The Perception Towards the Application of AI-Integrated Teaching Among Lecturers in Jiujiang University, Jiangxi Province

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ABSTRACT

This research aimed to (1) examine lecturers' attitudes, perceived benefits and core concerns towards AI-integrated teaching at Jiujiang University (JJU), a provincial application-oriented university in inland China; (2) analyze the institutional and individual factors influencing lecturers' readiness to adopt AI-integrated teaching practices; (3) explore the variations in perceptions and intended AI usage across different academic disciplines and professional ranks; and (4) propose evidence-based institutional support mechanisms and pedagogical frameworks for effective and responsible AI integration in regional higher education contexts. A mixed-methods explanatory sequential design was employed, combining a cross-sectional quantitative survey of 338 full-time lecturers and in-depth semi-structured interviews with 28 purposively selected participants. The research adopted statistical analyses (structural equation modeling, ANOVA, regression) and thematic analysis to process data, with validated scales for construct measurement (Cronbach's $\alpha > 0.80$, KMO = 0.876). Major Findings: (1) JJU lecturers exhibit cautious optimism towards AI-integrated teaching, with 76.3% recognizing its educational potential but only 34.9% actively integrating AI into core pedagogical activities, forming a significant attitude-practice gap; (2) professional development ($\beta=0.42$, $p<.001$) and digital literacy ($\beta=0.39$, $p<.001$) are the strongest predictors of adoption readiness, followed by ICT infrastructure quality ($\beta=0.28$, $p<.01$) and policy clarity ($\beta=0.18$, $p<.05$); (3) profound disciplinary disparities exist in adoption readiness, with Engineering (M=4.05) and Medicine (M=3.92) as high-adoption clusters, and Law (M=2.88) and Arts (M=2.95) as low-adoption clusters, driven by epistemological incompatibility; (4) the primary barriers to adoption are not fear of professional replacement (M=2.50 for perceived role threat), but data privacy risks (M=4.05), increased workload (M=3.91), and AI output accuracy/bias concerns (M=3.84); (5) lecturers demand discipline-sensitive professional development, integrated technical-pedagogical support, clear co-created policies, and formal incentives for AI innovation. The study recommends targeted strategies for JJU and similar regional universities to bridge the attitude-practice gap, including establishing a dedicated Digital Pedagogy and AI Center, implementing tiered disciplinary AI training, and building an AI-as-augmented-pedagogy framework with human-in-the-loop pedagogical principles.

Keywords: AI-integrated teaching; Lecturer perception; Adoption readiness; Regional higher education; Jiujiang University

1. Introduction

Artificial Intelligence (AI) is reshaping the landscape of higher education globally, evolving from experimental tools to mainstream pedagogical resources for intelligent tutoring, personalized learning, and automated assessment (Kumar et al., 2023). In China, AI integration in higher education is elevated to a national strategic priority under initiatives such as the Next Generation Artificial Intelligence Development Plan, with policy mandates for universities to embed AI into teaching and cultivate AI-literate graduates (Zhang & Wang et al., 2025). However, empirical research reveals a stark gap between national policy ambition and on-the-ground implementation, particularly in regional provincial universities—the institutions educating over 85% of China’s undergraduate population (Zhang et al., 2025). Unlike elite "Double First-Class" universities with abundant resources and dedicated AI research centers, regional universities face compounded challenges: limited ICT infrastructure, uneven faculty digital literacy, insufficient discipline-specific professional development, and vague institutional policies for AI governance (Moyo et al., 2023; Liang & Huang, 2023).

Jiujiang University (JJU), a comprehensive provincial application-oriented university in Jiangxi Province, China, epitomizes the realities of regional higher education in inland China. Established in 2002 with a "one university, two campuses, three affiliated hospitals" model, JJU hosts 33,030 students across 73 undergraduate programs and 3 master’s programs, employing 1,872 full-time faculty (90.54% with doctoral/master’s degrees, 51.02% as dual-qualification industry-academia teachers) (Jiujiang University, 2025). Ranked the "First Tier" of Jiangxi’s application-oriented universities for three consecutive years (2022–2024), JJU is tasked with aligning its teaching practices with national AI policies and Jiangxi Province’s 1269 Manufacturing Action Plan, which demands AI-literate graduates for regional economic development. Yet, like most regional universities, JJU lacks context-specific empirical evidence on faculty perceptions and readiness for AI-integrated teaching—an essential foundation for designing effective, localized AI integration strategies.

Faculty perceptions are the linchpin of successful AI adoption in higher education (Banerjee et al., 2025). The Technology Acceptance Model (TAM) and Diffusion of Innovation Theory identify lecturers' perceived usefulness, ease of use, and institutional support as core determinants of technology adoption (Davis, 1989; Rogers, 2003). Recent longitudinal research (2022–2024) shows that faculty positive attitudes towards AI rose from 34% to 76%, with professional development as the strongest predictor of actual integration (Banerjee et al., 2025). However, existing studies predominantly focus on elite coastal universities, with minimal research on regional inland institutions (Zhang et al., 2025). Over 70% of published research on Chinese higher education AI adoption samples "Double First-Class" universities, and less than 8% examines non-STEM disciplines (Huang et al., 2023)—creating a critical knowledge deficit for universities like JJU, which span nine disciplinary domains (from Medicine and Engineering to Law and Arts) and face unique resource constraints.

This research addresses this gap by investigating lecturers' perceptions towards AI-integrated teaching at JJU. It responds to the urgent need for context-specific evidence to inform AI integration strategies in regional application-oriented universities, where AI adoption is not only a pedagogical imperative but also a driver of regional human capital development and educational equity (Phakamach et al., 2023). By examining the attitudes, influencing factors, and disciplinary/rank variations in AI adoption readiness at JJU, this study provides a replicable model for similar regional universities in China and other developing economies, mitigating the coastal-inland educational divide in AI integration (Moyo et al., 2023).

2. Literature Review and Research Related

2.1 AI-Integrated Teaching in Higher Education

AI-integrated teaching refers to the intentional embedding of AI technologies (e.g., intelligent tutoring systems, learning analytics, automated assessment, generative AI) into instructional design, delivery, and evaluation to enhance teaching effectiveness and student learning outcomes (Kumar et al., 2023). Global research confirms AI's potential to automate routine administrative tasks (e.g., grading, attendance tracking), personalize learning pathways for diverse students, and enrich teaching content with simulations and interactive materials (Banerjee et al., 2025). However, AI integration in core teaching functions lags far behind administrative applications in most universities, especially in resource-constrained contexts (Zhang et al., 2025). A 2025 study of eight Chinese universities found that AI was primarily used for student management and administrative efficiency, with only 29% of faculty integrating AI into lesson design and assessment (Zhang & Wang et al., 2025).

2.2 Factors Influencing Faculty Adoption of AI-Integrated Teaching

Research identifies two broad categories of factors shaping faculty AI adoption readiness: institutional factors and individual factors (Johnson et al., 2023). Institutional factors include high-quality professional development, robust ICT infrastructure, clear AI governance policies, and formal incentives for innovation (Banerjee et al., 2025; Kumar et al., 2023). Longitudinal studies show that discipline-specific, practice-embedded professional development increases AI adoption rates by 70%, far exceeding generic AI awareness workshops (Phakamach et al., 2023). ICT infrastructure quality—including reliable internet, AI-enabled Learning Management Systems (LMS), and technical support—also acts as a critical enabler, with intra-institutional digital divides (e.g., between STEM and humanities departments) exacerbating adoption disparities (Zhang et al., 2025).

Individual factors center on faculty digital literacy, teaching experience, and technological perceptions (Siddhu & Arshed, 2024). Digital literacy—defined as the ability to use, evaluate, and create with digital technologies—is the strongest individual predictor of AI adoption, with age showing a moderate negative correlation ($r=-0.34$) with literacy levels (Moyo et al., 2023). Technological perceptions, including perceived usefulness (AI's ability to enhance teaching) and perceived threat (AI replacing teacher roles), also shape adoption intentions; notably, most faculty do not view AI as a professional threat, but rather as a supplementary tool (Siddhu & Arshed, 2024). Teaching experience, by contrast, has no significant direct effect on adoption readiness, with experienced faculty adopting AI only when its pedagogical value is clearly demonstrated (Banerjee et al., 2025).

2.3 Disciplinary and Rank-Based Variations in AI Adoption

Disciplinary epistemology is a fundamental, understudied moderator of AI adoption in higher education (Huang et al., 2023). STEM disciplines (Engineering, Medicine, Science) adopt AI tools at rates three times higher than humanities and social sciences (Law, Arts, Literature), as AI's data-driven, predictive logic aligns with STEM's quantitative, simulation-based pedagogies (Johnson et al., 2023). For humanities faculty, AI is often perceived as epistemologically incompatible with their core pedagogical goals—e.g., normative reasoning in Law, critical interpretation in Literature, and human expression in Arts (Siddhu & Arshed, 2024). Professional rank also influences adoption: junior faculty exhibit higher readiness than senior faculty, driven by career incentives to demonstrate innovation, while senior faculty prioritize perceived pedagogical value and time efficiency (Banerjee et al., 2025).

2.4 AI Integration in Regional Higher Education

Regional universities in developing economies face unique barriers to AI integration, including limited funding, inadequate technical support, and a lack of context-specific AI pedagogical frameworks (Moyo et al., 2023). In African higher education, for example, only 38% of institutions have reliable internet, and less than 20% of faculty have advanced digital literacy (Moyo et al., 2023). While China's regional universities have better infrastructure, they still face gaps: ICT budgets are a fraction of elite universities, AI expertise is concentrated in a small number of high-level talents, and professional development is often generic (Liang & Huang, 2023). Additionally, regional universities' mission of training application-oriented graduates demands AI integration that aligns with local industry needs—yet few studies link AI teaching practices to regional economic development imperatives (Phakamach et al., 2023).

2.5 Theoretical Foundations

This study is grounded in two complementary theoretical frameworks:

1. Technology Acceptance Model (TAM) (Davis, 1989): Posits that user adoption of technology is driven by perceived usefulness (the degree to which a tool enhances performance) and perceived ease of use (the degree to which a tool is free of effort). Extended TAM includes external factors (e.g., institutional support, digital literacy) that shape these core perceptions (Venkatesh & Davis, 2000).

2. Diffusion of Innovation Theory (Rogers, 2003): Conceptualizes technology adoption as a social process shaped by innovation characteristics (compatibility, complexity, observability), social system influences (disciplinary norms, peer networks), and change agents (leadership, early adopters).

An integrated conceptual framework combining TAM and Diffusion of Innovation Theory is employed to capture both individual cognitive evaluations and systemic institutional/disc disciplinary dynamics of AI adoption—addressing the limitations of single-theory approaches (Banerjee et al., 2025).

3. Research Methodology

3.1 Purpose of the Research

The primary objectives of this study are to:

1. Systematically assess JJU lecturers' attitudes, perceived benefits, and core concerns towards AI-integrated teaching, establishing an empirical baseline for institutional decision-making.

2. Identify and analyze the key institutional (professional development, ICT infrastructure, policy clarity) and individual (digital literacy, teaching experience) factors influencing AI-integrated teaching adoption readiness.

3. Evaluate variations in perceptions and intended AI usage across different academic disciplines and professional ranks at JJU.

4. Develop evidence-based recommendations for institutional support mechanisms and pedagogical frameworks for effective, responsible AI integration in regional application-oriented universities.

3.2 Population and Sample

The target population is 1,872 full-time lecturers at JJU (2024–2025 academic year), spanning nine disciplinary domains, two campuses, and three affiliated hospitals/industrial colleges. A mixed-methods sampling strategy was used:

1. Quantitative sample: A stratified random sample of 338 lecturers (18.1% of the population), stratified by academic discipline (9 strata) and professional rank (3 strata: senior, mid-career, junior) to ensure representativeness. The sample size was determined via G Power 3.1 analysis (power=0.95, α=0.05, medium effect size f^2=0.15), with a 30% non-response rate accommodation.

2. Qualitative sample: 28 purposively selected lecturers (maximum variation sampling) representing high/low adoption readiness, diverse disciplines (high-AI-relevance: Engineering/Medicine; low-AI-relevance: Law/Arts), professional ranks, faculty types (dual-qualification/pure academic), and stance profiles (enthusiasts, cautious optimists, skeptics, neutral). The sample size was determined by thematic saturation (no new themes emerging after the 25th interview).

3.3 Data Collection Technology

1.Quantitative data: An online survey was distributed via JJU's official email and LMS (LimeSurvey platform), consisting of validated scales for measuring AI adoption readiness (Cronbach's α=0.89), institutional factors (α=0.85), individual factors (α=0.82), and technological perceptions (α=0.87). The survey used a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree) and demographic questions (discipline, rank, teaching experience, faculty type).

2. Qualitative data: Semi-structured in-depth interviews (45–75 minutes each) were conducted face-to-face or via secure videoconference. The interview protocol explored lecturers' AI usage experiences, perceived benefits/barriers, institutional support needs, and pedagogical visions for AI integration. All interviews were audio-recorded and transcribed verbatim.

3.4 Data Processing and Analysis Technology

1. Quantitative analysis: Data were screened for missing values (0.5% MCAR, handled via expectation-maximization imputation) and outliers. Analyses were performed using SPSS 27.0 and AMOS 26.0, including:

Descriptive statistics (means, standard deviations, frequencies) for attitudes and perceptions.

Structural Equation Modeling (SEM) to test the integrated conceptual framework and identify predictors of adoption readiness.

One-way ANOVA and Tukey's HSD post-hoc tests to examine disciplinary and rank-based variations.

Independent samples t-tests to compare adoption readiness across groups (e.g., professional development participants vs. non-participants).

2. Qualitative analysis: Transcripts were coded and analyzed using NVivo 14 via thematic analysis (Braun & Clarke, 2006), involving six phases: familiarization with data, initial coding, theme searching, theme review, theme definition, and narrative generation. Peer debriefing and member checking were used to ensure trustworthiness.

3.Data integration: Quantitative and qualitative findings were integrated at the interpretive level, with qualitative themes explaining statistical patterns (e.g., disciplinary disparities) and quantitative data generalizing qualitative insights (e.g., perceived barriers). A joint display table was used to juxtapose effect sizes and thematic excerpts for triangulation.

3.5 Research Instruments and Variables Used

The survey questionnaire included two core variable categories, operationalized via validated scales from prior research (adapted for JJU's context):

Dependent variable: AI-integrated teaching adoption readiness (12 items) – lecturers' behavioral intention and actual utilization of AI-powered pedagogical tools.

Independent variables:

Institutional factors (10 items): professional development availability, ICT infrastructure quality, policy clarity.

Individual factors (8 items): digital literacy levels, teaching experience.

Technological perceptions (9 items): perceived usefulness of AI tools, perceived threat to teaching roles.

Control variables: academic discipline, professional rank.

3.6 Reliability and Validity Testing

Reliability: Cronbach's α coefficients for all multi-item scales ranged from 0.82 to 0.91, indicating excellent internal consistency (Nunnally, 1978).

Validity:

Content validity: Scales were adapted from peer-reviewed studies and reviewed by three experts (2 educational technology scholars, 1 JJU senior lecturer) for context relevance.

Construct validity: Confirmatory factor analysis (CFA) confirmed good model fit ($\chi^2/df=2.15$, CFI=0.95, TLI=0.93, RMSEA=0.058).

Sampling adequacy: KMO and Bartlett's Sphericity Test showed KMO=0.876 ($p<0.001$), indicating excellent sampling adequacy for factor analysis.

4. Research Results

4.1 Demographic Information

4.1.1 Quantitative Sample (n=338)

The sample closely mirrored JJU's faculty population demographics, with no significant deviations in discipline (χ^2=3.56, p=0.31) or professional rank (χ^2=1.24, p=0.54):

Professional rank: Senior (Professor/Associate Professor) 38.2% (n=129), mid-career (Lecturer) 41.7% (n=141), junior (Assistant Lecturer) 20.1% (n=68).

Academic discipline: Engineering 24.6% (n=83), Medicine 20.4% (n=69), Economics/Management 13.3% (n=45), Science 11.2% (n=38), Literature/Education 9.8% (n=33), Law 6.2% (n=21), Arts 5.3% (n=18), others 9.2% (n=31).

Faculty type: Dual-qualification (industry-academia) 52.4% (n=177), pure academic 47.6% (n=161).

Teaching experience: Mean=11.4 years (SD=7.8), ranging from 1–3 years (early-career) to >20 years (seasoned).

4.1.2 Qualitative Sample (n=28)

Discipline: High-AI-relevance (Engineering/Medicine) 9, low-AI-relevance (Law/Arts)7, mixed (Economics/Management/Literature/Education)12.

Professional rank: Senior 7, mid-career 10, junior 11.

Stance profile: AI enthusiasts 4, cautious optimists13, skeptics6, neutral/observing5.

Faculty type/campus: Dual-qualification 10, affiliated hospital/industrial college 4, Danfeng Campus 15, Ziwei Campus9.

4.2 Lecturers' Attitudes, Perceived Benefits and Primary Concerns

4.2.1 Overall Attitudes and the Attitude-Practice Gap

JJU lecturers exhibited cautious optimism towards AI-integrated teaching: the mean score for overall attitude was 3.68 (SD=0.89, 5-point Likert). A total of 76.3% of respondents agreed/strongly agreed that "AI has the potential to significantly enhance teaching effectiveness and student learning outcomes at JJU". However, a significant attitude-practice gap existed: only 34.9% of lecturers reported actively integrating AI tools beyond basic LMS administrative functions into core pedagogical activities (e.g., lesson design, assessment, student feedback).

4.2.2 Perceived Benefits

Lecturers identified a clear hierarchy of perceived benefits (5-point Likert, Table 1), with administrative efficiency as the most strongly endorsed:

Perceived Benefit	Mean (M)	Standard Deviation (SD)
Administrative Efficiency (automated	4.12	0.76

Perceived Benefit	Mean (M)	Standard Deviation (SD)
grading, attendance tracking)		
Personalized Student Support (adaptive learning, at-risk student identification)	3.95	0.82
Content & Method Enrichment (simulations, case study generation, interactive materials)	3.87	0.91

Table 1: Descriptive Statistics of Perceived Benefits of AI-Integrated Teaching (n=338)

Qualitative interviews revealed that STEM faculty valued AI for its ability to enhance practical training (e.g., AI-powered circuit simulators in Engineering, virtual labs in Medicine), while non-STEM faculty recognized its potential for administrative efficiency and personalized student feedback.

4.2.3 Primary Concerns

Despite positive attitudes, lecturers expressed significant multifaceted concerns (Table 2), with data privacy and ethical risks as the top concern. Notably, perceived threat to teacher roles received the lowest mean score, confirming that faculty do not view AI as an existential professional threat:

Primary Concern	Mean (M)	Standard Deviation (SD)
Data Privacy & Ethical Risks (student data storage/ownership, intellectual property)	4.05	0.88
Increased Workload (learning AI tools, redesigning course materials, monitoring AI outputs)	3.91	0.85
Accuracy & Bias of AI Outputs (factual	3.84	0.90

Primary Concern	Mean (M)	Standard Deviation (SD)
errors, cultural/epistemological bias)		
Threat to Teacher's Role (AI replacing core teaching functions)	2.50	1.10

Table 2: Descriptive Statistics of Primary Concerns Regarding AI-Integrated Teaching (n=338)

Qualitative data elaborated on these concerns: Law/Medicine faculty expressed unease about AI’s use of sensitive student/industry data; most faculty feared AI integration would add to their already heavy workload without institutional support; and humanities faculty highlighted AI’s lack of cultural/contextual awareness (e.g., AI-generated literary analysis with Western-centric tropes).

4.3 Factors Influencing AI-Integrated Teaching Adoption Readiness

Structural Equation Modeling (SEM) was used to test the integrated conceptual framework, with the model showing good fit to the data ($\chi^2/df=2.31$, CFI=0.94, TLI=0.92, RMSEA=0.062, SRMR=0.048). Standardized path coefficients identified the relative strength of predictors (Table 3):

1. Institutional factors: Professional development ($\beta=0.42$, $p<.001$) was the strongest predictor, followed by ICT infrastructure quality ($\beta=0.28$, $p<.01$) and policy clarity ($\beta=0.18$, $p<.05$). Lecturers who participated in AI-related workshops had significantly higher adoption readiness (M=3.98, SD=0.72) than non-participants (M=3.35, SD=0.89; $t=6.78$, $p<.001$).

2. Individual factors: Digital literacy ($\beta=0.39$, $p<.001$) was the second strongest overall predictor. Teaching experience had no significant direct effect ($\beta=0.07$, $p>.05$).

3. Technological perceptions: Perceived usefulness ($\beta=0.48$, $p<.001$) was a strong positive driver, while perceived threat to teacher roles had a non-significant negative effect ($\beta=-0.09$, $p>.05$).

Predictor Category	Specific Predictor	Standardized Path Coefficient (β)	p-value
Institutional Factors	Professional Development	0.42	<.001

Predictor Category	Specific Predictor	Standardized Path Coefficient (β)	p-value
	ICT Infrastructure Quality	0.28	<.01
	Policy Clarity	0.18	<.05
Individual Factors	Digital Literacy	0.39	<.001
	Teaching Experience	0.07	>.05
Technological Perceptions	Perceived Usefulness	0.48	<.001
	Perceived Threat to Teacher Role	-0.09	>.05

Table 3: Standardized Path Coefficients of Predictors on AI Adoption Readiness (SEM, n=338)

Qualitative interviews clarified that generic professional development was ineffective; lecturers demanded discipline-specific, practice-embedded training (e.g., "AI for legal case analysis" for Law faculty, "AI for medical simulation" for Medicine faculty). ICT infrastructure disparities were also revealed: faculty at remote industrial college sites and older campus buildings faced unreliable internet and limited access to AI-enabled LMS modules.

4.4 Disciplinary and Rank-Based Variations in Adoption Readiness

4.4.1 Disciplinary Variations

One-way ANOVA confirmed statistically significant disciplinary differences in adoption readiness ($F(8,329)=10.23$, $p<.001$). Tukey’s HSD post-hoc tests identified three distinct clusters (Table 4):

High-adoption cluster: Engineering (M=4.05, SD=0.71), Medicine (M=3.92, SD=0.68) – AI’s logic aligns with their quantitative, simulation-based pedagogies.

Middle cluster: Science (M=3.60), Economics/Management (M=3.55), Literature/Education (M=3.20) – moderate adoption, with AI used primarily for administration and basic content enrichment.

Low-adoption cluster: Arts (M=2.95, SD=0.89), Law (M=2.88, SD=0.92) – AI is perceived as epistemologically incompatible with core pedagogical goals (e.g., normative reasoning in Law, human expression in Arts).

Academic Discipline	Mean Adoption Readiness	Standard Deviation (SD)
Engineering	4.05	0.71
Medicine	3.92	0.68
Science	3.60	0.80
Economics/Management	3.55	0.83
Literature/Education	3.20	0.87
Arts	2.95	0.89
Law	2.88	0.92

Table 4: Mean AI Adoption Readiness by Academic Discipline (n=338)

4.4.2 Rank-Based Variations

ANOVA also revealed significant rank-based differences ($F(2,335)=5.12$, $p<.01$). Junior faculty had the highest adoption readiness, followed by mid-career faculty; senior faculty had the lowest (Table 5). Qualitative data showed junior faculty adopted AI for career innovation incentives, while senior faculty prioritized time efficiency and clear pedagogical value:

Professional Rank	Mean Adoption Readiness	Standard Deviation (SD)
Junior (Assistant Lecturer)	3.80	0.74
Mid-career (Lecturer/Associate Professor)	3.65	0.80
Senior (Full Professor)	3.40	0.85

Table 5: Mean AI Adoption Readiness by Professional Rank (n=338)

4.5 Lecturers' Perceived Support Needs and Pedagogical Visions

Qualitative interviews identified five core institutional support mechanisms and a unifying pedagogical vision for AI integration at JJU:

1. Disciplinary and tiered professional development: Shift from generic workshops to foundation modules (AI basics/ethics), disciplinary AI-pedagogy labs, and ongoing communities of practice.

2. Integrated technical-pedagogical support center: A one-stop "Center for Digital Pedagogy and AI" combining IT specialists and instructional designers to resolve technical and pedagogical challenges.

3. Clear, co-created institutional policies: Cross-disciplinary task forces to develop living policies for data privacy, academic integrity, and intellectual property in AI use.

4. Formal incentives for AI innovation: Recognition in performance reviews/promotions, AI teaching innovation grants, and course load reductions for AI pioneers.

5. Equitable ICT infrastructure investment: A digital equity audit to eliminate "digital deserts" at remote sites and ensure all departments have access to AI-enabled tools.

Lecturers' pedagogical vision centered on AI as an augmented pedagogy (not a replacement for teachers), with three core principles:

Human-in-the-loop design: AI outputs as a starting point for human critique, discussion, and synthesis (e.g., AI-generated legal briefs analyzed for logical gaps by students/faculty).

Critical AI literacy: Teaching students to evaluate AI outputs for bias/accuracy and use AI ethically—integrated into disciplinary content.

Augmentation of human teaching: AI automates routine tasks to free faculty time for high-touch activities (mentoring, nuanced feedback, complex discussions).

4.6 Hypothesis Testing Summary

Eight research hypotheses were tested via SEM and qualitative analysis (Table 6). All hypotheses except H7 (untestable with current data) were supported (fully/partially):

Hypothesis	Statement	Result
H1	Professional development positively influences adoption readiness.	Fully Supported ($\beta=0.42$, $p<.001$)
H2	ICT infrastructure quality positively influences adoption readiness.	Fully Supported ($\beta=0.28$, $p<.01$)
H3	Digital literacy positively influences adoption readiness.	Fully Supported ($\beta=0.39$, $p<.001$)
H4	Perceived usefulness positively influences readiness; perceived threat negatively influences readiness.	Partially Supported (perceived usefulness: $\beta=0.48$, $p<.001$;

Hypothesis	Statement	Result
		perceived threat: non-significant)
H5	Adoption readiness positively influences perceived learner performance outcomes.	Fully Supported ($\beta=0.31$, $p<.01$)
H6	Academic discipline moderates the relationship between institutional support and readiness.	Fully Supported (multi-group SEM: $\Delta\chi^2=28.45$, $p<.01$)
H7	Learners' baseline digital literacy moderates the relationship between readiness and learner performance.	Untestable (no paired faculty-student data)
H8	Social system influences (disciplinary norms, peer networks) positively moderate the relationship between technological perceptions and readiness.	Fully Supported (qualitative thematic evidence)

Table 6: Research Hypothesis Testing Results

5. Discussions, Conclusion, and Recommendations

5.1 Discussions

5.1.1 The Attitude-Practice Gap: A Rational Response to Barriers

The significant attitude-practice gap at JJU aligns with global research (Johnson et al., 2023) and confirms that faculty resistance to AI is operational and ethical, not ideological. Lecturers recognize AI's potential for administrative efficiency and personalized learning but are deterred by practical barriers (workload, infrastructure) and ethical concerns (data privacy). The low score for perceived role threat (M=2.50) strongly supports Siddhu & Arshed (2024), who found that most educators view AI as a supplementary tool, not a replacement. This finding refutes the myth of "faculty technophobia" and highlights the need for practical, solution-focused AI integration strategies (e.g., workload support, data privacy policies) rather than persuasive campaigns.

5.1.2 The Primacy of Discipline-Specific Professional Development

The finding that professional development is the strongest predictor of adoption readiness (β=0.42) validates Banerjee et al. (2025) and extends it to regional university contexts. Qualitative data reveal that generic AI workshops are ineffective; lecturers demand training tailored to their disciplinary pedagogical needs (e.g., AI for legal case analysis, AI for medical simulation). This aligns with Phakamach et al. (2023), who found that practice-embedded professional development increases AI adoption rates by 70%. For regional universities like JJU, this means shifting AI training from "one-size-fits-all" sessions to disciplinary co-creation labs where faculty and instructional designers build AI-enhanced lesson plans together.

5.1.3 Disciplinary Epistemology: A Neglected Moderator

The profound disciplinary disparities in adoption readiness (F=10.23, p<.001) are one of the study's most consequential findings, confirming Huang et al. (2023) that disciplinary epistemology is a core, understudied moderator of AI adoption. STEM faculty adopt AI because its data-driven, predictive logic aligns with their quantitative, simulation-based pedagogies; Law/Arts faculty resist AI because it conflicts with their core goals (normative reasoning, human expression). This finding challenges the notion of AI as a "universal" educational tool and highlights the danger of institution-wide AI mandates that ignore disciplinary differences. For JJU, effective AI integration requires discipline-specific strategies: STEM-focused AI for practical training, and humanities-focused AI for administrative efficiency and critical literacy development (not content generation).

5.1.4 Regional University AI Integration: Equity and Context

This study confirms that regional universities face unique AI integration challenges distinct from elite universities (Liang & Huang, 2023): intra-institutional digital divides (remote industrial college sites with poor infrastructure), limited AI expertise, and a mission to align AI teaching with local industry needs (Jiangxi's 1269 Manufacturing Action Plan). The findings highlight the need for equity-focused AI integration in regional universities—ensuring that all faculty (regardless of discipline/campus) have access to infrastructure and training. Additionally, AI integration in regional universities must be application-oriented, linking AI tools to local industry needs to fulfill their mission of training regional human capital (Phakamach et al., 2023).

5.2 Core Conclusion

This mixed-methods study of Jiujiang University lecturers' perceptions towards AI-integrated teaching yields five core conclusions:

1. JJU lecturers exhibit cautious optimism towards AI-integrated teaching, with widespread recognition of its educational potential but a significant attitude-practice gap (76.3% positive attitudes vs. 34.9% actual integration). The gap is driven by practical/ethical barriers, not fear of professional replacement.

2. Professional development (institutional) and digital literacy (individual) are the strongest predictors of AI adoption readiness. Generic professional development is ineffective; discipline-specific, practice-embedded training is critical for driving actual integration.

3. Disciplinary epistemology is a fundamental moderator of AI adoption, with STEM disciplines (Engineering/Medicine) as high-adoption clusters and humanities (Law/Arts) as low-adoption clusters due to AI's perceived epistemological incompatibility with non-STEM pedagogical goals.

4. The primary barriers to AI adoption are data privacy/ethical risks, increased workload, and AI output accuracy/bias—not a threat to teacher roles (the lowest-rated concern). Intra-institutional digital divides and vague AI governance policies further exacerbate these barriers.

5. JJU lecturers demand differentiated institutional support (disciplinary training, integrated technical-pedagogical support, clear co-created policies) and a unifying pedagogical framework of AI as augmented pedagogy, with human-in-the-loop design and critical AI literacy as core principles.

5.3 Recommendations

Based on the study's findings, three sets of actionable recommendations are proposed for Jiujiang University and similar regional application-oriented universities:

5.3.1 Institutional Policy Recommendations

1. Establish a Center for Digital Pedagogy and AI: A dedicated one-stop support center combining IT specialists (for technical issues) and instructional designers (for pedagogical design) to provide just-in-time support for AI integration.

2. Implement a Tiered, Discipline-Sensitive Professional Development Framework:

(1) Foundation Modules: Mandatory AI basics, ethics, and data privacy for all faculty.

(2) Disciplinary AI-Pedagogy Labs: Intensive workshops for each discipline to co-create AI-enhanced lesson plans and assessments.

(3) Communities of Practice: Fund ongoing peer-learning groups for faculty to share AI best practices.

3. Co-Create Clear, Adaptive AI Governance Policies: Form a cross-disciplinary task force (faculty, administration, IT) to develop living policies for data privacy, academic integrity, and intellectual property—with regular updates to address evolving AI technologies.

4. Formalize Incentives for AI Innovation: Recognize AI integration in performance reviews/promotions, offer AI teaching innovation grants (¥5,000–¥20,000 per project), and provide course load reductions for faculty who pioneer AI-integrated teaching.

5. Conduct a Digital Equity Audit and Targeted Investment: Systematically assess ICT infrastructure across all campuses/sites; invest in reliable internet, AI-enabled LMS modules, and technical support for remote/under-resourced departments.

5.3.2 Pedagogical Practice Recommendations

1. Adopt AI as Augmented Pedagogy: Design AI-integrated lessons with human-in-the-loop principles—using AI to generate content/outputs that students/faculty critique, discuss, and refine (e.g., AI-generated legal briefs for logical analysis).

2. Start Small, Scale Fast: Encourage faculty to integrate AI into one high-impact, low-stakes task first (e.g., automated quiz grading, at-risk student identification) to build confidence before scaling to more complex activities.

3. Integrate Critical AI Literacy into Disciplinary Content: Teach students to evaluate AI outputs for bias/accuracy, design effective AI prompts, and use AI ethically—e.g., discussing algorithmic bias in Sociology, AI authorship ethics in Literature.

4. Leverage AI for Regional Industry Alignment: Design AI-integrated lessons that link to Jiangxi's 1269 Manufacturing Action Plan—e.g., AI for supply chain modeling in Business, AI for industrial quality control in Engineering.

5.3.3 Recommendations for Future Research

1. Longitudinal and Quasi-Experimental Studies: Track faculty/student cohorts over time to establish causal relationships between AI integration and learner performance (GPA, employability); use quasi-experimental designs to compare AI-integrated and traditional courses.

2. Student Perception and Experience Research: Center the student voice in AI integration research, exploring how students perceive and use AI-integrated teaching, and how their digital literacy moderates learning outcomes (testing H7).

3. Comparative Research Across Regional Universities: Conduct mixed-methods research at 2–3 regional universities in Jiangxi/China to identify generalizable AI integration patterns and context-specific challenges.

4. Ethnographic Research in Low-Adoption Disciplines: Conduct in-depth ethnographic research in Law/Arts departments to explore the cultural/epistemological roots of AI resistance and design discipline-specific AI integration strategies.

5. AI Integration and Regional Economic Development: Research the link between AI-integrated teaching at regional universities and graduate employability in local industries—testing the alignment of AI pedagogy with regional economic needs.

REFERENCES

Banerjee, S., Zhang, Y., & Chen, L. (2025). Longitudinal faculty attitudes toward AI in higher education: A multi-institutional study (2022–2024). Higher Education Technology Press.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Huang, W., Li, J., & Zhou, M. (2023). Disciplinary differences in AI adoption in Chinese universities: A systematic review. Journal of Educational Technology & Society, 26(4), 112–125.

Jiujiang University. (2025). University profile and strategic development report 2025. Internal institutional document.

Johnson, R., Smith, T., & Wang, H. (2023). Faculty stances on AI integration: From enthusiastic adoption to skeptical observation. International Journal of Educational Technology in Higher Education, 20(1), 45–67.

Kumar, V., Sharma, D., & Lee, Y. (2023). Artificial intelligence in higher education: A global review of adoption trends and pedagogical impacts. Computers & Education, 187, 104848.

Liang, Q., & Huang, R. (2023). Digital divides and regional disparities in Chinese higher education: Challenges for inland universities. Asia Pacific Education Review, 24(3), 411–425.

Moyo, T., Nkosi, B., & Adeyemi, A. (2023). Infrastructure and digital literacy barriers to AI adoption in African higher education. Journal of Higher Education in Africa, 21(2), 89–110.

Phakamach, P., Senarat, S., & Limna, P. (2023). AI literacy as an employability skill: Implications for higher education curriculum reform. Journal of Teaching and Learning for Graduate Employability, 14(1), 102–120.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Siddhu, G., & Arshed, N. (2024). Perceived threat and teacher identity in the age of AI: A cross-cultural study. Teaching and Teacher Education, 139, 104432.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204.

Zhang, L., Wang, H., & Chen, X. (2025). AI integration in Chinese universities: Policy ambition versus implementation reality. Higher Education Policy, 38(2), 215–234