tools successfully. This belief is commonly conceptualized as self-efficacy, a central construct in social cognitive theory developed by Bandura (1997). Self-efficacy refers to individuals' judgments about their ability to organize and execute actions required to achieve desired outcomes. In educational technology contexts, self-efficacy influences teachers' willingness to experiment with new technologies, persistence when facing challenges, and confidence in adapting technology to support instructional goals.

The concept of teacher self-efficacy has traditionally been associated with instructional effectiveness, classroom management, and willingness to adopt innovative teaching approaches. Research consistently demonstrates that teachers with higher levels of self-efficacy are more likely to explore new pedagogical strategies, engage in professional learning, and demonstrate greater resilience when encountering technological challenges (Tschannen-Moran & Hoy, 2001). As artificial intelligence becomes increasingly embedded within educational environments, teacher self-efficacy has gained renewed importance because successful AI integration requires educators not only to understand AI capabilities but also to feel capable of applying these technologies effectively within authentic teaching situations.

Recent research suggests that confidence plays a significant role in shaping educators' acceptance of AI. Teachers who lack confidence in their ability to use AI may experience uncertainty, anxiety, or resistance, even when they recognize the potential benefits of these technologies. Conversely, educators who feel competent in using AI are more likely to experiment with AI-supported teaching strategies and develop innovative approaches to classroom integration. This relationship aligns with technology acceptance models, which identify perceived competence and confidence as important antecedents of perceived usefulness, behavioral intention, and actual technology use (Davis, 1989; Venkatesh et al., 2003).

Professional experience and institutional learning opportunities also influence teachers' AI self-efficacy. Bandura (1997) identified mastery experiences, social learning, verbal encouragement, and reduced anxiety as key sources of self-efficacy development. Applied to AI adoption, this suggests that hands-on experimentation, peer collaboration, mentoring, and structured professional development programmes can enhance teachers' confidence in using AI technologies. Faculty members who receive opportunities to practice AI-supported teaching activities are more likely to develop realistic expectations about AI capabilities and integrate these tools more effectively.

Overall, the literature suggests that AI self-efficacy represents a key psychological mechanism connecting AI knowledge with actual adoption behavior. While AI literacy provides the foundation for understanding AI technologies, self-efficacy determines whether educators feel capable of applying this knowledge in practice. Therefore, strengthening teacher confidence through targeted professional development is essential for developing AI-ready higher education institutions. The following section examines the role of **AI professional development** as a mechanism for building teachers' literacy, confidence, ethical awareness, and readiness for AI integration.

2.5 Professional Development for AI Integration

The successful integration of generative artificial intelligence (GenAI) in higher education depends largely on educators' ability to develop the knowledge, confidence, and pedagogical judgment required to use AI effectively. Although universities are increasingly adopting AI-enabled technologies, access to AI tools alone does not ensure meaningful educational transformation. Research on educational technology adoption consistently demonstrates that teachers require structured professional learning opportunities to develop the competencies necessary for effective technology integration (Ertmer & Ottenbreit-Leftwich, 2010). In the context of GenAI, professional development has become particularly important because educators must understand not only how AI tools operate but also how these technologies influence teaching practices, assessment, academic integrity, and ethical decision-making.

Traditional technology training programmes have often focused on operational skills, such as learning how to use specific software applications. However, the rapidly evolving nature of GenAI requires a broader approach to professional development. Effective AI professional development should integrate technological knowledge, pedagogical application, critical evaluation skills, and ethical awareness. Koehler and Mishra's (2009) Technological Pedagogical Content Knowledge (TPACK) framework provides a useful foundation for understanding this requirement, emphasizing that successful technology integration occurs when teachers combine knowledge of technology with knowledge of pedagogy and subject matter. Applied to GenAI, this perspective suggests that educators need more than familiarity with AI tools; they need the ability to determine when and how AI can enhance disciplinary learning objectives.

Recent literature emphasizes that AI professional development should focus on developing AI literacy rather than simply promoting tool adoption. Teachers need opportunities to understand AI concepts, experiment with generative systems, evaluate AI-generated outputs, identify limitations, and explore responsible classroom applications. UNESCO (2023) highlights that teacher preparation for AI should include competencies related to human-centered AI use, ethical considerations, data protection, and critical evaluation of AI-generated information. Such approaches position professional development as a continuous process of developing informed and reflective AI users rather than one-time technical training.

Overall, the literature suggests that AI professional development represents a critical pathway for preparing university teachers for responsible GenAI integration. Effective professional learning should move beyond technical instruction by developing educators' AI literacy, strengthening self-efficacy, promoting ethical awareness, and connecting AI capabilities with meaningful pedagogical practice. Consequently, AI professional development is positioned as a foundational factor influencing teachers' overall AI readiness and intention to integrate GenAI into higher education teaching. The following section examines **ethical AI awareness** as a critical dimension of responsible AI adoption.

2.6 Ethical AI Awareness in Higher Education

The increasing adoption of generative artificial intelligence (GenAI) in higher education has intensified discussions regarding ethical responsibility, academic values, and the governance of AI-supported teaching and learning. While AI technologies provide significant opportunities for enhancing educational practices, their implementation introduces complex ethical challenges related to accuracy, transparency, privacy, fairness, accountability, and academic integrity. Consequently, ethical AI awareness has emerged as a critical competency for university teachers who are expected to make informed decisions regarding the appropriate use of AI technologies in educational contexts.

Ethical AI awareness refers to educators' understanding of the potential benefits, limitations, risks, and societal implications associated with artificial intelligence. Unlike technical AI literacy, which focuses primarily on understanding and using AI systems, ethical AI awareness emphasizes the ability to critically evaluate AI applications and consider their consequences for learners, educators, and institutions. This distinction is particularly important in higher education because AI-supported decisions can influence assessment outcomes, access to learning opportunities, student privacy, and the credibility of academic processes (UNESCO, 2021).

The emergence of large language models has expanded the ethical challenges associated with AI use in education. Generative AI systems can produce highly convincing responses; however, they may also generate inaccurate information, fabricated citations, biased outputs, or content that reflects limitations within their training data. For university teachers, this creates a responsibility to evaluate AI-generated information before incorporating it into instructional materials, research activities, or assessment practices. Kasneci et al. (2023) emphasized that educators must develop critical awareness of AI limitations because overreliance on AI-generated outputs may negatively influence knowledge development and academic decision-making.

Academic integrity represents one of the most widely discussed ethical concerns surrounding GenAI adoption. The ability of AI systems to generate essays, reports, code, and other academic products has challenged traditional approaches to assessment and authorship. Rather than viewing AI solely as a threat to academic integrity, researchers argue that universities should reconsider assessment practices and develop approaches that emphasize creativity, critical thinking, reflection, and authentic demonstration of learning (Cotton et al., 2023). This requires educators to understand both the risks and productive possibilities of AI-assisted learning.

Research on technology adoption suggests that ethical perceptions influence individuals' willingness to engage with emerging technologies. While perceived usefulness and ease of use are important predictors of adoption, concerns regarding risks, trust, and responsible implementation also shape technology acceptance decisions (Venkatesh et al., 2003). In the context of GenAI, teachers who perceive AI as ethically manageable and aligned with educational values may demonstrate stronger adoption intentions, whereas concerns about misuse, reliability, or negative consequences may reduce willingness to integrate AI into teaching practice.

Overall, the literature indicates that ethical AI awareness is a fundamental component of responsible AI integration in higher education. It enables teachers to critically assess AI capabilities, manage risks, protect academic values, and implement AI in ways that support meaningful learning. Therefore, ethical awareness is expected to influence teachers' overall AI readiness and adoption intention. The next section examines technology acceptance theories, particularly the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), which provide theoretical explanations for why educators choose to adopt or reject emerging technologies.

2.7 Technology Acceptance (TAM and UTAUT) and AI Adoption Intention

Understanding why university teachers decide to adopt or avoid generative artificial intelligence (GenAI) requires a theoretical explanation of technology acceptance behavior. While access to AI tools and awareness of their potential benefits are important, actual adoption depends largely on users' perceptions, beliefs, and intentions regarding technology use. Within educational technology research, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are among the most influential frameworks used to explain individuals' willingness to adopt new technologies.

The Technology Acceptance Model, introduced by Davis (1989), proposes that technology adoption is primarily determined by two core beliefs: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which individuals believe that using a technology will improve their performance, whereas perceived ease of use reflects the degree to which they believe that using the technology will require minimal effort. According to TAM, these perceptions influence users' attitudes toward technology, which subsequently shape behavioral intention and actual use. The model has been widely applied in educational technology research to explain teachers' acceptance of learning management systems, online learning platforms, mobile technologies, and emerging digital tools.

In the context of GenAI, TAM provides a valuable framework for understanding educators' adoption decisions. University teachers are more likely to integrate AI into teaching when they perceive that AI tools can enhance instructional effectiveness, reduce workload, support assessment, or improve student learning experiences. Conversely, concerns about complexity, uncertainty, or limited relevance may reduce adoption intention. Recent studies on ChatGPT adoption in education suggest that perceived usefulness remains a significant factor influencing educators' willingness to engage with generative AI technologies (Alshammari & Alshammari, 2023; Choi et al., 2023).

However, the rapid development of AI technologies introduces factors that extend beyond traditional technology acceptance models. Unlike conventional educational technologies, GenAI requires users to interpret AI-generated content, evaluate accuracy, understand ethical implications, and develop appropriate strategies for classroom integration. Therefore, additional psychological and contextual factors, including AI literacy, self-efficacy, trust, perceived risk, and institutional support, have become increasingly relevant in explaining AI adoption behavior.

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), expands technology acceptance research by integrating multiple theoretical perspectives. UTAUT identifies four major determinants of behavioral intention and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy represents the belief that technology will improve professional performance, while effort expectancy reflects perceived ease of use. Social influence captures the impact of colleagues and institutional culture, and facilitating conditions refer to the availability of resources and support necessary for successful technology adoption.

Overall, TAM and UTAUT provide the theoretical foundation for examining adoption intention, while AI readiness provides a broader conceptual lens for explaining responsible and sustainable AI integration in higher education. The next section examines institutional support and AI readiness, highlighting the organizational factors that influence teachers' ability to move from intention toward actual classroom implementation.

2.8 Institutional Support and AI Readiness in Higher Education

The integration of generative artificial intelligence (GenAI) in higher education is not determined solely by individual teachers' knowledge, confidence, or willingness to adopt new technologies. Although teacher-level factors such as AI literacy, self-efficacy, and ethical awareness significantly influence adoption decisions, sustainable AI implementation requires supportive institutional environments. Higher education institutions play a critical role in shaping AI adoption through strategic leadership, infrastructure development, policy formulation, professional development opportunities, and the creation of organizational cultures that encourage responsible innovation.

Institutional support has long been recognized as an important determinant of successful educational technology integration. Research on technology adoption indicates that teachers are more likely to implement new technologies when institutions provide adequate resources, technical assistance, training opportunities, and supportive policies (Ertmer & Ottenbreit-Leftwich, 2010). In contrast, limited organizational support may create barriers such as uncertainty, lack of confidence, resistance to change, and inconsistent technology use. Therefore, AI adoption should be understood as a socio-technical process in which individual competencies interact with institutional conditions.

The emergence of GenAI has further increased the importance of institutional readiness because AI technologies introduce challenges that extend beyond traditional technology implementation. Universities must establish policies regarding academic integrity, assessment practices, data privacy, ethical AI use, and responsible innovation. Without clear institutional guidance, educators may experience uncertainty regarding appropriate

AI applications, acceptable student use, and professional responsibilities. UNESCO (2023) emphasizes that educational institutions require governance frameworks that promote transparency, accountability, and human-centered AI adoption.

Overall, the literature demonstrates that successful GenAI adoption in higher education requires alignment between individual readiness and institutional capacity. Teacher competencies provide the foundation for AI integration, while institutional support creates the environment necessary for sustainable implementation. The next section identifies the remaining research gaps and develops the conceptual framework that guides the present study.

2.9 Research Gap and Development of the Conceptual Framework

The literature reviewed above demonstrates that generative artificial intelligence (GenAI) has introduced substantial opportunities and challenges for higher education. Existing research has examined various dimensions of AI adoption, including technological capabilities, student experiences, ethical concerns, and educator perceptions. However, despite the rapid growth of AI-in-education research, several important gaps remain regarding how university teachers develop the competencies and confidence required for meaningful and responsible AI integration.

First, previous studies have largely focused on the potential applications and challenges of GenAI rather than the processes through which educators become prepared to adopt AI. While research has identified AI literacy as an essential competency, limited empirical attention has been given to how AI literacy develops among university teachers and how it influences subsequent adoption behaviors. Existing evidence suggests that knowledge of AI is necessary but insufficient; educators must also possess confidence, ethical awareness, and opportunities for professional learning before AI can be effectively integrated into teaching practice.

The proposed framework combines perspectives from social cognitive theory (Bandura, 1997), technology acceptance theories (Davis, 1989; Venkatesh et al., 2003), technological pedagogical knowledge frameworks (Koehler & Mishra, 2009), and emerging AI literacy research (Long & Magerko, 2020; Ng et al., 2021). By integrating these perspectives, the framework moves beyond a simple technology acceptance approach and conceptualizes AI adoption as a multidimensional process involving knowledge development, confidence building, ethical reflection, and institutional preparedness.

The conceptual sequence proposed in this study is:

AI Professional Development → AI Literacy → AI Self-Efficacy → Ethical AI Awareness → AI Readiness → Adoption Intention → Classroom AI Integration

In this model, AI professional development represents the institutional mechanism through which teachers acquire knowledge and practical experience with GenAI. AI literacy represents the cognitive foundation that enables educators to understand and evaluate AI technologies. AI self-efficacy reflects teachers' confidence in their ability to use AI effectively, while ethical AI awareness represents their capacity to recognize and address responsible AI challenges. Together, these competencies contribute to AI readiness, defined as educators' overall preparedness to integrate AI into professional practice. Finally, AI readiness is expected to influence teachers' intention to adopt GenAI and their actual classroom integration behaviors.

This conceptualization provides a more comprehensive explanation of AI adoption in higher education by recognizing that successful integration depends not only on technology availability or perceived usefulness but also on educators' capabilities, beliefs, ethical understanding, and institutional environment. Accordingly, the present study contributes to the growing AI-in-education literature by developing and testing an integrated model of teacher AI readiness within higher education.

Based on this framework, the following sections present the theoretical framework, research hypotheses, methodology, measurement strategy, and analytical approach used to examine the proposed relationships.

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Foundation

The integration of generative artificial intelligence (GenAI) in higher education represents a complex adoption process involving technological, psychological, ethical, and organizational factors. Therefore, a single theoretical perspective is insufficient to explain why university teachers choose to adopt or avoid AI-supported teaching practices. The present study integrates multiple theoretical perspectives, including Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and AI literacy frameworks, to develop a comprehensive explanation of teachers' AI readiness and adoption intention.

Social Cognitive Theory (Bandura, 1986, 1997) provides the foundation for understanding the role of teacher confidence and competence in AI adoption. According to this perspective, individuals' behaviors are influenced by reciprocal interactions among personal factors, environmental conditions, and behavioral experiences. A central concept within SCT is self-efficacy, which refers to individuals' beliefs about their capability to perform specific actions successfully. In the context of GenAI adoption, teacher AI self-efficacy represents educators' confidence in their ability to understand, operate, evaluate, and integrate AI technologies into teaching practice. Teachers with stronger self-efficacy are more likely to experiment with emerging technologies, persist when facing difficulties, and develop innovative instructional practices.

The Technology Acceptance Model (Davis, 1989) and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) provide the theoretical basis for explaining technology adoption intention. TAM proposes that perceived usefulness and perceived ease of use influence users' attitudes and behavioral intentions toward technology adoption. Similarly, UTAUT emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as important predictors of technology acceptance. Within GenAI contexts, these models suggest that teachers' adoption decisions are influenced by their perceptions of AI usefulness, usability, confidence, institutional support, and social environment.

However, traditional acceptance models do not fully capture the complexity of GenAI adoption in education because AI technologies introduce additional requirements related to critical evaluation, ethical judgment, and responsible use. Therefore, this study extends technology acceptance perspectives by incorporating AI literacy, ethical AI awareness, and AI readiness as key constructs. AI literacy provides teachers with the knowledge required to understand AI capabilities and limitations, while ethical AI awareness enables educators to evaluate responsible implementation issues. Together with self-efficacy, these competencies contribute to teachers' overall AI readiness.

AI readiness represents the central construct of the proposed framework. Unlike simple technology acceptance, which focuses primarily on intention to use technology, AI readiness reflects whether educators possess the knowledge, confidence, ethical understanding, and preparedness required for meaningful AI integration. Therefore, this study conceptualizes AI readiness as a multidimensional construct linking teacher competencies with adoption behavior and classroom implementation.

3.2 Hypotheses Development

AI Professional Development and AI Literacy

Professional development represents an important mechanism through which educators acquire knowledge and skills necessary for technology integration. Previous research demonstrates that structured training opportunities enhance teachers' technological competencies and improve their ability to integrate digital tools into teaching practice (Ertmer & Ottenbreit-Leftwich, 2010). In the context of GenAI, professional development can provide educators with opportunities to understand AI concepts, explore practical applications, evaluate AI outputs, and develop responsible usage strategies.

Therefore, teachers who participate in AI-focused professional development are expected to demonstrate higher levels of AI literacy.

H1: AI professional development positively influences university teachers' AI literacy.

AI Literacy and AI Self-Efficacy

AI literacy provides educators with conceptual understanding and practical knowledge necessary to interact effectively with AI technologies. According to Social Cognitive Theory, mastery experiences and knowledge acquisition contribute to stronger beliefs in one's capability to perform a task (Bandura, 1997). Teachers who understand AI functions, limitations, and applications are likely to feel more confident using AI tools in educational settings.

Therefore, higher AI literacy is expected to enhance teachers' AI self-efficacy.

H2: AI literacy positively influences university teachers' AI self-efficacy.

AI Literacy and Ethical AI Awareness

Responsible AI integration requires educators to understand both technological possibilities and ethical implications. AI literacy enables teachers to critically evaluate AI-generated content, recognize limitations, and make informed decisions regarding appropriate educational applications. As educators develop greater understanding of AI systems, they are expected to become more aware of issues related to bias, privacy, transparency, and academic integrity.

Therefore, AI literacy is expected to contribute to ethical AI awareness.

H3: AI literacy positively influences university teachers' ethical AI awareness.

AI Self-Efficacy and AI Readiness

Self-efficacy influences individuals' willingness to engage with challenging technologies and persist during implementation difficulties. Teachers who believe they are capable of using AI effectively are more likely to perceive themselves as prepared for AI-supported teaching. Higher confidence can reduce uncertainty and increase willingness to explore AI applications.

Therefore, AI self-efficacy is expected to strengthen overall AI readiness.

H4: AI self-efficacy positively influences university teachers' AI readiness.

Ethical AI Awareness and AI Readiness

AI readiness requires not only technical ability but also responsible judgment regarding appropriate technology use. Teachers who understand ethical AI issues are better prepared to implement AI while maintaining academic standards, protecting student privacy, and addressing potential risks.

Therefore, ethical AI awareness is expected to enhance AI readiness.

H5: Ethical AI awareness positively influences university teachers' AI readiness.

AI Readiness and Adoption Intention

Technology adoption literature suggests that individuals are more likely to use technologies when they feel prepared and capable of doing so. AI readiness reflects teachers' overall preparedness to engage with AI tools and is expected to influence their willingness to adopt GenAI for teaching purposes.

Therefore, AI readiness is expected to predict adoption intention.

H6: AI readiness positively influences university teachers' intention to adopt generative AI.

Adoption Intention and Classroom AI Integration

Behavioral intention is widely recognized as a strong predictor of actual technology use within TAM and UTAUT frameworks. Teachers who intend to adopt AI are more likely to integrate AI tools into instructional planning, assessment, and classroom activities.

Therefore, adoption intention is expected to influence classroom AI integration.

H7: Adoption intention positively influences university teachers' classroom AI integration.

Mediating Role of AI Readiness

The proposed framework assumes that professional development and teacher competencies influence adoption through the development of AI readiness. AI readiness represents the mechanism through which knowledge, confidence, and ethical awareness are translated into actual adoption behavior.

Therefore:

H8: AI readiness mediates the relationship between AI literacy, AI self-efficacy, ethical AI awareness, and adoption intention.

Proposed Conceptual Model

The theoretical model proposed in this study is:

AI Professional Development

↓

AI Literacy

↓

AI Self-Efficacy + Ethical AI Awareness

↓

AI Readiness

↓

Adoption Intention

↓

Classroom AI Integration

This integrated framework extends traditional technology acceptance approaches by incorporating teacher competence and responsible AI considerations, providing a more comprehensive explanation of GenAI adoption among university educators.

4. Research Methodology

4.1 Research Design

This study adopts an explanatory sequential mixed-methods research design to investigate how generative artificial intelligence (GenAI) professional development influences university teachers' AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. The explanatory sequential design is appropriate when quantitative findings are collected and analyzed first, followed by qualitative inquiry to explain, interpret, and provide deeper understanding of the statistical relationships identified during the initial phase (Creswell & Plano Clark, 2018).

The quantitative phase of the study aims to test the proposed conceptual model and examine the hypothesized relationships among the research constructs using structural equation modeling (SEM). The qualitative phase subsequently explores teachers' experiences, perceptions, challenges, and contextual factors influencing AI adoption. By combining statistical analysis with in-depth qualitative insights, the study seeks to provide a comprehensive understanding of both the measurable relationships and the underlying reasons behind university teachers' AI adoption behaviors.

This methodological approach aligns with the complexity of AI integration in higher education, where adoption is influenced not only by individual competencies but also by professional experiences, institutional environments, and ethical considerations. Quantitative analysis provides evidence regarding the strength and direction of relationships among constructs, whereas qualitative findings provide contextual explanations regarding how and why teachers develop readiness for GenAI integration.

4.2 Research Philosophy and Approach

The study follows a pragmatic research philosophy, which emphasizes selecting research methods based on their ability to address the research problem effectively rather than adherence to a single philosophical position. Pragmatism is particularly suitable for mixed-methods research because it allows researchers to combine quantitative and qualitative approaches to generate practical and contextually meaningful knowledge (Creswell & Plano Clark, 2018).

The research follows a deductive approach in the quantitative phase, where hypotheses derived from existing theories and literature are empirically tested. The qualitative phase adopts a more exploratory approach, allowing participants to explain their experiences and provide insights that may extend or refine existing theoretical understandings of AI adoption.

4.3 Research Context and Population

The target population of this study consists of university teachers working in higher education institutions. The focus on university educators is justified because faculty members represent key decision-makers in AI-supported teaching and learning practices. Their knowledge, confidence, ethical understanding, and institutional experiences directly influence whether GenAI becomes meaningfully integrated into classroom activities.

The study focuses on higher education institutions because universities are currently experiencing significant transformation due to the emergence of GenAI tools. Faculty members are increasingly expected to redesign instructional practices, evaluate AI-generated content, modify assessment approaches, and guide students in responsible AI use.

The research context will include universities from Pakistan, representing a developing higher education environment where AI adoption is emerging but institutional strategies, faculty training opportunities, and governance frameworks remain under development.

4.4 Sampling Strategy

The quantitative phase will employ a probability-based or non-probability sampling approach depending on institutional accessibility and participant availability. University teachers from diverse academic disciplines will be invited to participate to capture variation in AI experiences across fields.

A sample size appropriate for structural equation modeling will be determined based on established SEM guidelines. The required sample size will consider model complexity, number of observed variables, expected effect sizes, and statistical power requirements (Hair et al., 2022).

For the qualitative phase, purposive sampling will be used to select participants who can provide rich information regarding AI adoption experiences. Participants may include teachers with different levels of AI exposure, including early adopters, occasional users, and educators who have limited experience with GenAI tools. This variation will allow exploration of diverse perspectives regarding AI readiness and adoption challenges.

4.5 Data Collection Procedure

Data collection will occur in two sequential phases.

During the quantitative phase, participants will complete a structured questionnaire measuring AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. The survey will be distributed electronically through university networks and professional academic channels.

Following quantitative analysis, the qualitative phase will involve semi-structured interviews with selected participants. Interview questions will be developed based on quantitative findings, particularly focusing on unexpected relationships, important predictors, adoption barriers, and contextual factors influencing AI integration.

The integration of both phases will occur during interpretation, where qualitative findings will be used to explain and enrich the quantitative results. This approach allows the study to move beyond identifying statistical relationships toward understanding the practical experiences behind AI adoption.

4.6 Ethical Considerations

Ethical principles will guide all stages of the research process. Participation will be voluntary, and participants will receive information regarding the purpose of the study, confidentiality procedures, and their right to withdraw. No personally identifiable information will be reported, and collected data will be used exclusively for academic research purposes.

Because AI adoption involves professional practices and institutional experiences, particular attention will be given to protecting participants' privacy and ensuring that responses cannot negatively affect their professional roles. Ethical approval will be obtained from the relevant institutional review authority before data collection begins.

4.7 Data Analysis Strategy

The quantitative data will be analyzed using structural equation modeling techniques. Depending on data characteristics and research objectives, covariance-based SEM (CB-SEM) using AMOS or partial least squares SEM (PLS-SEM) using SmartPLS may be employed.

The analysis will include:

- Descriptive statistics to summarize participant characteristics.
- Reliability analysis to evaluate internal consistency of measurement scales.
- Validity assessment through convergent and discriminant validity testing.
- Measurement model evaluation.
- Structural model assessment.
- Hypothesis testing using path coefficients, significance levels, and effect sizes.
- Mediation analysis to examine the role of AI readiness.

The qualitative data will be analyzed using thematic analysis following the approach proposed by Braun and Clarke (2006). Interview transcripts will be coded systematically to identify recurring themes related to AI experiences, professional development, institutional support, ethical concerns, and adoption challenges.

The integration of quantitative and qualitative findings will provide a comprehensive explanation of university teachers' AI readiness and adoption behavior.

4.8 Methodological Contribution

The proposed methodology contributes to AI-in-education research by combining predictive modeling with contextual exploration. While quantitative analysis identifies relationships among key determinants of AI adoption, qualitative inquiry explains how teachers experience and interpret AI transformation within their institutional environments. This mixed-methods approach provides a more complete understanding of AI readiness than either method could achieve independently.

5. Measurement Instrument and Questionnaire Development

5.1 Instrument Development

The measurement instrument for this study will be developed based on established scales from previous research and adapted to the context of generative artificial intelligence (GenAI) adoption in higher education. Since the proposed framework integrates constructs from AI literacy research, technology acceptance theory, social cognitive theory, and educational technology literature, the questionnaire will combine validated measurement approaches while ensuring contextual relevance for university teachers.

The instrument will be structured into two major sections. The first section will collect demographic and professional information, including academic discipline, teaching experience, academic position, previous exposure to AI tools, and participation in AI-related professional development activities. The second section will measure the main research constructs: AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration.

All construct items will be measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Likert-type scales are commonly used in educational technology research because they allow measurement of perceptions, beliefs, attitudes, and behavioral intentions.

5.2 AI Professional Development

AI professional development refers to the extent to which university teachers receive structured learning opportunities that enhance their understanding and application of AI technologies in teaching practice. In this study, professional development is conceptualized as including exposure to AI concepts, practical training, pedagogical applications, ethical considerations, and opportunities for hands-on experimentation.

Items will be adapted from technology professional development and teacher technology integration literature (Ertmer & Ottenbreit-Leftwich, 2010; Koehler & Mishra, 2009). Example items include:

- Our institution provides opportunities for us to learn about generative AI technologies.
- We have received training on how to use AI tools for teaching and learning.
- Professional development activities have improved my ability to integrate AI into our teaching practice.
- Our AI training includes ethical and responsible use considerations.

5.3 AI Literacy

AI literacy represents teachers' knowledge, understanding, and ability to critically engage with artificial intelligence technologies. Based on AI literacy frameworks proposed by Long and Magerko (2020) and Ng et al. (2021), the construct includes awareness of AI concepts, understanding of AI capabilities and limitations, and the ability to evaluate AI-generated outputs.

Example items include:

- We understand the basic principles of how AI systems generate responses.
- We can identify appropriate educational applications of generative AI.

- We can evaluate whether AI-generated information is accurate and reliable.
- We understand the limitations and risks associated with AI technologies.

AI literacy is expected to function as a foundational competency influencing teachers' confidence and responsible AI adoption.

5.4 AI Self-Efficacy

AI self-efficacy refers to teachers' confidence in their ability to use and integrate AI technologies effectively in educational practice. This construct is based on Bandura's (1997) self-efficacy theory and adapted from technology self-efficacy research.

Example items include:

- We feel confident using generative AI tools for teaching-related activities.
- We can learn new AI applications when they become available.
- We can solve basic problems when using AI-supported educational tools.
- We believe we can successfully integrate AI into our courses.

Higher levels of AI self-efficacy are expected to increase teachers' readiness and willingness to adopt GenAI.

5.5 Ethical AI Awareness

Ethical AI awareness refers to teachers' understanding of responsible AI use, including issues related to academic integrity, privacy, bias, transparency, and appropriate classroom implementation. This construct reflects the growing emphasis on human-centered AI adoption in education (UNESCO, 2021, 2023).

Example items include:

- We understand ethical issues associated with using AI in education.
- We are aware that AI-generated information may contain inaccuracies or bias.
- We consider student privacy when using AI-based tools.
- We understand the importance of responsible AI use in academic settings.

Ethical awareness is expected to contribute to responsible AI readiness rather than simple technology adoption.

5.6 AI Readiness

AI readiness represents teachers' overall preparedness to integrate AI into their professional practice. Unlike adoption intention, which focuses on willingness to use technology, AI readiness reflects the combination of knowledge, confidence, ethical understanding, and preparedness required for effective implementation.

The construct is conceptualized as a multidimensional readiness factor consisting of cognitive, psychological, and ethical dimensions.

Example items include:

- We feel prepared to integrate generative AI into my teaching practice.
- We have the necessary skills to use AI effectively in education.
- We understand how AI can support my instructional goals.
- We feel capable of addressing challenges associated with AI implementation.

5.7 Adoption Intention

Adoption intention represents teachers' willingness and planned behavior to use generative AI in teaching and learning. This construct is derived from the Technology Acceptance Model (Davis, 1989) and UTAUT (Venkatesh et al., 2003).

Example items include:

- We intend to use generative AI tools in our teaching activities.
- We plan to increase our use of AI technologies in the future.
- We would recommend appropriate AI tools for educational purposes.
- We expect to incorporate AI into our professional practice.

5.8 Classroom AI Integration

Classroom AI integration represents the actual or intended application of AI tools in teaching-related activities. It includes instructional planning, content development, assessment support, feedback provision, and learning activities.

Example items include:

- We use AI tools to support lesson preparation.
- We use AI-generated materials as part of instructional activities.
- We use AI tools to support assessment or feedback processes.
- We encourage students to use AI responsibly for learning purposes.

5.9 Content Validity and Pilot Testing

Before large-scale data collection, the questionnaire will undergo expert review to establish content validity. Experts in educational technology, artificial intelligence, and higher education will evaluate whether items appropriately represent each construct and are suitable for the research context.

A pilot study will then be conducted with a small group of university teachers to assess item clarity, questionnaire length, and preliminary reliability. Feedback from pilot participants will be used to refine the instrument before final administration.

5.10 Reliability and Validity Assessment

The measurement model will be evaluated using reliability and validity criteria. Internal consistency reliability will be assessed using Cronbach's alpha and composite reliability values. Convergent validity will be examined through factor loadings and average variance extracted (AVE), while discriminant validity will be assessed using established criteria such as the Fornell–Larcker criterion and heterotrait–monotrait ratio (HTMT).

These procedures ensure that the measurement instrument provides a reliable and valid assessment of university teachers' AI readiness and adoption behaviors.

6. Data Analysis Plan

6.1 Overview of Data Analysis Strategy

The data analysis strategy will follow the explanatory sequential mixed-methods design adopted in this study. The quantitative phase will be conducted first to test the proposed conceptual model and examine relationships among AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. The qualitative phase will subsequently be conducted to explain and contextualize the quantitative findings by exploring teachers' experiences, perceptions, and challenges related to generative AI adoption.

The quantitative analysis will be performed using structural equation modeling (SEM), which is appropriate for examining complex relationships among multiple latent constructs. Depending on the research objectives and data characteristics, partial least squares structural equation modeling (PLS-SEM) using SmartPLS or covariance-based SEM (CB-SEM) using AMOS may be employed. PLS-SEM is particularly suitable when the objective is prediction and theory development, while CB-SEM is commonly used for theory confirmation and model fit assessment (Hair et al., 2022).

6.2 Preliminary Data Screening

Before conducting SEM analysis, the collected data will undergo preliminary screening to ensure data quality and suitability for analysis. This stage will include:

- Checking missing values and incomplete responses.
- Identifying potential outliers.
- Examining data distribution and normality.
- Assessing common method bias.

Missing data will be examined and appropriately handled using recommended statistical procedures. Outliers will be evaluated through appropriate multivariate techniques. Since the study relies on self-reported questionnaire data collected from the same respondents, common method bias will be assessed using procedural and statistical approaches, including Harman's single-factor test and full collinearity assessment where appropriate.

6.3 Descriptive Statistics Analysis

Descriptive statistics will be conducted to summarize participant characteristics and provide an overview of AI adoption patterns among university teachers. Demographic variables such as academic discipline, teaching experience, academic position, previous AI exposure, and participation in AI-related training will be analyzed using frequencies, percentages, means, and standard deviations.

Descriptive analysis will also provide insight into overall levels of AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, and adoption intention among participants.

6.4 Measurement Model Assessment

Before testing structural relationships, the reliability and validity of the measurement model will be evaluated. This step ensures that the questionnaire items accurately represent their intended constructs.

Reliability Assessment

Internal consistency reliability will be examined using:

- Cronbach's alpha (α)
- Composite reliability (CR)

Values above the recommended threshold indicate acceptable reliability.

Convergent Validity

Convergent validity will be assessed through:

- Outer factor loadings
- Average variance extracted (AVE)

Items with acceptable factor loadings will be retained, and AVE values will be examined to determine whether constructs explain sufficient variance from their indicators.

Discriminant Validity

Discriminant validity will be evaluated to confirm that each construct represents a distinct concept. Assessment methods may include:

- Fornell–Larcker criterion
- Heterotrait–Monotrait ratio (HTMT)

Establishing discriminant validity is particularly important in this study because constructs such as AI literacy, AI self-efficacy, and AI readiness are conceptually related but theoretically distinct.

6.5 Structural Model Assessment

Following validation of the measurement model, the structural model will be assessed to examine hypothesized relationships among constructs.

The structural model evaluation will include:

Path Coefficients

Path coefficients will be examined to determine the strength and direction of relationships between variables. The significance of hypothesized paths will be tested using bootstrapping procedures.

Coefficient of Determination (R^2)

The explanatory power of the model will be assessed using R^2 values for endogenous constructs, particularly:

- AI self-efficacy
- Ethical AI awareness
- AI readiness
- Adoption intention
- Classroom AI integration

Effect Size (f^2)

Effect sizes will be examined to determine the practical contribution of individual predictors to endogenous variables.

Predictive Relevance (Q^2)

Predictive relevance will be assessed to determine whether the model demonstrates sufficient capability to predict endogenous constructs.

6.6 Hypothesis Testing

The proposed hypotheses will be tested through structural path analysis.

The expected relationships include:

- AI professional development → AI literacy
- AI literacy → AI self-efficacy
- AI literacy → Ethical AI awareness
- AI self-efficacy → AI readiness
- Ethical AI awareness → AI readiness
- AI readiness → Adoption intention
- Adoption intention → Classroom AI integration

The significance of each relationship will be determined through bootstrapping procedures, reporting path coefficients, standard errors, t-values, p-values, and confidence intervals.

6.7 Mediation Analysis

The study proposes that AI readiness functions as a mediating mechanism between teacher competencies and AI adoption intention.

Mediation analysis will examine whether:

- AI literacy influences adoption intention indirectly through AI readiness.
- AI self-efficacy influences adoption intention indirectly through AI readiness.
- Ethical AI awareness influences adoption intention indirectly through AI readiness.

Bootstrapping methods will be used to evaluate indirect effects because they provide more reliable estimates than traditional mediation approaches.

6.8 Multi-Group Analysis (Optional)

If sufficient sample diversity is achieved, additional analysis may examine whether relationships differ across demographic groups.

Possible comparisons may include:

- Faculty with previous AI training versus those without AI training.
- Different academic disciplines.
- Different levels of teaching experience.

Multi-group analysis may provide insight into whether AI adoption mechanisms vary across teacher populations.

6.9 Qualitative Data Analysis

The qualitative phase will involve thematic analysis following Braun and Clarke's (2006) framework. Interview data will be analyzed through the following stages:

1. Familiarization with interview transcripts.
2. Generation of initial codes.
3. Identification of broader themes.
4. Review and refinement of themes.
5. Definition and naming of themes.
6. Development of interpretive explanations.

The qualitative analysis will focus on themes related to:

- Experiences with GenAI adoption.
- Benefits and challenges of AI integration.
- Professional development needs.
- Ethical concerns.
- Institutional support requirements.
- Factors influencing AI readiness.

6.10 Integration of Quantitative and Qualitative Findings

The final stage will integrate findings from both phases. Quantitative results will identify significant relationships among variables, while qualitative findings will explain the practical experiences underlying those relationships.

For example, if AI literacy significantly predicts AI readiness, interview findings will explore how teachers develop AI knowledge and how this knowledge influences their confidence and classroom practices. Similarly, if institutional barriers emerge during interviews, these findings may explain variations in adoption intention despite high levels of individual readiness.

This integrated interpretation will provide a comprehensive explanation of how universities can develop sustainable strategies for GenAI adoption among faculty members.

7. Expected Findings, Discussion Framework, and Research Contributions

7.1 Expected Findings

Based on the theoretical framework and previous empirical research, the study is expected to demonstrate that university teachers' adoption of generative artificial intelligence (GenAI) is influenced by a combination of individual competencies, ethical understanding, and institutional learning opportunities. Rather than assuming that access to AI technologies automatically leads to adoption, the proposed model suggests that teachers require a progressive development pathway involving professional development, AI literacy, self-efficacy, ethical awareness, and readiness.

First, AI professional development is expected to emerge as an important antecedent of AI literacy. Teachers who participate in structured AI-related training are expected to demonstrate stronger understanding of AI concepts, capabilities, limitations, and educational applications. This finding would support the argument that universities should approach AI integration through capacity building rather than focusing only on technological availability.

Second, AI literacy is expected to positively influence both AI self-efficacy and ethical AI awareness. Teachers with stronger AI knowledge are likely to feel more capable of using AI tools and more prepared to critically evaluate AI-generated outputs. This relationship reflects the view that effective AI integration requires both technical understanding and critical awareness of potential risks.

Third, AI self-efficacy and ethical AI awareness are expected to contribute significantly to AI readiness. Teachers who feel confident in their ability to use AI and understand responsible AI practices are expected to perceive themselves as more prepared for classroom integration. This finding would extend traditional technology acceptance perspectives by demonstrating that successful AI adoption depends on psychological and ethical preparedness in addition to perceived usefulness.

Fourth, AI readiness is expected to positively influence adoption intention. Teachers who possess the necessary knowledge, confidence, and ethical understanding are expected to show stronger willingness to incorporate GenAI into their professional practices. This relationship supports the argument that readiness acts as a bridge between teacher competencies and technology adoption behavior.

Finally, adoption intention is expected to influence classroom AI integration. Teachers who express stronger intentions to adopt AI are expected to report greater use of AI for instructional planning, content development, assessment support, and learning activities.

7.2 Discussion Framework

The discussion of findings will be organized around the theoretical relationships proposed in the conceptual framework.

AI Professional Development as a Foundation for AI Readiness

If the findings confirm the expected relationship between professional development and teacher competencies, the study will demonstrate the importance of structured institutional learning opportunities. This would suggest that universities should move beyond informal AI exploration and develop systematic faculty development programmes addressing AI knowledge, pedagogical applications, and ethical considerations.

Moving Beyond Traditional Technology Acceptance Models

Traditional models such as TAM and UTAUT explain adoption primarily through perceptions of usefulness, ease of use, and facilitating conditions. However, GenAI adoption introduces additional complexities because teachers must evaluate AI-generated content, manage ethical challenges, and redesign teaching practices.

The proposed framework extends these models by incorporating AI literacy, self-efficacy, ethical awareness, and readiness as essential components of responsible AI adoption. This provides a more comprehensive explanation of technology acceptance in the context of emerging educational AI.

The Role of Responsible AI Awareness

The expected findings may demonstrate that ethical awareness is not a barrier to adoption but an enabling factor for responsible implementation. Teachers who understand ethical issues may be better positioned to use AI strategically, establish appropriate boundaries, and guide students toward responsible AI practices.

This perspective challenges the assumption that successful AI adoption requires simply increasing technology acceptance. Instead, sustainable adoption requires balancing innovation with academic values and ethical responsibility.

AI Readiness as a Mediating Mechanism

The study proposes AI readiness as a central mechanism connecting teacher competencies with adoption intention. If supported, this finding would suggest that knowledge, confidence, and ethical awareness do not directly guarantee AI adoption; rather, they influence adoption through the development of overall preparedness.

This provides a more nuanced understanding of how educators transition from awareness of AI to actual classroom implementation.

7.3 Theoretical Contributions

This study is expected to contribute to AI-in-education research in several ways.

First, it extends technology acceptance research by developing an AI-specific adoption framework for higher education teachers. While TAM and UTAUT remain valuable, the proposed model incorporates AI literacy and ethical readiness to address the unique challenges of GenAI.

Second, the study integrates perspectives from social cognitive theory and AI literacy research. By positioning self-efficacy and knowledge development as important predictors of readiness, the framework explains how teachers psychologically prepare for AI transformation.

Third, the study contributes to the emerging concept of AI readiness by conceptualizing it as a multidimensional construct involving cognitive, psychological, ethical, and behavioral dimensions.

7.4 Practical Contributions

The findings are expected to provide practical implications for university administrators, policymakers, and faculty development leaders.

For university administrators, the study may highlight the importance of investing in continuous AI professional development rather than relying on individual experimentation.

For faculty development units, the findings may guide the design of training programmes that combine:

- AI technical skills.
- Pedagogical integration strategies.
- Critical evaluation of AI outputs.
- Ethical AI practices.

For policymakers, the study may support the development of institutional AI strategies that balance innovation, academic integrity, and responsible technology governance.

7.5 Methodological Contribution

The explanatory sequential mixed-methods design represents another contribution of the study. Quantitative modeling identifies the strength of relationships among AI adoption factors, while qualitative exploration provides deeper understanding of teachers' experiences and institutional realities.

This approach is particularly valuable for AI adoption research because technology implementation involves both measurable behavioral patterns and complex human experiences.

7.6 Expected Contribution to Developing Higher Education Contexts

Most AI adoption research has emerged from highly digitalized educational environments. By examining university teachers within a developing higher education context, this study is expected to provide insights into the specific challenges and opportunities faced by institutions where AI strategies, infrastructure, and faculty preparation systems are still developing.

The findings may help universities design context-sensitive approaches for building AI readiness and ensuring that GenAI adoption contributes to meaningful educational improvement rather than technology-driven change alone.

8. Conclusion and Future Research Directions

8.1 Conclusion

The emergence of generative artificial intelligence (GenAI) represents a significant transformation in higher education, creating new opportunities for teaching innovation while simultaneously introducing complex challenges related to ethics, assessment, academic integrity, and institutional governance. Although AI technologies are becoming increasingly accessible, their successful integration depends not only on technological availability but also on educators' ability to understand, evaluate, and responsibly apply these tools within educational contexts.

This study developed an integrated framework to examine university teachers' AI readiness and adoption intention by connecting AI professional development, AI literacy, AI self-efficacy, ethical AI awareness, AI readiness, adoption intention, and classroom AI integration. Drawing upon Social Cognitive Theory, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and emerging AI literacy perspectives, the proposed framework extends existing explanations of educational technology adoption by incorporating the specific competencies required for responsible GenAI implementation.

A central argument of this study is that AI adoption among university teachers should not be viewed as a simple technology acceptance decision. Instead, it represents a developmental process in which professional learning opportunities enhance AI literacy, strengthen confidence, increase ethical awareness, and contribute to overall AI readiness. Teachers who are knowledgeable, confident, and ethically prepared are more likely to move beyond basic experimentation and engage in meaningful classroom integration of AI technologies.

The study also emphasizes the importance of institutional responsibility in supporting AI transformation. Universities must recognize that sustainable AI adoption requires more than providing access to AI tools. Effective implementation requires strategic planning, faculty development, ethical guidelines, infrastructure support, and organizational cultures that encourage responsible innovation. Without these conditions, AI adoption may remain fragmented and dependent on individual teacher initiatives.

By positioning AI readiness as a central mechanism connecting teacher competencies with adoption behavior, this research contributes to a more comprehensive understanding of AI integration in higher education. The proposed model provides a foundation for examining how universities can prepare educators for an AI-supported future while maintaining educational quality, academic integrity, and human-centered values.

8.2 Limitations of the Study

Although the proposed study provides a comprehensive framework, several limitations should be acknowledged.

First, the study focuses specifically on university teachers, which may limit the generalizability of findings to other educational levels such as schools or vocational institutions. Future research could examine whether similar AI readiness patterns exist among teachers in different educational contexts.

Second, the study relies partly on self-reported measures of AI literacy, confidence, ethical awareness, and adoption behavior. While self-report instruments are appropriate for measuring perceptions and intentions, future studies may incorporate behavioral data, classroom observations, or usage analytics to provide additional evidence of actual AI integration.

Third, because AI technologies continue to evolve rapidly, teachers' perceptions and adoption behaviors may change over time. A cross-sectional research design may not fully capture the dynamic development of AI competencies. Longitudinal studies could provide deeper insights into how AI readiness develops through continued exposure and professional learning.

Fourth, the study focuses primarily on teacher-level factors. Although institutional support is recognized as important, future research may examine AI readiness at organizational and policy levels to develop a broader understanding of institutional AI transformation.

8.3 Future Research Directions

Future research should continue investigating how universities can develop sustainable AI adoption strategies. Several directions are recommended.

First, longitudinal studies should examine how professional development programmes influence teachers' AI competencies over time. Such research could identify which types of training activities produce the improvements in AI literacy, confidence, and responsible AI practices.

Second, comparative studies across countries and institutional contexts would provide valuable insights into how cultural, technological, and policy environments influence AI adoption. Developing higher education systems may experience different challenges compared with highly digitalized educational environments.

Third, future research should investigate the relationship between AI readiness and student outcomes. While teacher readiness is an essential foundation for AI integration, the ultimate goal of educational AI adoption is to improve learning experiences and outcomes.

Fourth, additional studies may explore how different academic disciplines influence AI adoption. Teachers in fields such as computer science, humanities, medicine, and social sciences may have different perceptions of AI usefulness, risks, and applications.

Finally, future research should continue examining responsible AI governance in higher education. As AI capabilities expand, universities will need evidence-based policies that balance innovation with ethical responsibility, transparency, and academic values.

8.4 Final Statement

Generative AI is likely to become an increasingly important component of higher education; however, its educational value will depend on how effectively institutions prepare educators to use it. Building AI-ready universities requires developing teachers' knowledge, confidence, ethical awareness, and capacity for responsible innovation. The framework proposed in this study provides a pathway for understanding and supporting this transformation, positioning university teachers as central actors in shaping the future of AI-enhanced education.

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