Bridging the Attitude-Engagement Gap: Instructor Perceptions, Predictors, and Institutional Adoption of Artificial Intelligence in Higher Education

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ABSTRACT

Artificial intelligence (AI) is reshaping the landscape of higher education, yet empirical understanding of how university instructors perceive, engage with, and evaluate AI in their teaching contexts remains limited. This study examines university instructors' general perceptions, institutional AI engagement, student experience impact, concerns about AI, and future expectations regarding artificial intelligence in higher education, and investigates whether these dimensions differ by demographic and professional characteristics and which factors predict institutional AI engagement. A quantitative cross-sectional survey design was employed. Data were collected from N = 229 university instructors across five academic schools using the QUIA instrument with five subscales of five items each — General Perceptions (GPI), Current AI Use (UAI), Student Experience Impact (ISE), Concerns About AI (CAU), and Future Expectations (EAI) — scored on a five-point Likert scale. Instructors expressed positive agreement across all five dimensions. Future Expectations (EAI) were highest and Current AI Use (UAI) lowest, revealing an attitude-engagement gap. Concern about AI replacing teachers was the only item below the neutral midpoint. Female instructors reported significantly higher Concerns About AI (CAU) than male colleagues. School of Education instructors reported the highest institutional AI engagement. Student Experience Impact (ISE) and General Perceptions (GPI) were the primary psychological predictors of institutional AI engagement, while gender and School of Education affiliation were the significant demographic predictors. Institutions seeking to increase responsible AI adoption should prioritize structured, discipline-specific professional development that enables instructors to experience AI's pedagogical benefits directly.

Keywords: Artificial intelligence, higher education, faculty AI perceptions, AI adoption, AI ethics, AI use

INTRODUCTION

Over the last decade, artificial intelligence has rapidly transformed higher education with tools ranging from intelligent tutoring systems and adaptive learning platforms to automated assessment software and student support chatbots. This fast-paced change has often outpaced the ability of many academic communities to fully adjust and make the most of these new possibilities (Lee et al., 2024; Zawacki-Richter et al., 2024). Artificial intelligence (AI) is increasingly changing higher education by influencing teaching practices, faculty development, and student engagement across global contexts.

University instructors' perceptions and use of AI are increasingly critical factors in successfully integrating AI into curricula, pedagogy, and institutional strategies (Alsuwat, 2026; Gómez-García et al., 2026). Studies highlight how demographic and professional dimensions such as gender, age, academic discipline, position, and years of experience shape instructors' AI readiness and application (Alsuwat, 2026; Masalimova et al., 2026). Yet, while institutional adoption continues to expand, a persistent and consequential gap has emerged. The educators at the center of the teaching and learning enterprise remain, in many contexts, unprepared and insufficiently supported to engage with these tools in professionally effective ways (Ngaine, 2025; Zou et al., 2025).

Purpose

This study examines university instructors' perceptions, current use, perceived impact, ethical concerns, and future expectations regarding artificial intelligence (AI) in higher education and investigates whether these dimensions vary by demographic and professional characteristics and which factors predicted current AI use. Specifically, the study seeks to identify the most influential factors associated with AI use among university instructors and to provide empirical evidence that can inform institutional strategies, faculty development programs, and policies supporting the effective integration of artificial intelligence in higher education.

Problem Statement

Artificial intelligence (AI) is increasingly transforming higher education through applications that support teaching, learning, assessment, research, and academic administration (Afzal & Shad, 2025). Universities worldwide are investing in AI-powered technologies with the expectation that they will enhance educational quality, improve efficiency, and personalize learning experiences (George & Wooden, 2023). Despite the growing availability of AI tools, the extent to which university instructors use AI and the factors that influence such use remain insufficiently understood (Al-Zahrani & Alasmari, 2024). Existing research has primarily focused on students' adoption of AI technologies, attitudes toward generative AI tools, or the technological capabilities of AI systems (Crompton & Burke, 2023). However, less attention has been given to university instructors, who play a central role in determining whether and how AI technologies are integrated into higher education practices (Mah & Groß, 2024).

Furthermore, previous studies have often examined individual factors such as perceptions, attitudes, or concerns in isolation, providing a fragmented understanding of AI use among faculty members (Buele & Llerena-Aguirre, 2025; Mah & Groß, 2024). The successful integration of AI in higher education depends not only on technological availability but also on instructors' perceptions of AI, perceived impact on teaching and learning, concerns regarding ethical and practical implications, and expectations about AI's future role in education. Demographic and professional characteristics such as gender, age, academic position, faculty affiliation, and years of experience may also influence instructors' engagement with AI technologies. However, empirical evidence regarding the relative contribution of these factors to actual AI use remains limited, particularly within developing and regional higher education contexts.

Therefore, there is a need to investigate the factors that influence university instructors' use of AI by examining the combined effects of perceptions, concerns, perceived impact, future expectations, and demographic and professional characteristics. Understanding these relationships can provide valuable insights for institutional policies, professional development initiatives, and strategic planning aimed at promoting the effective and responsible use of AI in higher education.

Significance of the Study

This study contributes to the growing body of research on artificial intelligence in higher education by examining the factors that influence university instructors' use of AI technologies. While previous studies have largely focused on students' attitudes toward AI or on the technological capabilities of AI applications, less attention has been given to the determinants of AI use among faculty members (Mah & Groß, 2024). By investigating instructors’ perceptions, perceived impact, concerns, future expectations, and demographic and professional characteristics, the study provides a more comprehensive understanding of faculty engagement with AI.

The findings may assist higher education institutions in designing professional development programs, developing AI-related policies, and implementing support mechanisms that encourage the effective and responsible use of AI in teaching, research, and academic administration. Furthermore, the study contributes empirical evidence from the higher education context that may inform future research and institutional decision-making regarding AI integration.

Research Questions

1. What are university instructors' perceptions, current use, perceived impact, concerns, and future expectations regarding artificial intelligence in higher education?

2. Do university instructors' perceptions, current use, perceived impact, concerns, and future expectations regarding artificial intelligence differ according to demographic and professional characteristics (gender, age, faculty, academic position, and years of experience)?
3. To what extent do QUIA subscales and demographic characteristics predict instructors' Current AI Use (UAI) in higher education?

LITERATURE REVIEW

Demographic and Professional Predictors of AI Readiness

Gender, academic position, and discipline are significant predictors of AI readiness and adoption. For instance, Saudi EFL university teachers demonstrated significant gender differences where male instructors reported higher AI readiness and integration, while academic position correlated with greater readiness and engagement, especially among associate professors (Alsuwat, 2026). Age and years of experience, however, often showed less pronounced effects, though qualitative data suggested nuanced generational differences in attitudes toward ethical and pedagogical dimensions of AI use (Alsuwat, 2026; Masalimova et al., 2026).

Across disciplines, STEM faculty generally reported higher engagement with AI tools, while humanities and social sciences showed more cautious or limited adoption, often reflecting institutional or cultural barriers (Masalimova et al., 2026; Токарева et al., 2021). Furthermore, the effectiveness of AI implementation is contingent upon an educator's level of digital competency, as gaps in practical skills and pedagogical knowledge can hinder the transition from theoretical readiness to consistent classroom application (Alnasib, 2023; Kohnke et al., 2023). Moreover, faculty familiarity and willingness to integrate these technologies significantly shape the effectiveness of AI-enabled learning activities and pedagogical practices (Ren & Wu, 2025).

Psychological and Attitudinal Dimensions

Positive attitudes toward AI are widespread among university instructors and often precede technical proficiency, resulting in a “willingness-usage gap” (Chan & Lee, 2023; Ofosu-Ampong, 2024). Theoretical models such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) are frequently extended to incorporate variables like technophobia, ethical reflection, and organizational culture, providing a nuanced understanding of adoption behaviors (Alsuwat, 2026; Rayan et al., 2026). Nonetheless, this intersection of psychological readiness and practical integration is frequently hindered by an intention–behavior gap, where positive attitudes often fail to translate into sustained classroom application (Ofosu-Ampong, 2024).

Cross-National and Disciplinary Variations in Faculty AI Readiness

Studies in Paraguay, Oman, and Egypt, for example, show that structural gaps in public higher education systems, as well as technophobia and perceived usefulness, significantly influence faculty readiness and willingness to integrate generative AI (Gómez-García et al., 2026; Rayan et al., 2026). Furthermore, research suggests that these differences are often shaped by the distinct ways different academic fields think about knowledge. For example, disciplines rooted in computational and quantitative approaches tend to embrace AI integration more readily, whereas those centered on qualitative, human-centered inquiry often approach it more cautiously (Qu et al., 2024). Additionally, the influence of departmental affiliation on faculty AI literacy appears inconsistent, as research suggests the impact of disciplinary background is often moderated by broader institutional and regional contexts rather than acting as a universal predictor. Recent research underscores the multidimensional nature of university instructors’ AI readiness and use, shaped by demographic, professional, institutional, and attitudinal factors(Khlaif et al., 2024; Zhang & Kee, 2025).

Conceptual Framework

The present study is based on the premise that university instructors' use of artificial intelligence (AI) in higher education is influenced by a combination of cognitive, affective, and contextual factors. Specifically, instructors' perceptions of AI, perceived impact of AI on educational practices, concerns regarding AI use, and expectations about the future role of AI are expected to shape their engagement with AI technologies in teaching, research, and academic activities.

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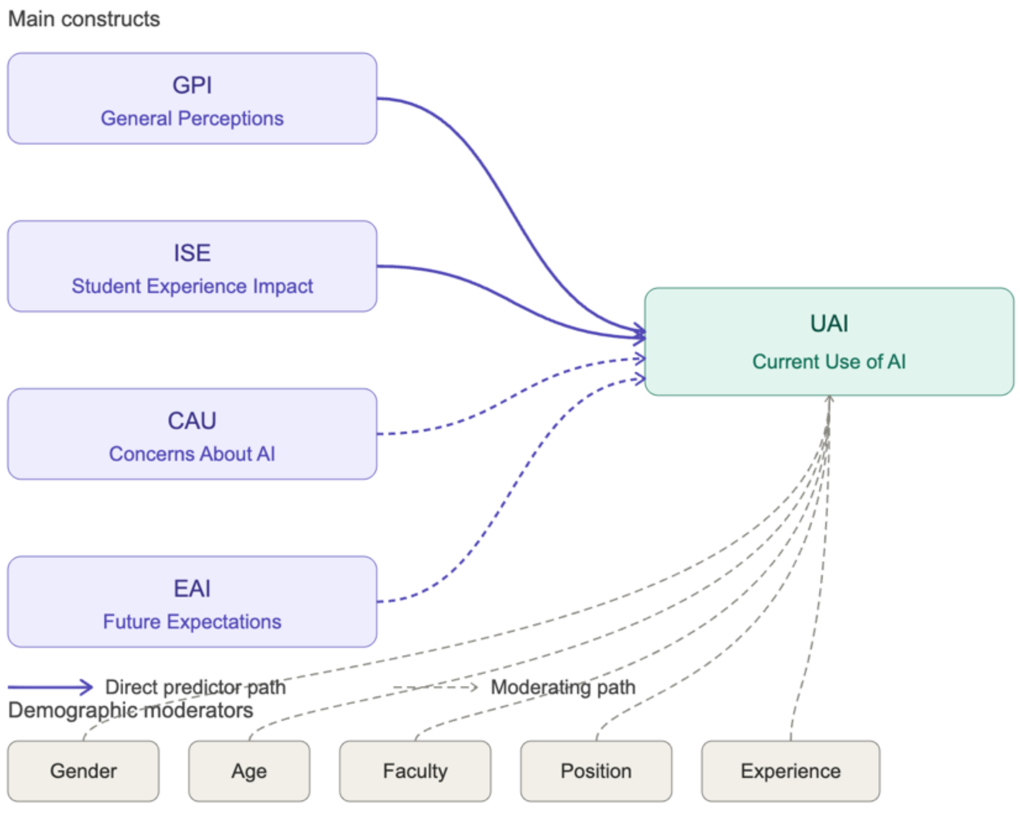
General perceptions of AI reflect instructors' beliefs about the potential value and benefits of AI in higher education. Positive perceptions may encourage instructors to explore and adopt AI tools. Similarly, instructors who perceive AI as having a positive impact on student learning and educational processes may be more likely to incorporate AI into their professional practices (Ofosu-Ampong, 2024). Future expectations regarding AI may also influence current use, as individuals who anticipate greater future benefits from AI may be more motivated to engage with these technologies. Conversely, concerns related to privacy, ethics, equity, and potential replacement of human roles may affect instructors' willingness to use AI (Saihi & Ahmed, 2026).

In addition to these psychological factors, demographic and professional characteristics, including gender, age, faculty affiliation, academic position, and years of experience, may contribute to variations in AI use (Buele & Llerena-Aguirre, 2025). Therefore, the study proposes that current AI use is influenced by both individual perceptions and contextual characteristics.

Based on the reviewed literature and the dimensions measured by the QUIA instrument, the present study proposes a conceptual framework in which university instructors' current use of AI is examined as a function of their perceptions, perceived impact, concerns, future expectations, and demographic and professional characteristics. Figure 1 illustrates the conceptual framework guiding the study.

Figure 1 Conceptual Framework of Factors Associated with University Instructors' Use of Artificial Intelligence in Higher Education



Source: Developed by the authors based on the Questionnaire on the Use of Artificial Intelligence (QUIA) developed by Vera (2023) and related literature on AI adoption in higher education

METHODOLOGY

Research Design

This study employed a quantitative nonexperimental cross-sectional survey design to investigate university instructors' perceptions, use, concerns, perceived impact, and future expectations regarding artificial intelligence in higher education and to identify factors associated with their current use of AI.

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Participants and Sampling

The study population comprised the entire faculty body of the Lebanese International University, a private university in Lebanon, totaling more than 1,500 academic professionals. All eligible faculty were invited to participate rather than recruiting toward a pre-specified target sample size; accordingly, no a priori power analysis was conducted. A total of 229 university instructors participated in the study, yielding a response rate of approximately 15.3%. The achieved sample size exceeds commonly cited minimum thresholds for exploratory factor analysis (e.g., 5–10 participants per item; Nunnally & Bernstein, 1994) and is broadly consistent with sample sizes used in comparable published validation studies of AI attitude and use instruments in higher education. The sample included 94 male (41%) and 135 female (59%) participants.

The response rate of approximately 15% raises the possibility of non-response bias. Faculty with stronger opinions about AI whether more favorable or more skeptical may have been more likely to complete the survey than those with limited AI experience or interest, potentially skewing the sample toward more polarized or engaged perspectives. We did not have access to institutional data on the demographic or disciplinary composition of the full invited population, so we could not formally compare respondents to non-respondents. Future research would benefit from response-rate-improving strategies (e.g., incentives, multiple contact waves) and from collecting non-respondent characteristics to allow direct bias assessment. Additionally, given the number of comparisons conducted in RQ2 (25 tests across five subscales and five demographic variables), findings should be interpreted with caution regarding potential Type I error inflation, as discussed above.Full demographic and professional details are provided in Table 1.

Table 1 Demographic/Professional Characteristics of the Study Sample (N = 229)

Characteristic	n	%
Gender		
Female	135	59.0
Male	94	41.0
Age range		
25–34	39	17.0
35–44	85	37.1
45–54	67	29.3
55–64	27	11.8
65 or older	11	4.8
Academic position		
Instructor	106	46.3
Lecturer	87	38.0
Assistant Professor	24	10.5
Associate Professor	7	3.1
Professor	5	2.2
Years of teaching experience		
1–5 years	60	26.2
6–10 years	40	17.5
11–15 years	39	17.0
16–20 years	39	17.0
21+ years	51	22.3
Faculty affiliation		
School of Arts & Sciences	85	37.1
School of Education	77	33.6
School of Business	34	14.8
School of Engineering	22	9.6
School of Pharmacy	11	4.8

Instrumentation

Data were collected using the Questionnaire on the Use of Artificial Intelligence (QUIA; Vera, 2023), a self-report instrument designed to assess university instructors' perceptions, experiences, concerns, and expectations regarding AI in higher education. The QUIA was developed by Vera (2023) and disseminated in English via Rediie (Red Internacional de Investigadores en Educación) under a Creative Commons license. No prior peer-reviewed psychometric validation of the QUIA was identified at the time of this study; accordingly, the reliability and factor structure analyses reported here represent an initial empirical evaluation of the instrument. As the instrument was originally developed in English and Lebanese International University's language of instruction is English, the questionnaire was administered in its original form, and no translation or cross-cultural adaptation procedure was required.

The QUIA consists of two sections: a demographic section gathering information on gender, age, academic position, faculty affiliation, and years of experience, and a 25-item scale organized into five dimensions — General Perceptions (GPI), Current AI Use (UAI), Student Experience Impact (ISE), Concerns About AI (CAU), and Future Expectations (EAI) — each comprising five items rated on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Composite scores for each dimension were computed by averaging item responses, with higher mean scores reflecting stronger endorsement of the measured construct.

The Current Use of AI in Higher Education subscale (UAI; Q6–Q10) warrants specific clarification regarding its item content. Rather than measuring direct personal pedagogical use of AI tools in the classroom, UAI items capture instructors' experienced exposure to AI in institutional and professional contexts including their institution's use of AI for course recommendation and student support (Q6, Q8), personal access to AI-enhanced learning platforms (Q7), AI presence in their research environment (Q9), and their overall assessment of AI's impact on higher education (Q10). This distinction between Current AI Use and individual pedagogical AI adoption is acknowledged as a limitation of the instrument and is discussed further in the limitations section. All other subscale labels and definitions are reported as specified in the original QUIA instrument (Vera, 2023).

Because all participants were drawn from the same institution, institutional-level items within the UAI subscale (notably Q6 and Q8) describe a shared objective environment. Accordingly, variation in UAI scores among respondents reflects differences in individual awareness, subjective perception, and departmental micro-context rather than differences in actual institutional AI deployment. UAI is therefore interpreted throughout this study as a measure of instructors' subjective perceptions of institutional AI presence rather than an objective index of institutional engagement.

Instrument Reliability & Normality Assessment

Cronbach's alpha was computed for each of the five sub-scales and for the overall instrument to assess internal consistency prior to inferential analyses. Results are presented in Table 2.

Table 2. Internal consistency coefficients for the QUIA sub-scales (N = 229). Α = Cronbach's alpha. Interpretation thresholds: ≥.90 Excellent, ≥.80 Good, ≥.70 Acceptable, ≥.60 Questionable, <.60 Poor

Table 2 Internal consistency of QUIA subscales (N = 229).

Subscale	Items	α	Item-Total r Range	Interpretation
GPI — General Perceptions (Q1–Q5)	5	.797	.232–.742	Acceptable
UAI — Current Use (Q6–Q10)	5	.699	.390–.534	Questionable–Acceptable
ISE — Student Experience Impact (Q11–Q15)	5	.819	.538–.695	Good
CAU — Concerns About AI (Q16–Q20)	5	.625	.072–.585	Questionable
EAI — Future Expectations (Q21–Q25)	5	.890	.675–.799	Good
Overall Scale (all 25 items)	25	.895	—	Good

Note. Α = Cronbach's alpha. Item-total correlations reflect corrected item-total r. Interpretation: α < .60 = Unacceptable; .60–.70 = Questionable; .70–.80 = Acceptable; .80–.90 = Good; > .90 = Excellent

Three subscales demonstrated good to acceptable reliability: EAI (α = .890), ISE (α = .819), and GPI (α = .797). UAI approached acceptable reliability (α = .699), and all five of its items exceeded the recommended item-total correlation threshold of $r \geq .30$ (Nunnally & Bernstein, 1994), supporting the retention of the subscale for analysis with appropriate caution. One subscale yielded a questionable alpha: CAU (α = .625). For CAU, reliability was undermined by two items: Q18 ('I am greatly concerned that AI may replace teachers in the future'; $r = .277$) and Q20 ('I feel very well-informed about policies and practices related to AI in my educational institution'; $r = .072$). These items appear to tap dimensions conceptually distinct from core concern about AI — the former relating more to professional identity threat and the latter to institutional information quality — and findings for CAU are therefore interpreted with appropriate caution. For GPI, Q4 ('I am aware of the implementation of AI in my educational institution'; $r = .232$) showed a marginally low item-total correlation, reflecting that institutional awareness is a somewhat distinct dimension from positive attitude toward AI. The overall instrument demonstrated good internal consistency (α = .895), supporting its use as a multidimensional measure of AI orientation in higher education.

The normality of sub-scale score distributions was examined using the Shapiro-Wilk test and indices of skewness and kurtosis. Results are displayed in Table 3.

Table 3 Descriptive statistics and normality test results for QUIA sub-scales (N = 229). M = Mean; SD = Standard Deviation.

Subscale	M	SD	Skewness	Kurtosis	Shapiro-Wilk	p
GPI – General Perceptions (Q1–Q5)	3.894	0.700	−0.846	1.229	.947	<.001
UAI – Current Use (Q6–Q10)	3.429	0.645	−0.849	1.563	.951	<.001
ISE – Student Experience Impact (Q11–Q15)	3.748	0.619	−0.871	2.744	.941	<.001
CAU – Concerns About AI (Q16–Q20)	3.418	0.608	−0.237	1.094	.976	<.001
EAI – Future Expectations (Q21–Q25)	4.038	0.688	−1.117	3.074	.898	<.001

All five sub-scales exhibited skewness values ranging from −1.117 to −0.237 and kurtosis values from 1.094 to 3.074, well within the boundaries of |skewness| < 2 and |kurtosis| < 7 recommended for parametric analysis with samples of this size (Hair et al., 2010). Although the Shapiro-Wilk test reached statistical significance for all sub-scales; an anticipated outcome with N > 100, the combined evidence from distributional indices and the Central Limit Theorem supports the use of parametric procedures (independent samples t-tests, one-way ANOVA, Pearson correlation, and multiple regression) for all subsequent analyses.

Given the cross-sectional, single-time-point, self-report design, Harman's single-factor test (Harman, 1976) was conducted to assess the potential for common method bias. All 25 QUIA items were entered into an unrotated factor analysis with extraction forced to a single factor. The single unrotated factor accounted for 33.98% of total variance, below the 50% threshold commonly used to indicate the absence of a substantial single-method factor (Podsakoff et al., 2003). Additionally, the unrotated solution yielded six factors with eigenvalues greater than 1.0 rather than a single dominant factor, further supporting the multidimensional structure of the QUIA and reducing concern that common method variance substantially inflated the observed relationships among subscales.

Data Collection Procedures

Data were collected using a structured self-administered online questionnaire developed specifically for this purpose — the QUIA (University Instructors' AI) Survey and administered electronically via Google Forms to faculty members across all five academic schools of the participating institution. Prior to the commencement of data collection, ethical approval was obtained from the relevant institutional review board. Participation in the study was entirely voluntary. No personally identifiable information was collected at any stage of the study.

Data Analysis

The analysis of data collected through the QUIA Survey was conducted using JASP 0.98, an open-source statistical analysis platform with a graphical interface designed for transparent and reproducible research. Given the cross-sectional, single-time-point, self-report design, Harman's single-factor test was conducted to assess the potential for common method bias. All 25 QUIA items were entered into an unrotated factor analysis with extraction forced to a single factor.The analytic sequence followed a structured, sequential logic: instrument validation was conducted first to confirm the psychometric integrity of the QUIA sub-scales before inferential procedures were applied; normality testing was then performed to confirm the appropriateness of parametric methods; and the research questions were addressed in order using the statistical techniques described below.

RESULTS

RQ1: Descriptive Profile of AI Engagement

The first research question examined university instructors' overall orientations toward AI across the five QUIA subscales. Subscale means are interpreted as follows: 1.00–1.80 = Strongly Disagree; 1.81–2.60 = Disagree; 2.61–3.40 = Neutral; 3.41–4.20 = Agree; 4.21–5.00 = Strongly Agree. Subscale-level results are presented in Table 4.

Table 4 Subscale descriptive statistics (N = 229). M = Mean; SD = Standard Deviation; Mdn = Median. Responses on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Subscale	N	M	SD	Mdn	Range	Interpretation
GPI — General Perceptions (Q1–Q5)	229	3.894	0.700	4.000	1.00–5.00	Agree
UAI — Current Use (Q6–Q10)	229	3.429	0.645	3.400	1.00–5.00	Moderate/borderline agreement
ISE — Student Experience Impact (Q11–Q15)	229	3.748	0.619	3.800	1.00–5.00	Agree
CAU — Concerns About AI (Q16–Q20)	229	3.418	0.608	3.400	1.00–5.00	Moderate/borderline agreement
EAI — Future Expectations (Q21–Q25)	229	4.038	0.688	4.000	1.00–5.00	Agree

Note. Interpretation bands: 1.00–1.80 = Strongly Disagree; 1.81–2.60 = Disagree; 2.61–3.40 = Neutral; 3.41–4.20 = Agree; 4.21–5.00 = Strongly Agree.

University instructors expressed positive agreement across all five dimensions of AI engagement. Future Expectations (EAI) yielded the highest mean (M = 4.038, SD = 0.688), indicating strong collective optimism about AI's future role in higher education. General Perceptions (GPI) were similarly elevated (M = 3.894, SD = 0.700), reflecting broad endorsement of AI's potential to improve educational quality, transform teaching practice, and personalize student learning. Student Experience Impact (ISE; M = 3.748, SD = 0.619) fell in the upper portion of the Agree range, indicating that instructors perceived moderately high positive effects of AI on student learning. Concerns About AI (CAU; M = 3.418, SD = 0.608) and Current Use (UAI; M = 3.429, SD = 0.645) were the lowest-scoring subscales, both reflecting moderate/borderline agreement rather than clear agreement. The notably lower UAI mean relative to GPI and EAI suggests a meaningful attitude-practice gap in which instructors hold more positive attitudes toward AI than their actual current use reflects. Item-level results are presented in Table 5.

Table 5 Item-level descriptive statistics (N = 229). M = mean; SD = standard deviation. %SD, %D, %N, %A, %SA = percentage of respondents selecting Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree, respectively. HE = higher education.

Item	M	SD	%SD	%D	%N	%A	%SA	Interpretation
Q1. AI has great potential to improve quality of HE	4.044	0.990	3.5	4.8	11.4	44.5	35.8	Agree
Q2. AI can positively transform higher education	4.044	0.912	2.6	3.5	13.1	48.5	32.3	Agree
Q3. AI can personalize students' learning	3.843	0.933	2.2	7.4	17.0	50.7	22.7	Agree
Q4. Aware of AI implementation in institution	3.755	0.933	3.1	6.6	20.5	51.5	18.3	Agree
Q5. Experienced concrete benefits from AI	3.786	0.938	3.5	3.5	25.3	46.3	21.4	Agree
Q6. Institution uses AI to suggest courses	3.183	0.933	5.2	15.3	40.2	34.5	4.8	Neutral
Q7. Access to AI-based online learning platforms	3.415	0.977	4.8	12.2	28.4	45.9	8.7	Agree

Q8. Chatbots implemented in institution	3.052	0.967	7.4	17.5	41.9	28.8	4.4	Neutral
Q9. AI used in research/data analysis in my area	3.834	0.893	3.1	3.5	20.5	52.8	20.1	Agree
Q10. Impact of AI on HE has been positive	3.659	1.012	4.8	7.4	22.7	47.2	17.9	Agree
Q11. AI personalizes learning content to my needs	3.856	0.790	1.7	3.9	17.0	61.6	15.7	Agree
Q12. AI makes learning resources more accessible	4.122	0.696	0.9	1.3	9.6	61.1	27.1	Agree
Q13. AI improved ability to keep pace with online classes	3.668	0.915	1.7	8.7	27.1	45.9	16.6	Agree
Q14. AI influenced academic management	3.703	0.800	1.7	4.4	27.5	54.6	11.8	Agree
Q15. AI improved interaction with colleagues	3.389	0.849	3.1	7.4	44.5	37.6	7.4	Neutral
Q16. Concerned about privacy with AI systems	3.799	0.943	2.6	4.8	26.2	42.8	23.6	Agree
Q17. Concerned about equity in education due to AI	3.729	0.892	2.2	7.0	22.7	52.0	16.2	Agree
Q18. Concerned AI may replace teachers	2.668	1.171	14.8	37.1	23.1	16.2	8.7	Neutral
Q19. Ethical concerns about AI algorithms in education	3.703	0.883	2.6	4.8	27.9	48.9	15.7	Agree
Q20. Well-informed about AI policies in institution	3.192	0.887	3.9	14.8	44.1	32.3	4.8	Neutral
Q21. AI will play more significant role in HE future	4.070	0.780	1.3	2.6	11.4	57.2	27.5	Agree
Q22. AI will enhance quality of learning	4.118	0.827	2.2	1.3	11.8	52.0	32.8	Agree
Q23. AI could make HE more accessible	3.886	0.871	3.5	1.3	19.2	55.0	21.0	Agree
Q24. AI will be essential in online education	4.048	0.844	2.2	2.6	12.2	54.1	28.8	Agree
Q25. Specific HE areas will benefit from AI	4.070	0.803	2.6	0.4	11.8	57.6	27.5	Agree

Within the General Perceptions subscale (Q1–Q5), Q1 and Q2 recorded the highest means (both M = 4.044), with 80.3% and 80.8% of respondents agreeing or strongly agreeing respectively, affirming confidence in AI's transformative potential. Q3 through Q5 fell slightly lower (M range: 3.755–3.843) but remained clearly in the Agree range. Within Current Use (Q6–Q10), Q8 ('Chatbots have been implemented in my educational institution'; M = 3.052) and Q6 ('My institution actively uses AI to suggest courses or learning resources'; M = 3.183) both fell in the Neutral range, with 24.9% and 20.5% of respondents disagreeing respectively, reflecting limited deployment of proactive AI systems in their institutions. By contrast, Q9 ('AI is used in research or data analysis in my area'; M = 3.834) and Q10 ('The impact of AI on higher education has been positive'; M = 3.659) scored considerably higher within the same subscale, indicating that AI exposure through research contexts is more prevalent than institution-led pedagogical deployment.

Within Student Experience Impact (Q11–Q15), Q12 ('AI makes learning resources more accessible'; M = 4.122) was the single highest-rated item across the entire instrument, with 88.2% of respondents agreeing or strongly agreeing. Q15 ('AI has improved interaction and communication with colleagues'; M = 3.389) was the lowest-rated item in this subscale, falling at the Neutral boundary, suggesting that AI's impact on social and collegial dimensions of academic work is less evident than its effects on learning content and accessibility. Within Concerns About AI (Q16–Q20), Q18 ('I am greatly concerned that AI may replace teachers in the future'; M = 2.668) was the only item across the entire instrument to fall below the neutral midpoint, with 51.9% disagreeing or strongly disagreeing. This finding indicates that teacher displacement anxiety, while prominent in public narratives, is not a dominant concern among university instructors in this sample. Q20 ('I feel very well-informed about AI policies in my institution'; M = 3.192, 18.7% disagreeing) approached the Neutral range, signalling gaps in institutional AI governance communication. Within Future Expectations (Q21–Q25), all five items recorded means above 3.886 and at least 79.9% agree or strongly agree responses, collectively confirming strong and consistent optimism about AI's future role in higher education.

RQ2: Demographic and Professional Differences in AI Engagement

The second research question investigated whether instructors' AI engagement subscale scores differed significantly by gender, age, academic position, years of teaching experience, and faculty affiliation.

Given that 25 comparisons were conducted across the five subscales and five demographic variables (gender, age group, academic position, years of experience, and faculty affiliation), the family-wise Type I error rate across this full set of tests was elevated beyond the nominal $\alpha = .05$ threshold. Bonferroni correction was applied to

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post-hoc pairwise comparisons within each significant omnibus test; however, no correction was applied across the 25 omnibus tests themselves, as these analyses were exploratory in nature. Applying a Bonferroni-corrected threshold across the full set of 25 tests ($\alpha = .05/25 = .002$) would retain only the CAU gender difference ($p = .002$) as significant, while the ISE experience effect ($p = .043$), UAI faculty effect ($p = .003$), and CAU faculty effect ($p = .046$) would not survive correction. Accordingly, findings beyond the CAU gender difference should be interpreted with appropriate caution as exploratory rather than confirmatory.

Gender differences.

Independent samples t-tests compared male (n = 94) and female (n = 135) instructors across all five subscales (Table 6). A statistically significant difference emerged only for Concerns About AI (CAU), $t(227) = -3.134$, $p = .002$, Cohen's $d = -.415$, with female instructors (M = 3.521, SD = 0.553) reporting significantly higher AI-related concerns than male counterparts (M = 3.270, SD = 0.654). This constitutes a moderate effect. Future Expectations (EAI) approached but did not reach conventional significance, $t(227) = -1.967$, $p = .050$, $d = -.260$. No statistically significant gender differences were found for GPI, UAI, or ISE.

Table 6 Independent samples t-test results by gender (N = 229).

Subscale	Male M (SD) n=94	Female M (SD) n=135	t	df	p	d	Sig
GPI	3.881 (0.796)	3.904 (0.626)	−0.243	227	.808	−.032	ns
UAI	3.419 (0.623)	3.436 (0.661)	−0.189	227	.850	−.026	ns
ISE	3.660 (0.700)	3.809 (0.550)	−1.804	227	.072	−.237	ns
CAU	3.270 (0.654)	3.521 (0.553)	−3.134	227	.002	−.415	**
EAI	3.932 (0.762)	4.113 (0.624)	−1.967	227	.050	−.260	ns

Note. D = Cohen's d effect size. ** $p < .01$; ns = not significant. Two-tailed tests.

Age, academic position, and years of experience.

One-way ANOVAs revealed no statistically significant differences across age groups for any of the five subscales (all $F < 2.334$, all $p > .057$), nor across academic positions (all $F < 0.886$, all $p > .473$). A significant effect of years of teaching experience was found for Student Experience Impact (ISE) only, $F(4, 224) = 2.512$, $p = .043$, $\eta^2 = .043$. Post-hoc pairwise comparisons with Bonferroni correction identified a significant difference between instructors with 21 or more years of experience (M = 3.902, SD = 0.525) and those with 6–10 years of experience (M = 3.525, SD = 0.632), $p\_adj = .025$. Instructors in the early-career (1–5 years; M = 3.813) and senior (21+ years; M = 3.902) groups reported the highest perceived student impact, while those in the mid-career range (6–10 years; M = 3.525) reported the lowest, suggesting a non-linear experience effect. No significant experience-related differences were found for GPI, UAI, CAU, or EAI.

Faculty affiliation.

Faculty affiliation produced statistically significant differences on two subscales (Table 7). For Current Use (UAI), $F(4, 224) = 4.190$, $p = .003$, $\eta^2 = .070$ (medium effect), post-hoc Bonferroni analysis revealed that School of Education instructors (M = 3.642, SD = 0.607) reported significantly higher current AI use than School of Arts & Sciences instructors (M = 3.238, SD = 0.682), $p\_adj = .001$. For Concerns About AI (CAU), $F(4, 224) = 2.465$, $p = .046$, $\eta^2 = .042$ (small effect), School of Business instructors (M = 3.694, SD = 0.617) reported significantly higher AI-related concerns than School of Arts & Sciences instructors (M = 3.334, SD = 0.574), $p\_adj = .031$. No significant faculty differences were found for GPI, ISE, or EAI.

Table 7 One-way ANOVA results by faculty affiliation (N = 229).

Subscale	Arts & Sci M(SD) n=85	Business M(SD) n=34	Education M(SD) n=77	Engineering M(SD) n=22	Pharmacy M(SD) n=11	F	p	η²	Sig
GPI	3.816 (0.800)	3.912 (0.625)	3.919 (0.663)	4.036 (0.578)	3.982 (0.583)	0.559	.693	.010	ns
UAI	3.238 (0.682)	3.424 (0.607)	3.642 (0.607)	3.436 (0.604)	3.418 (0.352)	4.190	.003	.070	**

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ISE	3.621 (0.674)	3.794 (0.565)	3.875 (0.604)	3.645 (0.494)	3.891 (0.524)	2.090	.083	.036	ns
CAU	3.334 (0.574)	3.694 (0.617)	3.413 (0.644)	3.427 (0.429)	3.236 (0.720)	2.465	.046	.042	*
EAI	3.974 (0.726)	4.035 (0.620)	4.057 (0.752)	4.145 (0.487)	4.200 (0.465)	0.481	.750	.009	ns

Note. H^2 = eta-squared. ** p < .01; * p < .05; ns = not significant. Post-hoc Bonferroni correction applied.

RQ3: Predicting Current AI Use

The third research question examined the extent to which QUIA subscales and demographic characteristics predicted instructors' current use of AI (UAI). Hierarchical multiple regression was conducted in two steps. Model 1 entered the four QUIA subscales (GPI, ISE, CAU, EAI) as predictors. Model 2 added demographic variables, which were dummy-coded as follows: gender (ref: Male; 1 dummy variable), age group (ref: 25–34; 4 dummies), academic position (ref: Instructor; 4 dummies), years of experience (ref: 1–5 years; 4 dummies), and faculty affiliation (ref: School of Arts & Sciences; 4 dummies), yielding 17 dummy-coded demographic predictors in total. All Variance Inflation Factor (VIF) values were below 3.3, confirming no multicollinearity concerns. Results are presented in Table 8.

Model 1 was statistically significant, $F(4, 224) = 46.956$, $p < .001$, and explained 45.6% of the variance in current AI use (Adjusted $R^2 = .446$). Student Experience Impact (ISE) was the strongest predictor ($\beta = .452$, $p < .001$), and General Perceptions (GPI) also contributed significantly ($\beta = .269$, $p = .001$). Concerns About AI (CAU; $\beta = .066$, $p = .189$) and Future Expectations (EAI; $\beta = .006$, $p = .936$) were non-significant.

Model 2 added 17 dummy-coded demographic predictors and explained 53.4% of variance (Adjusted $R^2 = .487$), $F(21, 207) = 11.301$, $p < .001$. The demographic block produced a significant incremental improvement, $\Delta R^2 = .078$, $F(17, 207) = 2.040$, $p = .011$. Among demographic predictors, two were statistically significant. Female gender (vs male) significantly and negatively predicted current AI use ($\beta = -.269$, $p = .021$), indicating that female instructors reported lower current AI use after controlling for psychological predictors. School of Education (vs School of Arts & Sciences) significantly and positively predicted current AI use ($\beta = .455$, $p < .001$), consistent with Education faculty's greater professional engagement with pedagogical technology. All other demographic dummy variables were non-significant. Notably, instructors with 16–20 years of experience showed a marginally non-significant trend toward higher use compared to the 1–5 year reference group ($\beta = .360$, $p = .059$). GPI ($\beta = .267$, $p < .001$) and ISE ($\beta = .413$, $p < .001$) retained significance in Model 2, confirming their robustness as the primary psychological predictors of current AI use.

Table 8 Hierarchical multiple regression predicting UAI (Current Use), N = 229.

Predictor	Model 1 β	p	Model 2 β	p	VIF	Sig.
Psychological subscales						
GPI — General Perceptions	.269	.001	.267	.001	2.51	***
ISE — Student Experience Impact	.452	<.001	.413	<.001	2.16	***
CAU — Concerns About AI	.066	.189	.068	.188	1.18	ns
EAI — Future Expectations	.006	.936	.050	.498	2.43	ns
Gender (ref: Male)						
Female	—	—	−.269	.021	1.44	*
Age group (ref: 25–34)						
35–44	—	—	−.183	.280	2.98	ns
45–54	—	—	−.126	.501	3.21	ns
55–64	—	—	.289	.211	2.45	ns
65 or older	—	—	−.282	.369	2.00	ns
Academic position (ref: Instructor)						
Lecturer	—	—	.045	.695	1.40	ns
Assistant Professor	—	—	−.043	.817	1.43	ns
Associate Professor	—	—	.148	.629	1.23	ns
Professor	—	—	−.268	.450	1.19	ns

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Years of experience (ref: 1–5 years)						
6–10 years	—	—	.278	.097	1.77	ns
11–15 years	—	—	.132	.460	2.01	ns
16–20 years	—	—	.360	.059	2.26	ns†
21+ years	—	—	.175	.376	2.98	ns
Faculty affiliation (ref: Arts & Sciences)						
School of Business	—	—	.204	.186	1.33	ns
School of Education	—	—	.455	.001	1.62	***
School of Engineering	—	—	.137	.449	1.26	ns
School of Pharmacy	—	—	.156	.525	1.23	ns
R^2	.456		.534			
Adj. R^2	.446		.487			
F	46.956** F(4,224)		11.301** F(21,207)			
ΔR^2	—		.078* F(17,207)=2.040, p=.011			

Note. B = standardized coefficient; VIF = Variance Inflation Factor. All categorical variables dummy-coded: Gender ref = Male; Age ref = 25–34; Position ref = Instructor; Experience ref = 1–5 years; Faculty ref = School of Arts & Sciences. *** p < .001; ** p < .01; * p < .05; † p < .10; ns = not significant.

Sensitivity Analysis — Criterion Contamination Check

Because Q10 ('In my experience, the impact of AI on higher education has been positive') shares conceptual territory with GPI items, a sensitivity analysis was conducted removing Q10 from the UAI composite. The trimmed UAI (Q6–Q9; $\alpha = .665$, M = 3.371, SD = 0.666) correlated with the original at $r = .959$ ($p < .001$). With trimmed UAI as the outcome, GPI remained significant in Model 1 ($\beta = .185$, $p = .024$) and Model 2 ($\beta = .200$, $p = .016$), as did ISE (Model 1: $\beta = .439$, $p < .001$; Model 2: $\beta = .375$, $p < .001$). The reduction in R^2 from .456 to .325 and in the GPI coefficient from .269 to .185 confirms modest inflation from Q10, but the directional consistency and significance of both predictors across both specifications supports the robustness of the primary findings. Results are presented in Table 9.

Table 9 Sensitivity Analysis: Comparison of Regression Results for Original UAI (Q6–Q10) and Trimmed UAI (Q6–Q9, Q10 Removed).

Predictor	Original UAI β	p	Trimmed UAI β M1	p	Trimmed UAI β M2	p	Sig.
Psychological subscales							
GPI — General Perceptions	.269	.001	.185	.024	.200	.016	* / *
ISE — Student Experience Impact	.452	<.001	.439	<.001	.375	<.001	*** / ***
CAU — Concerns About AI	.066	.189	.101	.070	.102	.071	ns / ns
EAI — Future Expectations	.006	.936	-.047	.559	.002	.982	ns / ns
Significant demographic predictors (Trimmed Model 2 only)							
Female (ref: Male)	—	—	—	—	−.257	.044	* (M2)
16–20 years (ref: 1–5 years)	—	—	—	—	.414	.047	* (M2)
School of Education (ref: Arts & Sciences)	—	—	—	—	.577	<.001	*** (M2)

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R^2	.456		.325		.440
Adj. R^2	.446		.313		.384
F	46.956** F(4,224)		26.924** F(4,224)		7.758** F(21,207)
ΔR^2	—		—		.116* F(17,207)=2.518, p=.001

Note. Original UAI β = Model 1 coefficients with full UAI (Q6–Q10). Trimmed UAI β M1 = Model 1 with Q10 removed. Trimmed UAI β M2 = Model 2 (+ demographics) with Q10 removed. Only significant demographic predictors shown for Model 2. Sig. column reflects significance for original / trimmed Model 1 respectively. *** $p < .001$; ** $p < .01$; * $p < .05$; ns = not significant.

DISCUSSION

This study examined university instructors' general perceptions, institutional AI engagement, student experience impact, concerns about AI, and future expectations regarding artificial intelligence in higher education, together with their demographic and professional correlates. The findings, based on a validated 25-item instrument administered to 229 instructors across five disciplinary faculties, present a multidimensional and theoretically coherent picture of AI orientation in higher education. The following discussion interprets the results in relation to each research question and situates them within the broader literature on technology acceptance and AI in education.

Broadly Positive Orientations Across All Dimensions

The most prominent finding of this study is that university instructors demonstrated positive orientations toward AI across all five measured dimensions, with all subscale means falling within the Agree range. The subscales were ranked from highest to lowest as follows: Future Expectations (EAI; $M = 4.038$), General Perceptions (GPI; $M = 3.894$), Student Experience Impact (ISE; $M = 3.748$), Current AI Use (UAI; $M = 3.429$), and Concerns About AI (CAU; $M = 3.418$). This pattern suggests that instructors are more optimistic about AI's future potential than about its current institutional implementation, consistent with previous research reporting increasingly positive faculty attitudes toward educational AI adoption (Mah & Groß, 2024).

The gap between Future Expectations (EAI) and Current AI Use (UAI) is particularly informative. While instructors expressed strong confidence in AI's future role, their perceptions of current institutional AI implementation were comparatively lower, especially regarding chatbot deployment and AI-based course recommendation systems. This attitude–engagement gap likely reflects institutional rather than individual barriers, including limited infrastructure, insufficient professional development, and unclear AI governance (Plaza & Marolla-Gajardo, 2026; Xi et al., 2020). Supporting this interpretation, the item assessing awareness of institutional AI policies (Q20) approached the Neutral range, suggesting that communication about AI governance remains insufficient and reinforcing calls for greater transparency and education-specific AI guidelines (Chan, 2023; Jin et al., 2024).

Finally, concern about AI replacing teachers (Q18) was the only item scoring below the neutral midpoint ($M = 2.668$), with 51.9% of instructors disagreeing that this was a major concern. This indicates that teacher displacement anxiety is relatively low, suggesting that instructors largely view AI as a tool that complements rather than replaces professional teaching, consistent with recent findings in the literature (Ren & Wu, 2025; Mah et al., 2025). Overall, the findings portray faculty as cautiously optimistic, emphasizing AI's potential to enhance teaching and learning while recognizing the need for stronger institutional support to translate positive attitudes into practice.

Demographic Differentiation

Demographic and professional characteristics revealed targeted rather than widespread differences in AI engagement, with significant effects limited to specific subscales. As noted in the Results, only the CAU gender difference survives correction for the full family of 25 comparisons conducted; the remaining findings discussed below should therefore be considered exploratory and interpreted with corresponding caution.The most consistent finding concerned gender differences in Concerns About AI (CAU), as female instructors (M = 3.521) reported significantly higher concerns than male colleagues (M = 3.270), $t(227) = -3.134$, $p = .002$, $d = -.415$. This supports broader evidence that women often show greater sensitivity to ethical, privacy, and equity dimensions of technology, including concerns about algorithmic bias and data surveillance in AI systems (Dringó-Horváth et al., 2025; Stephany & Duszynski, 2026). However, the absence of gender differences in GPI, UAI, ISE, and EAI suggests that gender does not influence AI optimism or engagement levels, but rather shapes the critical evaluation of AI-related risks. Female instructors' heightened awareness may therefore serve as an institutional resource for developing more reflective and equity-oriented AI integration practices.

Years of experience influenced Student Experience Impact (ISE), with instructors in the 21+ year group (M = 3.902) reporting significantly higher perceived impact than those with 6–10 years of experience (M = 3.525), $p_{(\text{adj})} = .025$. This aligns with research suggesting that experienced educators are better positioned to evaluate the effects of emerging technologies through accumulated professional perspectives (Alnasib, 2023; Dringó-Horváth et al., 2025; Mananay, 2024). The higher ISE scores among novice instructors (1–5 years; M = 3.813) compared with the 6–10 year group indicate a possible non-linear experience effect, as early-career educators may enter the profession with greater exposure to AI-supported learning environments. Neither age nor academic position produced significant differences, suggesting that rank and seniority are not key determinants of AI orientations in this institution.

Faculty affiliation generated the most notable structural differences. Education instructors reported the highest Current AI Use (UAI: M = 3.642), significantly exceeding Arts & Sciences instructors (M = 3.238), $p_{(\text{adj})} = .001$, likely reflecting greater exposure to pedagogical technologies, educational research, and curriculum innovation. Business instructors reported higher Concerns About AI (CAU: M = 3.694) than Arts & Sciences instructors (M = 3.334), $p_{(\text{adj})} = .031$, possibly due to stronger disciplinary engagement with AI governance, data ethics, and algorithmic accountability. The absence of faculty differences in GPI, ISE, and EAI suggests that disciplinary background influences institutional engagement and ethical awareness rather than overall AI optimism or perceived benefits.

Predictors of Current AI Use

Before interpreting the regression findings, an important theoretical qualification is warranted. Technology acceptance frameworks such as the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) are individual-level models designed to explain personal technology adoption. However, the UAI subscale in this study measures instructors' Current AI Use (e.g., exposure to AI tools, platforms, and research environments) rather than individual pedagogical AI use. Consequently, the results should not be viewed as a direct test of TAM or UTAUT, but rather as evidence of factors associated with institutional AI engagement. Although Student Experience Impact (ISE) aligns conceptually with TAM's perceived usefulness construct, its relationship with UAI reflects institutional embeddedness rather than individual behavioral intention. Future studies should employ measures of individual AI adoption to more directly test TAM and UTAUT predictions.

The hierarchical regression identified Student Experience Impact (ISE) and General Perceptions (GPI) as the two strongest psychological predictors of Current AI Use (UAI). Model 1, including the four QUIA subscales, explained 45.6% of the variance, $F(4, 224) = 46.956$, $p < .001$. ISE emerged as the strongest predictor ($\beta = .452$, $p < .001$), indicating that instructors who perceive greater benefits of AI for student learning report higher institutional AI engagement. GPI also significantly predicted UAI ($\beta = .269$, $p = .001$), suggesting that positive overall beliefs about AI are associated with greater institutional exposure. In contrast, Concerns About AI (CAU; $\beta = .066$, $p = .189$) and Future Expectations (EAI; $\beta = .006$, $p = .936$) were not significant.

Model 2, which added 17 dummy-coded demographic variables, explained 53.4% of the variance, $F(21, 207) = 11.301$, $p < .001$, with a significant increase in explanatory power ($\Delta R^2 = .078$, $p = .011$). Female instructors reported lower Current AI Use than males after controlling for psychological variables ($\beta = -.269$, $p = .021$), revealing a suppression effect not observed in the bivariate analysis. Additionally, instructors from the School of

Education reported significantly higher Current AI Use than those from the School of Arts & Sciences ($\beta = .455$, $p < .001$), highlighting the influence of disciplinary context. Importantly, ISE ($\beta = .413$, $p < .001$) and GPI ($\beta = .267$, $p < .001$) remained significant, confirming their robustness across models.

The non-significance of CAU indicates that AI-related concerns do not necessarily reduce institutional AI engagement, suggesting that concern and engagement can coexist. This finding implies that ethical awareness and critical reflection should be integrated into AI professional development rather than treated as prerequisites for engagement. However, CAU's relatively low internal consistency ($\alpha = .625$) may have attenuated its effect. A disattenuation analysis estimated a corrected correlation of $r = .100$ with UAI, indicating only a small association that would likely remain non-significant at the current sample size.

It should be noted that the GPI regression coefficient was subject to modest criterion contamination due to the inclusion of Q10 ('In my experience, the impact of AI on higher education has been positive') within the UAI subscale. A sensitivity analysis removing Q10 confirmed that GPI's independent contribution remains significant ($\beta = .185$–$.200$ across models) though attenuated relative to the primary analysis. This qualification does not negate the finding that general AI perceptions independently predict institutional AI engagement, but it does suggest the effect size should be interpreted conservatively. ISE's predictive contribution is unaffected by this concern, as there is no item-level overlap between ISE and UAI.

CONCLUSION

This study examined university instructors' AI orientations, including perceptions, institutional AI engagement, perceived student impact, concerns, and future expectations, while identifying demographic, professional, and attitudinal factors associated with these dimensions. Based on data from 229 instructors across five disciplinary schools and a validated 25-item instrument, the findings provide an evidence-based understanding of AI engagement in contemporary higher education. The overarching finding is one of constructive ambivalence: instructors demonstrate strong optimism about AI's future potential and educational benefits, particularly for accessibility and personalization, yet their perceived Current AI Use remains comparatively lower. This gap appears to reflect structural conditions rather than resistance, including limited implementation, insufficient professional development, and unclear governance. Higher perceived AI benefits for students were associated with stronger institutional AI engagement, while Education faculty reported greater AI engagement, suggesting that disciplinary context shapes AI exposure. The low level of concern about AI replacing teachers further indicates that instructors largely perceive AI as a complementary professional tool rather than a threat.

The study contributes several important insights. First, AI optimism and AI concerns emerged as largely independent dimensions, supporting the co-existence perspective proposed by Cardona et al. (2023), whereby instructors can engage with AI while maintaining critical awareness. Second, Student Experience Impact (ISE) was the strongest psychological correlate of institutional AI engagement, aligning with TAM's perceived usefulness construct, although interpreted at the institutional rather than individual adoption level. Third, General Perceptions of AI (GPI) independently predicted institutional AI engagement, highlighting the role of foundational attitudes. Fourth, the gender suppression effect where female instructors showed lower Current AI Use after controlling for psychological factors suggests the need for gender-sensitive professional development. Fifth, disciplinary differences in AI engagement and concerns support faculty-specific rather than generic institutional AI development strategies.

However, the interpretation of UAI requires caution. The Current Use of AI in Higher Education subscale measures institutional AI deployment and experienced exposure rather than direct personal pedagogical use. Therefore, the regression findings identify predictors of institutional AI embeddedness rather than individual AI adoption behavior. Because TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) are individual-level behavioral frameworks, applying them to an institutional exposure measure introduces a level-of-analysis limitation. Future research should incorporate direct measures of instructors' personal AI practices, such as AI use in lesson planning, assessment, and feedback.

The single-institution design further limits generalizability because variation in UAI reflects differences in instructors' perceptions of a shared environment rather than objective differences in institutional implementation. Additionally, reliance on self-report measures collected at one time point introduces potential common method bias. Multi-institutional studies combining objective indicators of AI implementation with individual measures would strengthen causal interpretation.

Measurement limitations should also be considered. The UAI subscale partially overlaps conceptually with GPI through Q10, although sensitivity analysis confirmed that GPI remained a significant predictor after its removal (β = .185 vs .269). The CAU subscale showed relatively low reliability (α = .625), partly due to conceptually distinct items related to teacher replacement concerns and policy awareness. A disattenuation correction estimated the CAU–UAI correlation at r = .100, suggesting a small association that requires further investigation with improved measurement. The UAI reliability (α = .699) also indicates potential for refinement.

Overall, the findings suggest that AI integration in higher education is less a matter of changing instructors' attitudes than of creating institutional conditions that enable existing positive orientations to translate into responsible, equitable, and effective educational practice.

Ethics Statement

This study was reviewed and approved by the Institutional Review Board (IRB) of Lebanese International University (Ref: LIUIRB-260129-FK-443), approved on 24 March 2026. The study was conducted in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments.

Informed Consent Statement

Informed consent was obtained from all individual participants included in the study. Participants were informed of the study's purpose, the voluntary nature of participation, their right to withdraw at any time without penalty, and the confidentiality of their responses prior to completing the questionnaire.

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Conflict of Interest Statement

The authors declare no conflict of interest.

Data Availability Statement

The dataset generated and analyzed during the current study is available from the corresponding author upon reasonable request.

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