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LECTURERS' PERCEPTIONS ON THE INTEGRATION OF GENERATIVE AI IN HIGHER EDUCATION: DEMOGRAPHIC INFLUENCES, OPPORTUNITIES AND CHALLENGES

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ABSTRACT

Aim/Purpose	This study examines lecturers' perceptions of Generative Artificial Intelligence (GenAI) in higher education and how these perceptions vary with demographic characteristics, namely gender, age and teaching experience. It further investigates how such perceptions relate to lecturers' frequency of GenAI use and stage of adoption, identifying the opportunities and challenges lecturers associate with the integration of GenAI in educational practice.
Background	The rapid emergence of GenAI has introduced new possibilities and challenges for higher education, yet empirical research examining lecturers' perspectives, particularly within diverse contexts, remains limited. While existing studies have largely focused on students' use of GenAI or technical adoption models, less attention has been given to lecturers' perceptions, demographic influences, and the ethical and pedagogical implications of GenAI integration
Methodology	A mixed-methods research design was employed. Quantitative data were collected through an online survey administered to 98 lecturers from different higher education institutions spanning a range of disciplines (55% male, 45% female; 44% aged 25-45, 30% aged 46-55, 26% aged 56+). Qualitative data were gathered through semi-structured interviews with a purposive subsample of ten lecturers. Quantitative analyses included independent-samples t-tests, one-way

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ANOVA, and Spearman rank-order correlations, while qualitative data were analyzed using Braun and Clarke’s six-phase thematic analysis.

Contribution Theoretically, the study extends technology-adoption research by integrating the Technology Acceptance Model with an interpretive technology-in-practice perspective, suggesting that lecturers’ perceptions of GenAI are socially situated and systematically shaped by gender, age, and teaching experience, and that these perceptions in turn are strongly associated with frequency of use and depth of adoption. Practically, the findings highlight the need for differentiated professional development, updated ethical guidelines, and redesigned assessment practices that foster critical AI literacy, supporting responsible and sustainable GenAI integration in higher education.

Findings Quantitative findings revealed significant demographic differences in lecturers’ perceptions. Female lecturers reported more positive perceptions than male lecturers on several pedagogical dimensions. A clear age-related gradient emerged, with lecturers aged 25-45 expressing the most favorable perceptions and those aged 56+ the least. Strong positive correlations were observed between perceptions and frequency of GenAI use, between perceptions and stage of adoption ($r_s = 0.67$, $p < 0.01$) and between frequency of use and stage of adoption ($r_s = 0.74$, $p < 0.01$). Also, the thematic analysis of interview data identified three opportunity themes. These included: empowering lecturers in teaching and time management, enhancing pedagogical practices and student learning and improving accessibility to information and knowledge creation, alongside three challenging themes involving ethical and academic integrity concerns, technological limitations and dependency and threats to professional identity.

Recommendations for Practitioners Institutions should implement differentiated professional development and update ethical governance frameworks, with particular emphasis on redesigning assessment to foster critical GenAI literacy and authentic engagement.

Recommendations for Researchers Further studies should investigate how GenAI evolves from a technological tool into a sustained technology-in-practice within higher education systems.

Impact on Society The study underscores the importance of responsible GenAI integration to safeguard educational quality, equity, and human-centered academic values.

Future Research Future research should incorporate a larger, cross-cultural sample to explore how differing institutional, national, and policy environments moderate GenAI acceptance. Furthermore, while this investigation indicates an association between positive perceptions and the frequency of GenAI use, a step for subsequent studies is to empirically validate the longitudinal relationship between initial positive attitudes and the deep, sustained integration of GenAI into core curricula and assessment practices.

Keywords Generative AI, higher education, lecturers’ perceptions, demographic influences, challenges, opportunities

INTRODUCTION

Generative Artificial Intelligence (GenAI) is a branch of AI capable of producing original text, images, code, and other media by learning patterns from large datasets (Creely & Blannin, 2025; Peñalvo & Ingelmo, 2023). GenAI is also reshaping the conditions under which higher education operates. For lecturers, GenAI offers new ways to support teaching, assessment, and academic writing (Camilleri et al., 2025; Watted, 2025), but its rapid uptake also raises pressing questions about who is using it, how, and to what pedagogical effect. Recent work in higher education highlights that GenAI tools such as large language models (LLMs), multimodal assistants, and code generators are increasingly embedded in the everyday practices of lesson planning, assessment design, feedback provision, and academic writing support (Basty et al., 2025; Castillo-Martínez et al., 2024). GenAI has thus shifted from an invisible back-end system to a visible, dialogic interlocutor that co-produces texts, resources, and explanations with lecturers and students (Ko et al., 2025; Watted, 2025). Systematic reviews and empirical studies indicate that, when used deliberately, GenAI can scaffold academic writing, offer rapid formative feedback, personalize content, and free educators' time to focus more on relational and higher-order pedagogical work. However, this simultaneously raises new concerns around academic integrity, epistemic depth, bias, and professional identity (Bond et al., 2024; Castillo-Martínez et al., 2024; Liang et al., 2025; Prilop et al., 2025).

It is considered that in universities GenAI marks a qualitative shift in the landscape of technology-enhanced learning. Accordingly, this study investigates lecturers' perceptions of GenAI and examines potential misalignments between their orientations toward GenAI integration in formal higher education and the ways they interpret and negotiate its opportunities and risks in their own teaching. Although research on GenAI in higher education has expanded rapidly, the literature remains fragmented in at least three respects. First, while faculty perceptions are increasingly recognized as crucial, many studies prioritize students' viewpoints or capture lecturers' perspectives only superficially, offering limited insight into how educators construe GenAI's pedagogical value, ethical implications, and impact on professional identity (Camilleri et al., 2025; Crompton & Burke, 2023; Liang et al., 2025). Second, demographic variables such as gender, age, and teaching experience are often collected as descriptive controls but are rarely theorized or examined systematically as moderators of educators' attitudes and acceptance. This, inevitably, leaves things unclear including whether, and how, these characteristics shape lecturers' orientations toward GenAI (Fadlelmula & Qadhi, 2024; Petrucco et al., 2024). This omission has tangible consequences. Without a systematic account of how demographic characteristics shape perception and adoption, institutions risk designing a one-size-fits-all professional development that overlooks cohort-specific patterns of digital fluency, reinforces emerging digital inequalities among staff, and leaves uneven AI literacy unaddressed across academic disciplines and career stages (Selwyn, 2022; Tlili et al., 2023; Zawacki-Richter et al., 2019). Third, emerging work frequently reports attitudes, intentions, or general openness toward GenAI, yet gives comparatively less attention to how these perceptions relate to actual stages of integration and frequency of use in teaching practice, as well as to the concrete opportunities and challenges lecturers encounter in their classrooms (Bergdahl & Sjöberg, 2025; Henke, 2025).

Building on these gaps, the present study therefore advances the field in three ways. First, it moves demographic variables from descriptive controls to theorized moderators of perception and adoption, drawing on Orlikowski's (2000) technology-in-practice perspective in dialogue with the Technology Acceptance Model (Davis, 1989). Second, it links perceptions to enacted practice by relating them to lecturers' self-reported frequency of use and stage of GenAI integration, rather than to intention alone. Third, by combining survey data with semi-structured interviews, it brings forth the situated opportunities and challenges through which lecturers negotiate GenAI in their classrooms, with implications for differentiated professional development and institutional strategies that address rather than reproduce digital inequalities in higher education.

Against this backdrop, the present study addresses these gaps by examining lecturers' perceptions of GenAI in higher education and its potential implementation in instructional practice, with particular attention to how demographic characteristics and patterns of use influence lecturers' adoption of GenAI; and to identify the opportunities and challenges lecturers associate with implementing GenAI in educational practice.

THEORETICAL LITERATURE

PERCEPTIONS TOWARDS TECHNOLOGY ACCEPTANCE

The perceptions of technology mediate the relationship between technological affordances and pedagogical practice (Camilleri et al., 2025; Watted, 2023a, 2023b; Watted & Yazbak Abu Ahmad, 2026), shaping how lecturers envision GenAI in teaching and learning (Balalle & Pannilage, 2025; Buele & Llerena-Aguirre, 2025). Orlikowski (2000) frames this dynamic as technology-in-practice: whereby, when people encounter a technology, they form initial expectations of what it can do and how it may affect their work. These mental schemes are then continuously revised through hands-on use. Empirical work on ChatGPT illustrates this trajectory. Retkowsky et al. (2024) express how knowledge workers' understanding of the tool evolved from a simple question-answer device into an integral element of professional practice. Liu (2024) reports parallel shifts in beliefs, values, and even professional identity. Perceptions are therefore not static cognitive states but recursive modalities of structuration where, as users act on the artefact, they simultaneously revise their understanding of it and the organizational structures within which it operates (Giddens, 1984; Orlikowski, 1992).

Furthermore, perceptions evolve through naturalization, that is the gradual embedding of technology into routine practice until its presence becomes taken for granted. Positive perceptions often emerge when users acquire experiential familiarity, pedagogical autonomy, and institutional support that foster a sense of empowerment (Chiu, 2022). Conversely, negative perceptions frequently stem from uncertainties regarding pedagogical purpose, lack of professional development, or perceived threats to established instructional identities. Such findings align with constructivist views on learning, which posit that meaningful technological adoption arises through reflective sense-making rather than mere exposure (Gilakjani et al., 2013).

The interpretive-structurational perspective (Giddens, 1984; Orlikowski, 1992, 2000) provides a useful theoretical foundation for understanding technology acceptance as a socially embedded phenomenon. In context the Technology Acceptance Model (TAM; Davis, 1989) complements this perspective at the individual cognitive level by positing two beliefs. These involve: the Perceived Usefulness (the degree to which technology is expected to enhance task performance) and the Perceived Ease of Use (the degree to which it is expected to be effortless to use). Both predict the attitude toward technology, which in turn predicts behavioral intention and actual use. In educational research, TAM has been extended in several directions including: the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) which adds social influence and facilitating conditions; TAM3 that incorporates trust, anxiety, and computer self-efficacy (Venkatesh & Bala, 2008); and discipline-specific extensions for educators to integrate pedagogical beliefs and perceived professional value (Scherer et al., 2019; Teo, 2019). These extensions repeatedly show that, in school and university settings, contextual and dispositional variables including age, gender, prior digital experience, and peer norms consistently moderate the strength of the PU/PEOU as an intentional pathway (Granić & Marangunić, 2019; Scherer et al., 2019). On the other hand, while TAM isolates these beliefs as cognitive determinants, the interpretive and structuration approaches contextualize them within the broader socio-cultural and organizational milieu (Orlikowski, 2000). The integration of these theoretical positions posits that technology acceptance in education is not just a purely rational process of evaluating utility and usability, but a socially constructed practice influenced by the users' flexible interpretations towards technology, institutional rules and the recursive interaction between agents and artefacts (Alshammari & Alkhwaldi, 2025). Institutional policies, leadership, available resources, and peer networks therefore co-determine which technologies are embraced and how they are supported (Alshammari & Alkhwaldi, 2025; Granić & Marangunić, 2019).

Demographic variables play a more substantive role in this combined framework than is often acknowledged. Empirical syntheses of TAM-based studies in education report that gender is associated with differential weighting of usefulness versus ease-of-use beliefs, with male educators tending to weight perceived usefulness more strongly and female educators weighting ease of use, social influence, and ethical concerns (Scherer et al., 2019; Venkatesh & Morris, 2000). Age and career stage correlate with cohort-specific exposure to digital tools where younger and mid-career educators frequently report higher self-efficacy and lower computer anxiety, while later-career educators more often emphasize pedagogical risks and threats to professional identity (Granić & Marangunić, 2019; Selwyn, 2022). Also, teaching experience has a more ambivalent effect where, accumulated pedagogical expertise can either accelerate critical, purpose-driven adoption or reinforce skepticism toward tools perceived to disrupt established practice (Tondeur et al., 2017). Thus, reading through the technology-in-practice lens, it may be seen that these demographic patterns are not incidental controls but indicators of the situated technological frames through which lecturers interpret GenAI. Such patterns therefore help explain why uniform adoption strategies tend to produce uneven outcomes across faculty cohorts. For the purpose of this study, the interpretive–structurational lens, together with TAM, provides a useful framework for understanding lecturers' responses towards GenAI. The formation of technological frames and interpretive schemes occurs within specific social contexts and is shaped by educators' demographic profiles and professional histories, such as gendered role expectations, cohort-specific ICT exposure, and cumulative pedagogical experience. Thus, while prior GenAI acceptance studies in education have shown that PU and PEOU are important predictors of intention (Davis, 1989; López-Costa et al., 2025; Miranda & Chamorro-Mera, 2025; Velli & Zafiropoulos, 2024), much less is known about how these beliefs concretely relate to educators' enacted patterns of GenAI use and how they vary across demographic groups (Fteiha et al., 2025; López-Costa et al., 2025; Velli & Zafiropoulos, 2024).

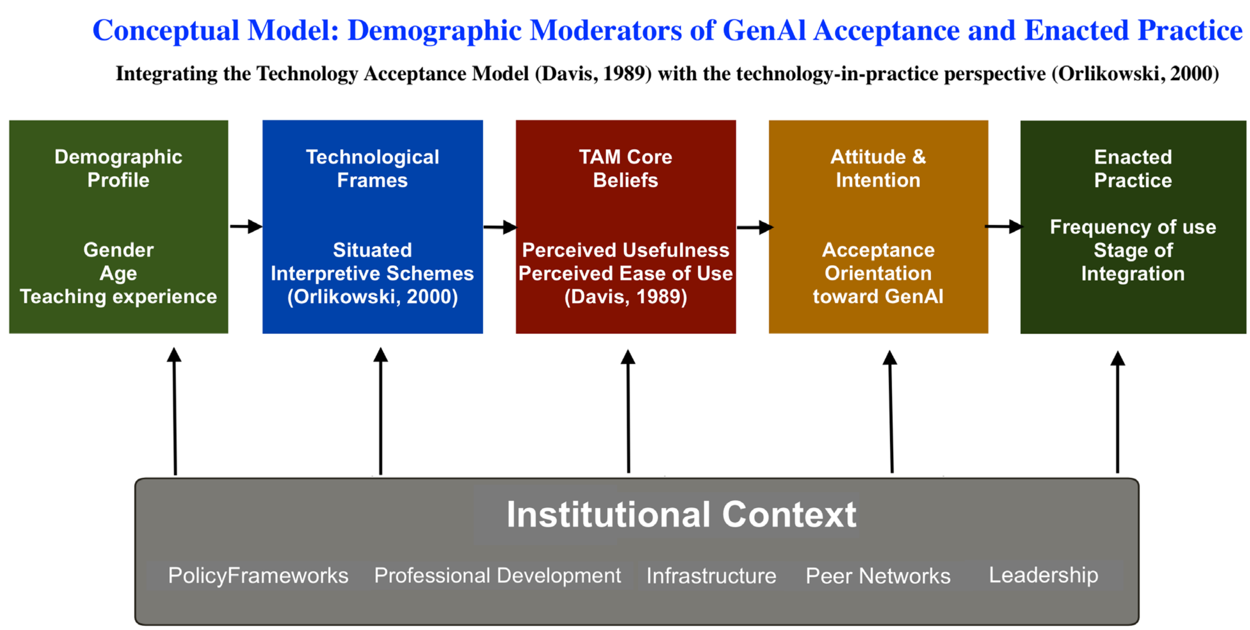

Figure 1: A conceptual model of GenAI acceptance among lecturers in higher education

Demographic factors (gender, age, teaching experience) condition the formation of technological frames, which in turn shape Perceived Usefulness and Perceived Ease of Use (TAM core). These beliefs determine attitudes and intentions, which translate into enacted practice operationalized through frequency of use and stage of integration within an institutional context that supplies (or withholds) policy, training, and infrastructure.

As delineated in Figure 1, the model provided conceptualizes a sequential, multi-stage process through five core dimensions which, reading left-to-right include: Demographic Profile, Technological Frames, TAM Core Beliefs, Attitude & Intention, and Enacted Practice. An educator's

Demographic Profile (comprising gender, age, and teaching experience) serves as the primary antecedent that directly shapes their Technological Frames, that is, their situated interpretive schemes regarding digital tools (Orlikowski, 2000). These personalized frames directly condition the TAM Core Beliefs, specifically Perceived Usefulness and Perceived Ease of Use (Davis, 1989). These cognitive evaluations subsequently inform the lecturer's overall Acceptance Orientation toward GenAI under Attitude & Intention, which ultimately translates into observable Enacted Practice, operationalized by both the frequency of use and the stage of technology integration. Crucially, as visualized by the foundational grey block at the base of Figure 1, this entire cognitive and behavioral chain is continuously anchored and influenced by the broader Institutional Context, including policy frameworks, professional development, infrastructure, peer networks, and leadership.

The Case of Generative AI and Educators' Beliefs.

When applied to GenAI, this interpretive-TAM framework acquires renewed significance. By mapping these theoretical connections directly to the components in Figure 1, it becomes clear how individual lecturer characteristics ripple forward to impact final instructional decisions. Educators may frequently engage in processes of sense-making to reconcile GenAI's abstract technical capacities with the practical realities of the classroom (Buele & Llerena-Aguirre, 2025; Camilleri et al., 2025). As a matter of fact, recent GenAI-specific studies in higher education echo this duality of instrumental optimism and critical apprehension. University lecturers report that GenAI can accelerate lesson preparation, generate illustrative examples, and support formative feedback (Watted, 2025). However, many also voice unease about students' over-reliance, erosion of academic writing and critical thinking, and uncertainty about how GenAI aligns with curricular and assessment standards (Buele & Llerena-Aguirre, 2025; Nevárez Montes & Elizondo-Garcia, 2025). Research further suggests that educators' prior experience with digital technologies, their pedagogical beliefs (for instance, more constructivist vs. transmissive orientations), and their institutional context shape how they position GenAI as a collaborator in knowledge construction, a cognitive scaffold, or a problematic shortcut to surface-level performance (Buele & Llerena-Aguirre, 2025; Calleja & Camilleri, 2025). Yet, despite the proliferation of such studies, systematic analyses that connect these beliefs to measurable stages of GenAI integration and frequencies of classroom use remain scarce, and demographic differences are only sporadically reported or theorized.

This dual gap between theorized beliefs and enacted practice, and between demographic description and demographic theorization, sets the agenda for the empirical literature reviewed next.

Perceptions of Generative AI in Higher Education

The scholarly literature on GenAI in higher education reveals a nuanced pattern of educator perceptions: broadly optimistic about pedagogical affordances and workload reduction, yet simultaneously cautious about ethical, epistemic, and professional risks (Balalle & Pannilage, 2025; Buele & Llerena-Aguirre, 2025; Watted, 2025). Three findings occur across this body of work.

Firstly, positive perceptions cluster around timesaving and enhancement functions where educators commonly report that GenAI can automate routine administrative tasks, provide rapid formative feedback, personalize student support, and free time for higher-order pedagogical activity (Al-Jaghoub et al., 2025). Systematic reviews likewise document that many academics and instructors regard GenAI as having real potential to increase productivity and provide adaptive learning pathways when integrated thoughtfully into teaching workflows (Castillo-Martínez et al., 2024). Secondly, the same syntheses caution that this body of evidence is unevenly distributed, proliferating rapidly overall (Bond et al., 2024; Liang et al., 2025) yet under-representing educators' own voices relative to those of students (Crompton & Burke, 2023; Watted & Barak, 2024). Thirdly, where educator perspectives are foregrounded, optimism is consistently conditional on perceived institutional support and professional development, suggesting that adoption is mediated by organizational rather than purely individual factors (Al-Jaghoub et al., 2025; Castillo-Martínez et al., 2024).

Another strand of work specifically interrogates demographic moderators, but with mixed results. Fadlelmula and Qadhi (2024) and Petrucco et al. (2024) both report that gender, age, and teaching experience are routinely included as control variables in GenAI acceptance studies yet are rarely modelled as theoretically meaningful moderators. Where they are modelled, findings diverge. Some studies report stronger acceptance among younger and male educators; others report no significant gender effect once the perceived ease of use is controlled. Still, others find that teaching experience exerts a non-linear influence in which mid-career educators are most receptive (Fadlelmula & Qadhi, 2024; Petrucco et al., 2024). This inconsistency points less towards a contradiction in the phenomenon rather than to a fragmentation in how it has been studied. This therefore implies that measurement instruments, cohort definitions, and analytic strategies vary substantially across studies.

In the context of the complex interplay between socio-cultural and institutional scenarios, systematic reviews and empirical studies on GenAI in higher education acknowledge that while demographic variables are often included as control or descriptive factors, their specific moderating effects on educators' attitudes and acceptance of GenAI technologies are underexplored and warrant further investigation (Fadlelmula & Qadhi, 2024; Petrucco et al., 2024). In context, a third issue cuts across both clusters: the gap between attitudes and enacted practice. Two stylized cases illustrate the asymmetry. A lecturer may report very positive attitudes toward GenAI yet trial it only once or twice across a program, using it narrowly to generate illustrative examples rather than embedding it in assessment or supervision. Conversely, another lecturer may express and demonstrate strong acceptance, designing practicum tasks that require students to engage critically with AI-generated materials and integrating GenAI into mentoring conversations on planning, differentiation, and assessment. In this sense, the relationship between attitudinal dispositions and the actual implemented behaviors of lecturers still requires empirical validation, particularly to determine whether positive perceptions reliably predict how frequently GenAI is used and how deeply it is integrated into teacher education curricula and classroom practice (Bergdahl & Sjöberg, 2025; Heine & König, 2025).

Moreover, empirical work on GenAI often lists perceived opportunities (such as creativity, efficiency and personalization) and challenges (including academic integrity, bias and skill erosion) without systematically relating these evaluations to lecturers' demographic profiles, stages of integration or reported usage patterns (Bond et al., 2024; Prilop et al., 2025; Zawacki-Richter et al., 2019). Across these reviews, two patterns recur: opportunity perceptions are most strongly associated with hands-on experience and institutional encouragement, whereas risk perceptions are more strongly associated with concerns about academic integrity and professional identity (Chan & Hu, 2023). There is thus limited evidence on whether distinct opportunities against risk perceptions are associated with different groups of lecturers and different forms of GenAI enactment in practice (Bergdahl & Sjöberg, 2025; Heine & König, 2025). Risk perceptions are subjective evaluations of potential threats associated with technology and vary across individuals according to experience, values, and institutional context. Consequently, related studies on trust in GenAI further suggest that socio-ethical concerns and institutional policy framing strongly influence educators' willingness to adopt these tools, yet call for more context-sensitive, mixed-methods research that triangulates survey data with in-depth qualitative accounts of lecturers' meaning-making around GenAI (Camilleri, 2023; Chan & Hu, 2023; Zawacki-Richter et al., 2024).

Taken together, the literature points to three interrelated gaps that include theoretical, methodological and contextual aspects that this study addresses as follows:

a. Theoretically, demographic variables such as gender, age, and teaching experience are routinely included as descriptive controls in TAM-based studies of GenAI but have rarely been theorized as situated factors that shape how perceptions translate into practice (Fadlelmula & Qadhi, 2024; Petrucco et al., 2024; Scherer et al., 2019). As reflected in the structural design of Figure 1, the present study explicitly repositions these demographic variables as foundational antecedents that actively condition technological frames rather than treating them merely as passive covariates. The present study repositions these variables as theoretically meaningful, drawing on Orlikowski's (2000) technology-in-practice lens to interpret demographic differences as indicators of distinct technological frames.

b. Methodologically, despite repeated calls to move beyond self-reported intention to enacted practice, the relationship between lecturers' perceptions, stage of GenAI integration, and frequency of GenAI use remains under-specified (Bergdahl & Sjöberg, 2025; Heine & König, 2025). This study therefore addresses this gap by directly operationalizing the rightmost box of Figure 1; "Enacted Practice"; through concrete metrics of use and integration. This study addresses this through a mixed-methods design that triangulates survey-based measures of perception with self-reported stage and frequency, complemented by interview accounts of enacted practice.

c. Contextually, more nuanced accounts are required for the specific opportunities and challenges that lecturers perceive when integrating GenAI into education, and of how these perceptions are embedded in technological frames, professional identities, and institutional contexts (Crompton & Burke, 2023; Zawacki-Richter et al., 2024). By systematically accounting for the foundational influence of the "Institutional Context" layer pictured in Figure 1, the present study contributes to a more ecologically valid account from a cross-disciplinary cohort of lecturers in higher education. Building on the theoretical, methodological, and contextual gaps identified above, this study pursues two interrelated goals as expressed in the next section.

RESEARCH GOAL AND QUESTIONS

The study goal is twofold: first, to examine lecturers' perceptions of the integration of GenAI in higher education, with particular attention to how demographic characteristics and patterns of use influence lecturers' adoption of GenAI; and second, to identify the opportunities and challenges lecturers associate with implementing GenAI in educational practice. To achieve this goal, the study addresses the following research questions:

1) Are there significant differences in lecturers' perceptions towards the integration of GenAI based on demographic variables such as gender, age and teaching experience?
2) What is the relationship between lecturers' perceptions, lecturers' stages of GenAI integration and the frequency of GenAI use?
3) What opportunities and challenges do lecturers perceive in the integration of GenAI in education?

METHODOLOGY

RESEARCH PARTICIPANTS

This study involved a diverse sample of lecturers (N = 98) from various higher education institutions. Participants were recruited through purposive and voluntary sampling from selected universities and colleges in order to include lecturers from different regions, age groups, disciplines, teaching experience levels, and institutional contexts. The selected institutions were chosen to reflect variation in higher education settings and to provide access to lecturers with relevant experience in teaching and educational technology. Participation in the online survey was voluntary. For the qualitative phase, a purposive subsample of lecturers was invited to participate in semi-structured interviews based on their willingness to elaborate on their experiences and to provide deeper insights into the opportunities and challenges associated with GenAI integration. This sampling approach was intended to capture a broad range of perspectives rather than to produce a statistically representative sample of all lecturers in higher education.

Gender-wise the sample comprised 45% female and 55% male lecturers. In terms of age distribution, 44% of participants were between 25 and 45 years old, 30% were between 46 and 55, while 26% were over 55 years old. Regarding teaching experience, 25% of lecturers had less than 10 years of experience, 22% had 11–15 years, another 22% of the cohort chosen had 16–20 years while 31% had more than 21 years of experience, all in higher education.

RESEARCH METHODS AND TOOLS

A mixed-methods research design was employed (Creswell & Creswell, 2017), integrating both quantitative and qualitative approaches to obtain a comprehensive understanding of lecturers' perceptions of GenAI in higher education. As described below, quantitative data were collected through an online survey, while qualitative insights were obtained via semi-structured interviews.

The online survey consisted of three main sections:

Part 1: This section included three items addressing participants' personal and demographic information, namely gender, age, and teaching experience.

Part 2: This section explored participants' use and adoption of GenAI through two questions. The first question asked whether participants had used GenAI and, if so, to indicate the frequency of use on a five-point scale (ranging from *1 = never* to *5 = always*). The second question required participants to identify their stage of GenAI integration, which included six progressive stages: Awareness, Learning, Understanding, Familiarity, Adaptation and Creative Application.

Part 3: This section examined participants' perceptions of GenAI implementation in education. The items were adapted from the validated instrument developed by Wozney et al. (2006), modified to align with the context of GenAI technology. This part included 15 items rated on a six-point Likert scale (*1 = strongly disagree* to *6 = strongly agree*). Several statements were reworded to ensure contextual relevance to GenAI use in higher education.

The content validity of the instrument was confirmed by three subject-matter experts in education who reviewed the items for clarity and relevance. The reliability of the survey was evaluated using Cronbach's alpha, yielding an acceptable level of internal consistency across all items ($\alpha = 0.82$).

Semi-structured interviews:

These were carried out with a purposive subsample of ten volunteering lecturers to complement the quantitative findings. The interviews aimed to gain deeper insight into the opportunities and challenges associated with GenAI integration in teaching and learning. Participants were encouraged to elaborate on their experiences, perceptions, and concerns, allowing for a more nuanced understanding of the findings obtained from the survey. The interviews were about 45 minutes long. They were conducted in person, using a research diary, audiotaped via Audacity tool (http://audacity.sourceforge.net), and fully transcribed.

DATA ANALYSIS

Quantitative data were analyzed using the Statistical Package for the Social Sciences (SPSS, Version 27). Descriptive statistics (means and standard deviations) were computed. Independent samples t-tests and one-way ANOVA were conducted to examine differences in lecturers' perceptions across gender, age, and teaching experience. Although each item was measured on a six-point Likert scale, analyses were performed on a composite perception score computed by averaging the 15 items (Cronbach's $\alpha = .82$). Consistent with prior methodological literature (Norman, 2010), such aggregated Likert-type scales can be treated as approximately continuous for the purposes of parametric analysis. Prior to these analyses, key assumptions were assessed: normality of the composite perception scores was examined via inspection of within-group Q–Q plots, which indicated no substantial departures from normality, and homogeneity of variances was evaluated using Levene's test and was satisfied across comparisons ($p > .05$) (Field, 2009). Finally, Spearman's rank-order correlations were calculated to examine associations among lecturers' perceptions, frequency of GenAI use, and stage of GenAI adoption.

Qualitative data from the semi-structured interviews were analyzed through thematic analysis (Braun & Clarke, 2006), involving coding, categorization, and theme development to identify recurring patterns related to the challenges and opportunities of GenAI integration. This was a six-phase process that procured a detailed approach to analyzing qualitative data, leading to a rich, detailed and complex account of the themes being investigated. The process entailed becoming familiar with the data by doing verbatim transcripts and reading them multiple times to achieve a deep understanding of the data's richness and context; generating codes to organize the data into chunks; grouping the different codes together into potential themes; reviewing the themes to check that they reflect the meanings evident in the data; defining and naming the themes and finally relating the findings to the literature review and research questions (Braun & Clarke, 2006). The authors also applied the inter-rater reliability approach through peer debriefing and checking to validate the credibility and accuracy of the nascent qualitative data.

RESULTS

DIFFERENCES IN LECTURERS' PERCEPTIONS AND USE OF GENERATIVE AI BASED ON DEMOGRAPHIC VARIABLES

This section is structured to align to the three research questions, with each subsection being dedicated to a research question. To address the first research question t-tests were conducted to examine whether lecturers' perceptions of GenAI integration differed significantly by gender. Table 1 presents the differences in lecturers' perceptions regarding the integration of GenAI based on gender.

Table 1: Differences in lecturers' perceptions regarding the integration of GenAI based on gender

Item	Male (N=54)		Female (N=44)		*t*
	M	SD	M	SD	
Increases academic achievement (e.g., grades)	3.40	0.90	3.71	0.78	-1.88
Results in students neglecting important traditional learning resources (e.g., library books).	3.20	1.19	2.59	1.13	2.06*
Is effective because I believe I can implement it successfully	3.43	0.87	3.98	0.66	-2.85**
Promotes student collaboration	3.31	0.87	3.64	0.88	-1.46
Promotes the development of communication skills (e.g., writing skills, presentation skills)	3.26	0.92	3.86	0.80	-2.72**
Is a valuable instructional tool	3.48	0.93	4.06	0.75	-2.73***
Makes lecturers feel more competent as educators	3.36	0.91	3.89	0.87	-2.72*
Is an effective tool for students of all abilities	3.29	0.94	3.73	0.98	-1.79*
Enhances my professional development	3.43	0.85	4.15	0.77	-3.49***
Eases the pressure on me as a teacher	3.29	0.87	4.04	0.83	-3.44***
Motivates students to get more involved in learning activities	3.45	0.85	3.86	0.88	-2.42*
Should reduce the number of lecturers employed in the future	3.20	0.88	3.69	0.93	-2.14*

Item	Male (N=54)		Female (N=44)		t
	M	SD	M	SD	
Will increase the amount of stress and anxiety students experience	3.31	0.85	3.46	1.03	-0.64
Requires extra time to plan learning activities	3.36	0.84	3.81	0.89	-2.06*
Improves student learning of critical concepts and ideas	3.34	0.85	3.78	0.90	-2.01*
Lecturers' Perceptions of GenAI in Education (Total)	3.32	0.68	3.75	0.64	-2.52**

*$p<0.05$ **$p<0.01$ ***$p<0.001$*

A significant gender difference was found for the overall perception score, with female lecturers reporting higher perceptions (M = 3.75, SD = 0.64) than male lecturers (M = 3.32, SD = 0.68), t (96) = −2.52, p < .01.

Female lecturers expressed significantly stronger agreement than male lecturers on several key benefit-related items. Specifically, females reported higher perceptions that GenAI is effective because they can implement it successfully (t (96) = −2.85, p < .01), promotes communication skills (t (96) = −2.72, p < .01), and is a valuable instructional tool (t (96) = −2.73, p < .001). Female lecturers also reported significantly higher agreement that GenAI enhances their professional development (t (96) = −3.49, p < .001), and eases teaching-related pressure (t (96) = −3.44, p < .001). In addition, female lecturers indicated greater perceived benefits in terms of feeling more competent as educators (t (96) = −2.72, p < .05), perceiving GenAI as effective for students of all ability levels (t (96) = −1.79, p < .05), and believing it motivates students' engagement in learning activities (t (96) = −2.42, p < .05). Gender differences also emerged on selected items reflecting concerns and workload implications. Male lecturers reported significantly higher agreement that GenAI leads students to neglect traditional learning resources (t (96) = 2.06, p < .05). Female lecturers, however, were more likely to agree that GenAI requires additional time to plan learning activities (t (96) = −2.06, p < .05) and that it may reduce the number of lecturers employed in the future (t (96) = −2.14, p < .05).

Overall, these findings suggest that female lecturers perceived GenAI as more pedagogically beneficial, while also recognizing some practical and professional challenges. Male lecturers appeared more concerned about students' possible over-reliance on GenAI. These gender-based differences highlight the need for targeted institutional support and professional development when promoting GenAI integration in higher education.

To further examine demographic variations, a one-way analysis of variance (ANOVA) was conducted to explore whether lecturers' perceptions and use of GenAI differed significantly across age groups. As shown in Table 2, the results revealed statistically significant differences in most items, indicating that age is a significant factor influencing attitudes toward GenAI integration in higher education.

Overall, the findings demonstrate a clear age-related gradient, with younger lecturers (25–45 years) expressing the most positive attitudes toward GenAI (M = 3.75, SD = 0.63), followed by those aged 46–55 years (M = 3.63, SD = 0.64). On the other hand, lecturers aged 56 years and above reported the least favorable perceptions (M = 3.00, SD = 0.64). The differences among the three age groups were statistically significant (F (2,95) = 7.40, p < .01).

Table 2: Differences in lecturers' perceptions and use of GenAI based on age

Item	25-45 Years (N=43)		46-55 Years (N=29)		More than 56 Years (N=26)		*F*
	M	SD	M	SD	M	SD	
Increases academic achievement (e.g., grades)	3.90	0.79	3.58	0.79	3.08	0.91	5.13**
Results in students neglecting important traditional learning resources (e.g., library books).	2.70	1.21	2.85	1.13	3.36	1.16	1.70
Is effective because I believe I can implement it successfully	3.95	0.75	3.75	0.76	3.13	0.81	6.13**
Promotes student collaboration	3.75	0.87	3.49	0.82	2.94	0.85	4.82*
Promotes the development of communication skills (e.g., writing skills, presentation skills)	3.84	0.86	3.58	0.88	2.98	0.85	5.17**
Is a valuable instructional tool	3.99	0.82	3.96	0.85	3.08	0.81	7.21**
Makes lecturers feel more competent as educators	3.93	0.83	3.66	0.92	2.98	0.85	6.24**
Is an effective tool for students of all abilities	3.78	0.91	3.49	1.05	2.98	0.85	3.74*
Enhances my professional development	3.99	0.76	3.96	0.89	3.13	0.81	6.66**
Eases the pressure on me as a teacher	4.01	0.80	3.66	0.96	2.94	0.75	8.61***
Motivates students to get more involved in learning activities	3.84	0.86	3.79	0.82	2.89	0.79	7.79***
Should reduce the number of lecturers employed in the future	3.73	0.89	3.54	0.97	2.79	0.82	5.88**
Will increase the amount of stress and anxiety students experience	3.55	0.97	3.49	0.94	2.98	0.80	2.14
Requires extra time to plan learning activities	3.60	0.88	3.96	0.76	3.03	0.86	5.54**
Improves student learning of critical concepts and ideas	3.78	0.83	3.75	0.80	2.89	0.83	6.81**
Teachers' Perceptions of GenAI in Education (Total)	3.75	0.63	3.63	0.64	3.00	0.64	7.40**

**p*<0.05 ***p*<0.01 ****p*<0.001*

Younger lecturers consistently reported stronger agreement with positive statements regarding the pedagogical, professional, and effective benefits of GenAI. They were more likely to perceive GenAI as a tool that enhances academic achievement ($F(2,95) = 5.13, p < .01$), fosters student collaboration ($F(2,95) = 4.82, p < .05$), develops communication skills ($F(2,95) = 5.17, p < .01$), and improves learning of critical concepts and ideas ($F(2,95) = 6.81, p < .01$). Younger lecturers also reported higher self-efficacy in implementing GenAI ($F(2,95) = 6.13, p < .01$), perceiving it as a valuable instructional tool *(F*(2,95) = 7.21, *p* < .01*)* that enhances professional development *(F(2,95) = 6.66, p < .01)* and reduces teaching pressure *(F*(2,95) = 8.61*, p* < .001*)*. In contrast, older lecturers (56+) expressed lower agreement across most dimensions and showed greater hesitation regarding the integration of GenAI. Their relatively low means suggest skepticism about GenAI's pedagogical value and a possible preference for more traditional teaching practices.

Follow-up or post-hoc comparisons using Scheffé's test were conducted succeeding significant one-way ANOVA results to determine the specific age-group differences in lecturers' perceptions of GenAI integration. The analyses revealed that lecturers in the 25–45 age group reported significantly more positive perceptions than those aged 56+ regarding GenAI's contribution to academic achievement ($p < .01$), effective implementation ($p < .01$), reduction of teaching pressure ($p < .05$), development of communication skills ($p < .01$), professional development ($p < .01$), support for students of all ability levels (p < .01), motivation of student engagement (p < .05), improvement of critical learning outcomes ($p < .01$), and facilitation of information access ($p < .001$). Additional significant differences were also found between the 46–55 and 56+ age groups for selected items, including perceptions of instructional value (p < .01), professional development (p < .05), reduction of teaching pressure ($p < .05$), student motivation (p < .01), time required for planning AI-based activities (p < .01), and learning of critical concepts ($p < .05$).

Collectively, the pattern of results indicates that younger lecturers are more technologically open, adaptive, and confident in integrating GenAI into their teaching. Conversely older lecturers are comparatively resistant or ambivalent, potentially due to lower digital self-efficacy, entrenched pedagogical habits and/or because they were educated and brought up with no or very limited digital technology use. This suggests that institutional support should be sensitive to age-related differences, particularly by providing targeted training and practical guidance for lecturers who may feel less confident or less familiar with GenAI-based teaching practices.

We further explored demographic influences, and a one-way analysis of variance (ANOVA) was conducted to examine differences in lecturers' perceptions of GenAI integration according to years of teaching experience. The results revealed statistically significant differences across several perception dimensions, as presented in Table 3.

Table 3: Differences in lecturers' perceptions and use of GenAI based on teaching experience

Item	1-10 Years (N=25)		11-15 Years (N=21)		16-20 Years (N=22)		More than 21 years(N=30)		*F*
	M	SD	M	SD	M	SD	M	SD	
Increases academic achievement (e.g., grades)	3.75	0.87	4.23	0.74	3.64	0.81	2.96	0.72	7.35***
Results in students neglecting important traditional learning resources	2.95	1.2	2.20	1.18	2.79	1.15	3.50	1.03	3.50*
Is effective because I believe I can implement it successfully	3.80	0.79	4.16	0.73	3.75	0.76	3.16	0.78	4.86**
Promotes student collaboration	3.60	0.93	4.05	0.89	3.46	0.87	2.91	0.66	5.12**
Promotes the development of communication skills	3.60	0.93	4.05	0.89	3.53	0.85	3.13	0.82	3.00*
Is a valuable instructional tool	3.80	0.84	4.16	0.86	3.69	0.84	3.41	0.91	2.02

Item	1-10 Years (N=25)		11-15 Years (N=21)		16-20 Years (N=22)		More than 21 years(N=30)		*F*
	M	SD	M	SD	M	SD	M	SD	
Makes lecturers feel more competent as educators	3.85	0.81	4.11	0.96	3.64	0.81	3.00	0.86	5.16**
Is an effective tool for students of all abilities	3.65	0.91	4.11	0.96	3.41	0.88	2.96	0.93	4.36**
Enhances my professional development	3.80	0.74	4.11	0.96	3.75	0.82	3.46	0.90	1.55
Eases the pressure on me as a teacher	3.85	0.76	4.11	0.96	3.69	0.84	3.04	0.86	4.82**
Motivates students to get more involved in learning activities	3.65	0.86	4.11	0.96	3.69	0.72	3.04	0.82	4.51**
Should reduce the number of lecturers employed in the future	3.60	0.83	4.05	1.00	3.46	0.81	2.79	0.86	5.87**
Will increase the amount of stress and anxiety students experience	3.50	0.87	4.05	1.00	3.41	0.94	2.79	0.73	5.64**
Requires extra time to plan learning activities	3.45	0.88	4.11	0.90	3.53	0.80	3.29	0.85	2.55
Improves student learning of critical concepts and ideas	3.65	0.81	4.16	0.86	3.64	0.86	2.91	0.86	6.50***
Teachers' Perceptions of GenAI in Education (Total)	3.63	0.64	3.98	0.73	3.52	0.61	3.00	0.58	5.39**

**p<0.05 **p<0.01 ***p<0.001*

Overall, the teaching experience had a significant effect on lecturers' overall perceptions of GenAI in education. Lecturers with 11–15 years of experience consistently reported the most positive perceptions (M = 3.98, SD = 0.73), whereas lecturers with more than 21 years of experience expressed the least positive perceptions (M = 3.00, SD = 0.58). The differences were statistically significant (F (3,94) = 5.39, p < .01).

Significant differences were observed for key pedagogical and professional dimensions, including perceptions that GenAI increases academic achievement (F (3,94) = 7.35, p < .001), supports successful implementation (F (3,94) = 4.86, p < .01), promotes student collaboration (F (3,94) = 5.12, p < .01), enhances communication skills (F (3,94) = 3.00 p < .05), improves lecturers' sense of professional competence (F (3,94) = 5.16, p < .01), is effective for students of all ability levels (F (3,94) = 4.36, p < .01), reduces teaching-related pressure (F (3,94) = 4.82, p < .01), motivates student engagement (F (3,94) = 4.51, p < .01), and improves students' learning of critical concepts (F (3,94) = 6.50, p < .001). Additionally, more experienced lecturers expressed stronger concerns regarding potential negative consequences, including increased student stress and anxiety (F (3,94) = 5.64, p < .01) and the possibility of reduced future employment opportunities for lecturers (F (3,94) = 5.87, p < .01).

The Scheffe post hoc analyses indicated that significant differences in lecturers' perceptions of GenAI integration were mainly driven by contrasts involving the most experienced group (more than 21 years). Lecturers with 11–15 years of teaching experience reported significantly more positive perceptions than those with more than 21 years regarding GenAI's contribution to academic achievement ($p < .001$), successful implementation ($p < .01$), student collaboration ($p < .01$), communication skills development ($p < .05$), lecturers' professional competence ($p < .01$), effectiveness for students of all abilities ($p < .01$), reduction of teaching pressure ($p < .01$), student engagement ($p < .01$), perceived risk to lecturers' employment ($p < .01$), student stress and anxiety ($p < .01$), and improvement of critical learning outcomes ($p < .001$). Additional significant differences were observed between lecturers with 1–10 years and those with more than 21 years of experience for academic achievement ($p < .05$) and lecturers' sense of competence ($p < .05$).

Taken together, the findings indicate that mid-career lecturers (11–15) years of experience demonstrate the highest levels of acceptance and perceived benefit of GenAI. On the other hand, late-career lecturers (with more than 21 years of experience) exhibit greater reservation, particularly regarding pedagogical impact and professional implications. These results indicate that while early-career academics embrace GenAI as an empowering vehicle for professional competence, senior educators view it through a critical lens that prioritizes traditional academic foundational practices over technological convenience.

Relationships Between Lecturers' Perceptions, Frequency of GenAI Use, and Stage of Adoption

To address the second research question: What is the relationship between lecturers' perceptions, lecturers' stages of GenAI integration and the frequency of GAI use?' *Spearman's rank-order correlation* analysis was conducted to examine the relationships between lecturers' perceptions of GenAI in education, their frequency of GenAI use, and their stage of GenAI adoption (Table 4).

Table 4: Spearman correlation between lecturers' perceptions, frequency of GenAI use and stage of GenAI adoption

Item	1	2	3
Perceptions of GenAI in Education (Total)	-		
Frequency of GenAI use	0.64**	-	
Stage of GenAI adoption	0.67**	0.74**	-

***p<0.01*

The results revealed strong and statistically significant positive correlations among all three variables, indicating a coherent and mutually reinforcing relationship between perception, use, and adoption level. A strong positive correlation was found between lecturers' perceptions of GenAI and their frequency of AI use ($r_s = .64$, $p < .01$), suggesting that those who held more favorable attitudes toward GenAI tended to use it more frequently in their teaching and professional activities. Similarly, perceptions of GenAI were strongly associated with the stage of AI adoption ($r_s = .67$, $p < .01$), implying that lecturers who viewed GenAI positively were also more advanced in integrating it into their pedagogical practices.

The strongest correlation emerged between frequency of GenAI use and stage of GenAI adoption ($r_s = .74$, $p < .01$), demonstrating a close link between habitual engagement with GenAI tools and the depth or maturity of adoption. In other words, frequent users are typically those who have progressed further along the implementation continuum, from initial experimentation to routine and sustained integration in teaching.

OPPORTUNITIES AND CHALLENGES LECTURERS PERCEIVE IN THE INTEGRATION OF GENAI IN EDUCATION

The qualitative data were used for the third research question: 'What opportunities and challenges do lecturers perceive in the integration of GenAI in education?', and six major themes, as displayed in Table 5 underneath, arose:

Table 5: Themes from interviews with lecturers focusing on opportunities and challenges in the integration of GenAI in education

Theme	Description	Interview Excerpts
Theme 1: Empowering lecturers in teaching and time management	GenAI is perceived as a professional assistant that streamlines teaching preparation, saves time, supports linguistic accuracy, and enhances creativity.	*"Instead of spending two hours searching for materials, now with GenAI it takes five minutes. It also helps with language correction in papers and class materials—it saves us a lot of time."* (B.S.) *"Before, it took me a long time to design digital questions, but now I just ask ChatGPT to prepare examples, I edit and adapt them to my logic and needs—it saves so much time*." (N.B.) "*I use AI mainly for proofreading in English, rewriting sentences, or adjusting the style of my research writing; it's a real help*." (H.Sh.)
Theme 2: Enhancing pedagogical practices and student learning	GenAI tools offer new ways to teach and assess, enabling personalized learning, the creation of adaptive content, and the promotion of critical thinking skills among students.	*"GenAI could personalize the learning path for each student, tailoring the content delivery based on their individual needs and pace."* (N.B.) *"I see GenAI as a tool to promote critical thinking... students can use it to create a draft, and then we discuss what is right or wrong, teaching them to question the source."* (W.M.) "*I use AI to help my students create videos, presentations, and animations. It develops both my digital literacy and theirs*." (E.A.) "*AI helps me design different tests for each student according to their level; it makes learning more personalized and saves hours of grading*." (N.A.)
Theme 3: Accessibility to information and knowledge creation	GenAI tools facilitate rapid information retrieval, overcome language barriers, and support the entire cycle of research and knowledge creation for both lecturers and students.	*"GenAI can translate and summarize complex texts, making resources more accessible to students who are not native speakers or who have less academic background*." (B.S.)

Theme	Description	Interview Excerpts
		"It provides rapid access to a vast amount of information, which supports our research and the creation of new knowledge that we can bring into the classroom." (S.) *"AI has opened new horizons in all fields of life, including teaching. You can ask ChatGPT any question and get detailed, organized answers.*" (H.Sh.) "*I used AI to create an artistic image for a Ministry of Education exhibition representing the college's vision; it merged science, faith, and art beautifully.*" (N.B.)
Theme 4: Ethical and academic integrity challenges	Lecturers face significant challenges related to academic honesty, plagiarism, the transparency of GenAI 's use, and the potential for a lack of critical engagement by students.	*"The biggest challenge is plagiarism; it's so easy for a student to produce a perfect paper without doing any work. We can no longer rely on traditional assignment formats.*" (N.B.) *"We need new assessment methods that test understanding, not just content regurgitation, because GenAI has made content production irrelevant.*" (B.S.) "*People use AI excessively without critical review and don't declare they used it. That's ethically wrong; it's not their thinking.*" (H.Sh.) *"Students can present AI-generated work as their own; when you ask them to explain it, they can't.*" (N.B.) *"It's unethical to create an exam using AI and then present it as my own work. We must disclose its use.*" (M.M.Z.)
Theme 5: Infrastructure, training, and institutional support gaps	A key challenge is the lack of institutional readiness, including insufficient technological infrastructure, a lack of targeted professional training, and the absence of clear institutional policies.	*"There is a huge gap in institutional support; we have no formal training on how to use these tools effectively in our subjects, and the IT system can't handle the tools.*" (W.M.) *"I feel like I want to innovate but [I'm] lacking the infrastructure, training, and ethical frameworks to do so confidently.*" (S.)

Theme	Description	Interview Excerpts
		"I don't really understand yet how to integrate AI in my teaching—it's still unclear to me." (W.M.) *"Not all teachers understand what AI really is; some rely on it blindly and make mistakes.*" (M.M.Z.)
Theme 6: Professional identity under threat	Lecturers expressed anxiety over job security, the potential diminution of their role, and the philosophical loss of the "human element" in education due to automation.	*"There was fear and intimidation that GenAI might take over our jobs—even for teachers and lecturers.*" (W.M.) *"If everything becomes automated, where is the joy and the struggle that make us human? Education loses its soul.*" (N.B.) *"GenAI may reduce some teaching tasks, raising questions about the future of our profession.*" (S.) *"I always discuss with my students how AI could change the labor market—it's important to think about it critically.*" (S.)

The integration of GenAI into higher education represents a paradigm shift that affects both the operational efficiency of lecturers and the philosophical foundations of pedagogy. The following six themes, as displayed in Figure 2, synthesize the current landscape of lecturers' perceptions and challenges.

1. Empowering lecturers in teaching and time management: GenAI serves as a high-functioning professional assistant, fundamentally altering the workflow of academic preparation. Lecturers report a drastic reduction in time spent on looking for resources, transforming hours of manual searching into minutes of targeted synthesis. Beyond time management, lecturers use these tools also linguistically, for proofreading and style adjustment for international research and classroom materials.
2. Enhancing pedagogical practices and student learning: The data suggests a transition toward adaptive pedagogy, where GenAI facilitates personalized learning pathways tailored to individual student needs. Rather than replacing instruction, these tools are being leveraged to promote higher-order cognitive skills. Lecturers use AI-generated drafts as 'boundary objects' for students to critique, thereby fostering a more robust sense of critical thinking and digital literacy.
3. Accessibility to information and knowledge creation: GenAI significantly lowers the barrier to information entry by providing rapid retrieval and summarization of complex academic texts. This theme highlights a crucial inclusivity benefit: the ability to translate and simplify resources for non-native speakers or students with limited academic backgrounds, thereby democratizing access to specialized knowledge and supporting creative research outputs.
4. Ethical and academic integrity and challenges: The most prominent challenge identified is the disruption of traditional academic integrity frameworks. Lecturers express a profound

need to move away from content regurgitation in assignments, as GenAI renders traditional output-based metrics obsolete. The data emphasizes a shift toward assessing the process of understanding rather than the final product, alongside a call for radical transparency in AI usage.

5. Infrastructure, training and institutional support gaps: Despite individual innovation, there is a marked disconnect between lecturers' ambition and institutional support. Participants identified a readiness gap characterized by inadequate technological infrastructure, a lack of targeted professional development, and a void in formal institutional policies. This suggests that without centralized ethical frameworks and training, the adoption of GenAI remains fragmented and uneven.
6. Professional identity under threat: This final theme reveals an underlying ontological anxiety regarding the future of the teaching profession. Lecturers voiced concerns over the potential automation of the human element: the joy and struggle of the learning process, and the fear that professional roles may be diminished. This highlights that the successful integration of AI requires not just technical skill, but a critical re-evaluation of what makes human-led education uniquely valuable.

Figure 2: Themes elicited from the qualitative data

The thematic analysis of the data revealed six primary dimensions of GenAI integration in higher education. The most significant area of concern identified by participants was Theme 4: Ethical and academic integrity and challenges, which yielded a significant amount of mentions and which shows how lecturers expressed profound anxiety over the ease of plagiarism and the potential for students to produce high-quality work without critical engagement, necessitating a shift from measuring content output to evaluating the learning process itself. In contrast, Theme 1: Empowering lecturers in teaching and time management shows how lecturers view GenAI as a vital driver for operational efficiency. They characterized GenAI as a professional assistant capable of reducing resource preparation time from hours to minutes while serving as a critical linguistic aid for international research and class materials. The remaining four themes highlight a clear tension between the pedagogical affordances of GenAI, such as personalized learning paths and democratized access for non-native speakers, and the systemic barriers that lecturers face. Qualitatively, the data underscores a significant readiness gap caused by inadequate institutional infrastructure and training, coupled with existential concerns regarding the automation of the human element and the future role of the educator in an increasingly automated landscape.

The quantitative and qualitative findings converge on a broadly positive but cautiously qualified view of GenAI integration in higher education, with lecturers recognizing its value for efficiency, pedagogy, and professional development while also emphasizing ethical, institutional, and identity-related concerns. Across the survey results, lecturers generally reported favorable perceptions of GenAI, especially younger, mid-career, and female respondents, who scored higher on its instructional usefulness, its capacity to support professional growth, and its potential to reduce teaching pressure. The interviews reinforced these patterns by showing that lecturers view GenAI as a practical assistant for saving time, improving language quality, supporting personalized learning, and expanding access to information, which aligns with the positive item-level trends in the quantitative data. At the same time, both strands of data highlight important reservations. The survey captured concerns about extra planning time, possible impacts on employment, and student reliance on traditional resources, while the interviews developed these concerns into richer themes around academic integrity, insufficient training and infrastructure, and fears that GenAI may undermine the human core of teaching. Taken together, the integrated findings suggest that GenAI is seen not as a straightforward replacement for conventional practice, but as a transformative tool whose benefits are widely acknowledged yet contingent on ethical guidance, institutional support, and thoughtful pedagogical adaptation.

DISCUSSION

This section interprets the key findings regarding lecturers' perceptions towards GenAI by aligning them with established theoretical frameworks such as the Technology Acceptance Model and the Technology Frames of Reference and related existing academic literature. In synthesis, the study highlights the dual nature of GenAI's impact and influence on lecturers' perceptions, the recursive dialogues, actions and reactions that are instigated between humans and autonomous machines and the theoretical mechanisms driving adoption and adaptation. Notably, it does so by treating demographic variables not as descriptive controls but as theoretically meaningful conditions that shape, and are shaped by, the institutional and cultural contexts in which GenAI is being enacted.

DIFFERENCES IN LECTURERS' PERCEPTIONS AND USE OF GENAI BASED ON DEMOGRAPHIC VARIABLES

The findings of this study contribute to the ongoing debate regarding the role of lecturers' demographic characteristics in shaping the adoption of GenAI in higher education. Consistent with prior research, the results indicate that demographic variables such as gender, age, and teaching experience do not exert uniform effects on lecturers' perceptions and use of GenAI but rather operate in context-dependent and nuanced ways, a pattern that has direct implications for how TAM should be translated within educational settings.

Regarding gender, the results align with studies reporting significant gender-related differences in perceptions of AI integration (Atadika et al., 2024), while contrasting with research that found no gender effects on behavioral intention (Darayseh, 2023; Nja et al., 2023). In this study, female lecturers expressed more positive perceptions towards GenAI, particularly in terms of pedagogical value and professional empowerment. This pattern is theoretically informative in two ways. First, it inverts the directionality reported in foundational TAM work, where male users weighted Perceived Usefulness more strongly and female users weighted Perceived Ease of Use and social influence (Venkatesh & Morris, 2000). The present results suggest that, in the GenAI-in-higher-education context, the gendered weighting of TAM constructs may be shifting, although this inference rests on a single-context sample and warrants replication. Female lecturers appear to translate ease-of-use and social-support beliefs into pedagogical-value judgements more readily than the original TAM gender literature would predict. Second, this shift is plausibly conditioned by institutional and cultural factors, notably the increasing visibility of women-led pedagogical innovation networks and the relative absence, in many higher education institutions, of the gendered technical-mastery norms that shaped earlier IT-acceptance studies. Gender, in other words, functions less as a stable individual characteristic and more as a marker of differential access to professional networks, instructional self-efficacy, and culturally available scripts for technology adoption.

With respect to age, younger lecturers demonstrated more favorable perceptions of GenAI, supporting evidence that familiarity with digital technologies enhances openness to AI adoption (Bakhadirov et al., 2024). At the same time, this finding is consistent with studies indicating that age-related differences can be mitigated through targeted training and institutional support (Nja et al., 2023; Teo, 2019). However, when interpreted through Orlikowski's (2000) technology-in-practice perspective, this age gradient reflects more than a simple generational digital-fluency effect. As the Results section expresses, older lecturers' relative reluctance is plausibly grounded in lower digital self-efficacy, entrenched pedagogical habits, and limited prior exposure to digital technology during their own formative education and professional training. Each of these is, in effect, a different facet of an interpretive frame within which the usefulness of GenAI is appraised. Self-efficacy accounts whether the tool feels manageable. Established pedagogical habits shape whether it feels compatible with what already works, and prior digital exposure shapes the baseline against which novelty is judged. This reframing has implications for TAM. Rather than treating age as a numeric moderator of Perceived Usefulness, the present findings tentatively suggest that age stands in for a broader interpretive frame within which usefulness is itself defined. On this reading, this study puts forward, as a tentative theoretical proposition, the idea that future work might test a TAM specification in which technological frames function as a higher-order construct. Thus, evaluating such a proposition would require designs that explicitly measure cohort-specific frames rather than relying on age as a demographic covariate. Teaching experience was negatively associated with positive perceptions of GenAI, echoing concerns in literature suggesting how experienced educators may approach disruptive technologies with greater caution due to their impact on established pedagogical practices and academic norms (Darayseh, 2023). This finding ratifies but also complicates prior work. It confirms accounts in which accumulated pedagogical expertise produces principled skepticism toward tools perceived to disrupt established practice (Tondeur et al., 2017). It also complicates them by indicating that, in the GenAI case, skepticism is not reducible to technophobia or generational lag. As a matter of fact, experienced lecturers in this sample voiced concerns that were predominantly pedagogical and ethical rather than technical, specifically concerning academic integrity, the integrity of the assessment relationship, and the protection of professional identity. Such concerns are precisely the kind that TAM, in its original form, does not theorize. We therefore tentatively propose, as a theoretical proposition emerging from this study, that future TAM-based work in the GenAI-in-higher-education context examines professional-identity threat and ethical-risk perception as candidate antecedents alongside Davis's (1989) original constructs. Whether such an extension is warranted will need to be established by future confirmatory studies with larger, multi-context samples. Overall, these findings are consistent with the view that demographic variables function as moderating rather than deterministic factors, and that they do so by indexing institutional, cultural, and professional histories that shape how usefulness, ease of use, and ethical risk are jointly perceived. This pattern points towards the importance of differentiated professional development and institutional support in fostering meaningful GenAI integration in higher education and therefore follows directly from the theoretical reframing rather than from demographic descriptives alone.

Taken together, the quantitative findings also indicate that lecturers' perceptions of GenAI are associated with adoption behaviors. More favorable perceptions were strongly associated with higher frequency of use and more advanced stages of adoption. The frequency of use was itself strongly associated with stage of adoption. The conventional TAM reading is that perceptions drive use, and the present correlations are consistent with but cannot adjudicate that reading. However, two caveats are essential.

First, correlational evidence cannot establish directionality. The relationship between perception and use is plausibly bidirectional and recursive. In the process, positive perceptions encourage initial use and, as Retkowsky et al. (2024) document, for ChatGPT in knowledge work, sustained hands-on engagement with GenAI tools also revises and consolidates those perceptions. Subsequently the interview data in the present study echo this recursive pattern, having several lecturers reporting that their evaluations of GenAI shifted measurably after structured classroom trials, with initial skepticism giving way to qualified endorsement (or, conversely, initial enthusiasm tempered by encountered limitations). The strong correlation between frequency of use and stage of adoption is most parsimoniously read as evidence of this recursive co-evolution rather than of a one-directional causal pathway. This finding aligns with Orlikowski's (2000) technology-in-practice perspective and tempers the more linear belief-attitude-intention-use chain implied by classical TAM (Davis, 1989).

Second, the qualitative findings clarify the mechanism behind the quantitative associations. The opportunity themes identified through thematic analysis empower lecturers in teaching and time management, enhancing pedagogical practices and student learning, improving accessibility to information and knowledge creation. These map closely onto the pedagogical dimensions on which female and younger lecturers reported the most favorable perceptions. The challenge themes including ethical and academic-integrity concerns, technological limitations and dependency, and threats to professional identity map closely onto the concerns voiced by more experienced lecturers in the survey. The convergence of the two data strands therefore offer tentative support for the interpretation that the demographic patterns reflect substantive differences in how GenAI is interpreted and enacted. It is also consistent with the possibility that the perception-use relationship is itself heterogeneous across demographic groups. In fact, for some lecturers, it is best modelled as perception-driven adoption, for others, as practice-driven perception revision, meaning that the appropriate professional-development response differs accordingly.

Opportunities and Challenges Lecturers Perceive in the Integration of GenAI in Education

The core finding is the dual impact of GenAI, which simultaneously serves as a powerful professional partner and a source of profound ethical and institutional disruption. The widespread adoption of GenAI for tasks like lecture preparation, content summarization, and language correction points to its high Perceived Usefulness, a central construct in the TAM (Davis, 1989). Lecturers leverage GenAI for significant efficiency gains, allowing them to reallocate time from routine administrative work to higher-value activities such as student support and personalized pedagogy. This positive perception fosters a reciprocal and reinforcing dynamism where a favorable attitude promotes greater frequency and depth of use, which in turn strengthens the perception of its educational value. This dynamic suggests that providing structured, positive exposure is key to overcoming initial hesitancy. Yet the present findings, rather than simply confirm, extend this TAM-based reading. Whereas classical applications of TAM treat Perceived Usefulness as an individual cognitive belief, the qualitative accounts in this study reveal that usefulness is socially produced. Lecturers reported that their sense of GenAI's value crystallized in conversations with colleagues, in encounters with student-generated AI work, and in negotiations with institutional policy. Usefulness, in this reading, is less of a private judgement and more as an emergent property of a community of practice. This observation supports calls to integrate TAM with situated and structurational perspectives (Orlikowski, 2000; Scherer et al., 2019) suggesting that institutional investment in collegial dialogue spaces is not merely an individual training process but is a critical mediator of the perception–use relationship.

On the other hand, the concerns raised by the lecturers, including pervasive plagiarism, the generation of false information: referred to as hallucinations (Huang et al., 2025), and the potential for erosion of core human skills, present a crisis point for academic integrity. The concept of 'cognitive offloading' (Carr, 2020; Selwyn, 2022) can be reflected in the anxiety experienced by the lecturers over students delegating complex intellectual tasks to GenAI, where reliance on technology diminishes independent critical thinking and complex problem-solving capacities. Challenges also include the difficulties in distinguishing authentic student work from AI-generated text, necessitating an immediate and radical shift in assessment strategies (Luckin, 2024). The emphasis on the use of such tools must move away from easily automated content production toward innovative, process-oriented tasks that test critical application, ethics, and real-time intellectual engagement. Furthermore, the fears about job relevance (Frey & Osborne, 2017) and the erosion of the human-relational core of teaching (Zins, 2004) underscore that GenAI integration demands a re-affirmation of the educator's role and professional identity. The future lecturer will not be a content provider, but a critical guide, ethical mentor, and facilitator of knowledge.

A theoretically suggestive reading of these challenges is that they point to a possible construct gap in TAM. TAM models reflect the function of usefulness and ease of use, but the lecturers in this study consistently weighed ethical risk and threat to professional identity, at least as heavily as either of these constructs. This pattern is not adequately captured by TAM2 or TAM3 (Venkatesh & Bala, 2008). Here, extensions emphasize social influence, output quality, and computer anxiety but not ethical risk or identity threat as standalone antecedents. On the basis of the present findings, we therefore advance a tentative theoretical proposition, emerging from this study, that future confirmatory research should explore whether an acceptance model for GenAI in higher education should incorporate ethical-risk perception and professional-identity protection alongside usefulness and ease of use. Whether these belong as constructs of equal standing with Davis's (1989) original antecedents, as moderators, or as context-specific extensions, remains an open empirical question. If this proposition is supported by future work, the present analysis suggests that classical TAM may under-predict the cautious or conditional adoption patterns observed among more experienced lecturers in this sample and may risk framing their hesitance as resistance rather than as principled professional judgement.

Several interpretive limitations should be made explicit at this point. First, all quantitative associations reported here are correlational, and although the reported magnitudes are sizeable, the sample of N=98 and the design cannot adjudicate the direction of the perception-use relationship. The bidirectional, recursive reading offered above is consistent with both the technology-in-practice literature and the interview data, but it remains a reading rather than a demonstration. Second, the demographic patterns interpreted here are conditioned by the institutional and cultural specificity of the participating cohort; transferability to other higher-education systems should be assessed in cross-cultural replications. Third, the theoretical extensions of TAM tentatively proposed in this discussion including: the integration of technological frames, ethical risk, and professional-identity threat, are best understood as propositions generated from the present correlational data. They will therefore require formal testing in a confirmatory model with a larger, multi-context sample before any stronger claims about model modification can be made. These limitations do not undermine the study's contribution; rather, they specify the conditions under which it should be read and the most productive directions for follow-up research.

CONCLUSION

The integration of GenAI in higher education represents a decisive inflection point, characterized by a fundamental tension between the immediate, tangible rewards of efficiency and personalization and the severe systemic risks to academic integrity and the nature of the educator's role. This study has therefore been set out to examine lecturers' perceptions of GenAI in higher education, how these perceptions vary with demographic characteristics, and how they relate to enacted use and adoption.

Three findings stand out. First, perceptions are systematically patterned by demographic profile: female lecturers and lecturers in the 25–45 age band reported significantly more favorable perceptions across multiple pedagogical dimensions, while more experienced lecturers expressed greater caution. Second, perceptions are tightly coupled with practice: positive perceptions correlated strongly with both frequency of GenAI use and stage of adoption. Third, the qualitative accounts converge with these quantitative patterns by surfacing a dual reality with opportunities centered on empowerment, pedagogical enhancement, and accessibility, alongside challenges based upon academic integrity, technological dependency, and threats to professional identity. Read together, the two strands suggest that GenAI integration cannot be understood as a uniform process but as a differentiated practice that varies by demographic profile and institutional condition.

To harness the opportunities while mitigating the existential threats, an effective two-pronged strategy is imperative. First, institutions must focus on Differentiated Professional Development by deploying targeted hands-on training that addresses the varying levels of technological confidence across age and gender cohorts, thereby validating the pedagogical value of GenAI encouraging its purposeful use. Second, a commitment to systemic governance and ethical frameworks is crucial, requiring an urgent updating of academic integrity policies (Camilleri, 2023; Cotton et al., 2024) and substantial investment in the infrastructure needed for AI adoption. Most critically, institutions must fundamentally evolve assessment practices to emphasize critical AI literacy (Long & Magerko, 2020) and authentic, context-specific engagement, thus reaffirming the educator's irreplaceable function as a mentor and cultivator of human analytical and ethical capacity.

Despite these contributions, several limitations should temper the interpretation of the findings and inform future research. With respect to design, the study employed a cross-sectional, mixed-methods approach. While this enabled triangulation of survey and interview data, it does not permit causal inference about the direction of the relationship between perceptions and use. The strong correlations reported here are consistent with both perception-driven adoption and practice-driven perception revision. Disentangling these pathways will require longitudinal designs that track perceptions and enacted use across the same cohort over time. With respect to sampling, the quantitative sample comprised 98 lecturers drawn from higher education institutions within a single geographic and cultural context, complemented by a purposive subsample of ten interviewees. Although the demographic distribution by gender, age, and teaching experience supported the planned analyses, the overall sample size limits statistical power for higher-order interactions and constrains the generalizability of the demographic patterns to other national and institutional settings. Self-selection into both phases may also have produced a sample more engaged with GenAI than the broader lecturer population. With respect to measurement, perceptions, frequency of use, and stage of adoption, these were all captured through self-reporting. While this is the standard instrument in TAM-based research and appropriate for capturing subjective interpretations, it is susceptible to social-desirability bias and recall limitations. Behavioral traces of GenAI use such as lesson plans, assessment rubrics, and student-facing materials were not analyzed and would have provided valuable corroboration in future work. The instrument also did not include validated subscales for ethical-risk perception or professional-identity threat, even though these emerged strongly in the qualitative data.

Future research should therefore pursue three priorities:

(i) A larger cross-cultural sample to assess the generalizability of the demographic patterns identified here;

(ii) Longitudinal designs to validate the relationship between initial positive attitudes and the deep, sustained integration of GenAI into core curricula; and

(iii) Assessment practices and confirmatory testing of the theoretical extensions proposed here, in which technological frames, ethical-risk perception, and professional-identity threat are formally specified as constructs in a GenAI-specific acceptance model.

Such work would therefore go beyond measuring mere adoption and move towards understanding the conditions under which GenAI is transformed from a technological artifact into a technology-in-practice.

THEORETICAL AND PRACTICAL IMPLICATIONS

Theoretically, this study extends technology-adoption research by integrating the Technology Acceptance Model (TAM) with an interpretive–structurational lens such as the Technology Frames of Reference (TFR) (Orlikowski & Gash, 1994). Consistent with TAM, the findings align with the view that perceived usefulness and positive beliefs about GenAI are key drivers of lecturers' adoption behaviors, including frequency of use and stage of integration (Davis, 1989). However, the results point to two directions in which TAM may benefit from further development. First, the present data is consistent with the proposition that perceived usefulness and ease of use are not formed in isolation but are socially situated and conditioned by demographic profile (Orlikowski, 2000; Orlikowski & Gash, 1994). Gender, age, and teaching experience operate not as descriptive controls but as moderating conditions that index different interpretive frames through which usefulness, ease of use, and ethical risk are jointly perceived. Second, the qualitative data point to ethical-risk perception and professional-identity concerns and as candidate constructs that in this sample, appeared to operate alongside, rather than, within the original TAM antecedents. On this basis we therefore advance, as a tentative theoretical proposition emerging from this study, that an acceptance model for GenAI in higher education could be used to explore whether it is useful or necessary to accommodate these constructs alongside Davis's (1989) original constructs, rather than assuming their inclusion beforehand. Ultimately confirming whether, and how, these constructs should be formally incorporated, will require larger, multi-context, and longitudinal designs. Together, these contributions advance current GenAI research beyond intention-based readings of TAM toward a dynamic, situated understanding of technology-in-practice.

Practically, the findings indicate that effective GenAI integration requires differentiated professional development rather than uniform implementation strategies. Institutions should provide targeted, hands-on training that addresses varying levels of confidence, experience, and pedagogical concerns. In parallel, clear ethical guidelines and redesigned assessment practices that emphasize critical AI literacy and authentic engagement are essential to mitigate risks related to academic integrity and cognitive offloading. In doing so, institutional strategy should treat the demographic patterns identified in this study not as a basis for stereotyping but as a guide for tailoring support to the distinct interpretive frames lecturers bring to GenAI. Together, these measures can support sustainable and pedagogically meaningful GenAI adoption in higher education.

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