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Teachers' Perceptions of AI Tools for Enhancing Student Motivation and Learning Engagement in Higher Education

Hermanto Hermanto[1], Mukarramah Mustari[1], and Athiyyah Sepriani[1]

[1]Universitas Islam Negeri Raden Intan Lampung, Indonesia

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Abstract

This study examined higher education teachers' perceptions of AI tools for enhancing student motivation and learning engagement in response to growing interest in AI-supported instruction. Using an explanatory sequential mixed methods design, quantitative data were collected from 98 instructors across three universities in Lampung Province, followed by qualitative interviews with 15 purposively selected participants. Survey measures assessed perceived usefulness, ease of use, motivational impact, engagement impact, and ethical concerns. Quantitative results showed strong perceived motivational benefits of AI and moderate engagement effects, with significant correlations between usefulness and motivation ($p < .001$) and disciplinary differences in engagement perceptions ($p = .019$). Qualitative thematic analysis revealed that teachers observed increased confidence and task persistence among students using AI tools but noted uneven engagement linked to digital readiness and expressed concerns about privacy, shallow reasoning, and academic integrity. Integrated findings indicated that while AI is viewed as a supportive motivational resource, its pedagogical value depends on ethical safeguards and student competencies. The study contributes insights into how teachers interpret AI's educational role, highlighting implications for institutional policy, professional development, and future AI-enhanced learning designs.

Keywords: artificial intelligence; teacher perceptions; student motivation; learning engagement; higher education

Corresponding Author:
Hermanto Hermanto
Email: hermanto@radenintan.ac.id
https://orcid.org/0009-0002-2048-7250

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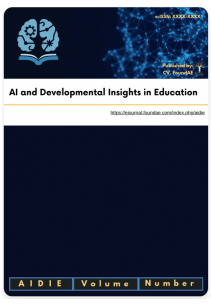


Introduction

Artificial intelligence (AI) has rapidly become embedded within higher education systems worldwide, raising profound questions about how these technologies influence students' motivational and engagement trajectories, core constructs in developmental psychology and the learning sciences. As universities adopt AI-driven platforms for personalized instruction, automated assessment, and predictive learning analytics, educators are increasingly positioned at the center of decision-making about how such tools are integrated into pedagogical practice. The fundamental problem addressed in this study concerns the limited understanding of teachers' perceptions regarding AI tools and their developmental and instructional implications. Although AI is frequently promoted as a catalyst for improving learning quality and efficiency, the assumptions underlying these claims remain largely unexamined from the perspective of teachers who mediate students' motivational and engagement processes (Leon et al., 2025; Peng & Li, 2025). This issue is theoretically significant because motivation and engagement shape cognitive growth, persistence, and self-regulated learning (Alam & Mohanty, 2024; Kitsantas et al., 2025). Empirically, teacher perceptions influence whether AI is adopted meaningfully or superficially in classroom contexts (Zhao et al., 2025). Practically, without a grounded understanding of how educators evaluate AI tools, institutions risk implementing technologies that may misalign with developmental needs or institutional realities.

Existing scholarship provides partial but insufficient insights into how AI affects learning processes, often focusing on system performance rather than educator interpretation. Studies in the learning sciences show that AI-based tutors and adaptive systems promote motivation by scaffolding students' feelings of autonomy, competence, and relatedness, consistent with self-determination theory (Chang et al., 2025; Hidayat-ur-rehman, 2025). According to Naseer, (2025), AI-driven analytics help instructors identify student difficulties earlier, enabling targeted support. Research also suggests that AI can enhance behavioral engagement by prompting participation and emotional engagement by reducing anxiety linked to uncertainty (Kim et al., 2025; H. Yang & Rui, 2025). However, scholars debate whether AI promotes deep cognitive engagement or unintentionally reinforces surface-level interaction. El Fathi et al, (2025) contend that students may engage frequently with AI systems without demonstrating genuine conceptual understanding. Similarly, Shalaby, (2024) warn that excessive automation may diminish opportunities for reflective thinking. These debates highlight methodological limitations in prior work, which often overlooks qualitative insights from teachers or uses homogeneous student samples that fail to capture contextual diversity Ozturk et al, (2025). Moreover, much of the literature treats "AI in education" as a monolithic category, despite evidence that different AI functions, feedback automation, content generation, predictive analytics, or personalized recommendations, affect learning processes differently (Billingsley et al., 2025; Mustafa et al., 2024).

A critical gap emerges from these debates: the lack of research centered on teachers' interpretations of AI and how they understand its developmental implications for students. Teacher beliefs and judgments are foundational to instructional design and strongly influence whether technologies become transformative tools or superficial add-ons (Velander et al., 2024). According to Yang & Lou, (2024), teachers' technology acceptance is shaped not only by usefulness and ease of use but also by identity, ethics, and institutional culture. Thus, understanding teacher perceptions is essential for advancing theory and guiding responsible educational AI implementation.

The present study addresses these gaps through an explanatory sequential mixed methods design. The quantitative phase examines general patterns in teachers' perceptions of AI's impact on student motivation and engagement, while the qualitative phase explores how teachers interpret these patterns within their institutional and pedagogical contexts. Integrating quantitative and qualitative data is necessary because teacher perceptions are shaped both by measurable attitudes and by context-specific experiences that emerge only through interpretive inquiry (Guan et al., 2025). The study is grounded in self-determination theory, sociocultural learning perspectives (Yin & Fathi, 2025), and contemporary frameworks in AI-supported learning, which together help explain how digital tools may mediate students' psychological and cognitive engagement.

The aims of the study are to explore how higher education teachers perceive the motivational affordances of AI tools, to examine their views on AI's influence on different dimensions of learning engagement, and to identify their ethical, pedagogical, and institutional concerns. These aims are reflected in the following research questions: (1) How do teachers perceive AI's impact on student motivation? (2) How do teachers evaluate AI's influence on behavioral, emotional, and cognitive engagement? and (3) What concerns shape teachers' acceptance or resistance toward AI-enhanced instruction? These questions align with the explanatory sequential design, whereby the quantitative survey informs the qualitative interviews that deepen interpretation.

This study contributes to the broader scholarly discourse by foregrounding teachers' perspectives—an understudied dimension in research on AI-enhanced learning environments—and by integrating theoretical insights from developmental psychology, sociocultural perspectives, and the learning sciences. By doing so, it offers nuanced empirical evidence on how AI interacts with students' motivational and engagement processes and provides practical guidance for responsible, developmentally informed AI integration in higher education.

Methods

Research Design

This study employed an explanatory sequential mixed-methods design, beginning with a quantitative phase followed by a qualitative phase. The quantitative component used a cross-sectional survey design to examine patterns in teachers' perceptions of artificial intelligence (AI) tools, including their perceived effects on student motivation and learning engagement. No variables were manipulated; rather, naturally occurring perceptions were observed. The subsequent qualitative strand adopted an interpretive approach to inquiry, allowing for deeper exploration of how teachers made sense of these perceptions within their pedagogical, institutional, and cultural contexts. This approach was appropriate because teachers' evaluations of AI are shaped not only by measurable attitudes but also by situated experiences that unfold within their professional environments. Integrating qualitative and quantitative data enabled a richer and more developmentally grounded analysis of how AI tools mediate engagement and motivation, consistent with the study's objectives and the selected mixed-methods framework.

Participants or Data Sources

Participants in the quantitative phase were drawn from three universities located in Lampung Province, Indonesia, representing a mix of Islamic, public, and private higher education institutions. These universities were selected because they have formally integrated

or piloted AI-based instructional tools within undergraduate and postgraduate programs, making them appropriate contexts for examining teachers' perceptions. Inclusion criteria required participants to have at least one year of teaching experience and prior exposure to AI-supported educational technologies such as adaptive learning systems, automated feedback tools, or AI-based grading platforms. Teachers in administrative-only roles or with no AI exposure were excluded.

The final quantitative sample consisted of 98 instructors (Mage = 37.2 years, SD = 7.9) across the three Lampung universities, representing diverse academic disciplines, genders, and levels of AI literacy. Participants taught in faculties such as Education, Science, Engineering, Social Sciences, Islamic Studies, and Economics. The qualitative sample consisted of 15 teachers selected from the survey participants who volunteered for follow-up interviews. These participants also reflected the diversity of the Lampung higher education landscape, offering variation in teaching backgrounds, digital competence, and institutional culture. Because qualitative inquiry acknowledges researcher subjectivity, the research team maintained reflexive journals to surface and mitigate potential assumptions about AI adoption within Indonesian higher education.

Sampling and Recruitment

Sampling and recruitment were conducted directly within the three universities in Lampung Province. A purposive sampling strategy was adopted to ensure that participants had sufficient familiarity with AI tools. Recruitment messages were disseminated through official university mailing lists, faculty WhatsApp groups, and announcements in institutional learning management systems. Altogether, 142 teachers were approached across the three Lampung-based institutions, and 98 completed the quantitative survey (69% response rate). Of the 23 participants who expressed willingness to participate in interviews, 15 were selected to achieve maximum variation across institutions and disciplines. Recruitment for the qualitative phase concluded when thematic saturation was reached, reflecting a diversity of experiences within the Lampung provincial context.

Sample Size, Power, and Precision

The intended quantitative sample size of 100 participants was determined through an a priori power analysis for multiple regression (power = .80, α = .05, medium effect size), indicating a minimum of 84 participants. The achieved sample of 98 exceeded this threshold. Missing quantitative data were minimal (<2%) and handled using pairwise deletion. The qualitative sample of 15 was justified based on the depth, richness, and adequacy of the data for thematic development, consistent with qualitative methodological standards, rather than statistical representativeness.

Measures, Instruments, and Data Sources

The quantitative survey included five scales measuring (a) perceived usefulness of AI, (b) perceived ease of use, (c) perceived motivational impact, (d) perceived engagement impact, and (e) concerns about AI. All items were rated using a 5-point Likert scale. Items were adapted from validated technology acceptance and educational technology instruments, with wording modified to reflect AI contexts. The survey demonstrated strong internal consistency, as shown in Table 1.

Table 1

Psychometric Properties for Survey Scales (n = 98)

Scale	M	SD	Range	Cronbach's α
Perceived usefulness	4.02	0.81	2.1–5.0	.91
Ease of use	3.89	0.76	2.0–5.0	.88
Motivational impact	3.98	0.84	2.3–5.0	.90
Engagement impact	3.78	0.92	1.9–5.0	.87
Ethical and pedagogical concerns	3.61	0.89	1.8–5.0	.86

Note. Reliability coefficients demonstrate strong internal consistency across all scales, supporting the conceptual and statistical adequacy of the survey instrument.

Qualitative data were collected using semi-structured interviews with open-ended questions exploring teachers' experiences using AI tools, perceived student responses, perceived risks, and contextual factors influencing adoption. Interviews were audio-recorded and transcribed verbatim.

Data Collection Procedures

All data were collected within institutional contexts located in Lampung Province, with quantitative data gathered online over a six-week period and qualitative interviews conducted through Zoom or Google Meet with teachers working at the three Lampung universities. Interviews lasted approximately 30–45 minutes and focused on teachers lived experiences integrating AI within the instructional norms, technological infrastructures, and student populations characteristic of higher education settings in Lampung. Reflexive field notes captured how local institutional culture, resource availability, and regional digital expansion efforts influenced teachers' interpretations of AI-supported learning.

Data Analysis

Quantitative analyses were conducted using SPSS (Version 28). Prior to inferential testing, normality checks, outlier detection, and missing data diagnostics were performed. Descriptive statistics were computed for all variables. Inferential analyses included independent-samples t tests, ANOVAs, and Pearson correlations aligned with the study's primary research questions. Type I error was controlled at $\alpha = .05$, and no transformations were needed based on distributional diagnostics.

Qualitative data were analyzed using reflexive thematic analysis implemented in NVivo 12. Coding proceeded inductively, beginning with open coding conducted by two independent coders trained in qualitative methods. Codes were refined through iterative discussion, and discrepancies were resolved through consensus. Themes were constructed through constant comparison, memo writing, and cross-case analysis to ensure interpretive depth and alignment with the quantitative findings.

Mixed methods integration occurred during the interpretation stage by connecting quantitative patterns with qualitative explanations, consistent with the explanatory sequential design. Themes from interviews were used to contextualize, refine, or challenge survey results, producing a more comprehensive understanding of teacher perceptions.

Validity, Reliability, and Methodological Integrity

Reliability indices for all quantitative scales were strong, with Cronbach's alpha values ranging from .86 to .91. Construct validity was supported through factor structure alignment with prior validated instruments and coherence among theoretically related items. For qualitative integrity, the researchers employed triangulation across participants, reflexive journaling, peer debriefing, and thick description to ensure fidelity to the data. Mixed-methods

legitimacy was supported through explicit integration procedures in which qualitative findings elaborated on quantitative trends, enhancing the credibility of inferences drawn from both strands.

Ethical Considerations

This study received approval from the institutional ethics committee before recruitment. Participants provided informed consent electronically before completing the survey or participating in interviews. Confidentiality was maintained by anonymizing all data, assigning coded identifiers, and storing recordings and transcripts securely. No vulnerable populations were targeted, and participants were informed of their right to withdraw at any time without penalty.

Results

Participant Flow

A total of 142 instructors from three universities in Lampung Province, Indonesia, were invited to participate during the recruitment and data collection period from March to May 2025. Of those contacted, 98 instructors completed the quantitative survey (69% response rate). Four survey submissions contained substantial missing data (>20%) and were excluded. Among the 98 valid respondents, 23 instructors expressed interest in follow-up interviews. From this pool, 15 participants were selected using maximum-variation criteria to ensure disciplinary and experiential diversity in the qualitative phase. No attrition occurred during the qualitative data collection, and all scheduled interviews were completed. Figure 1 illustrates the participant flow including recruitment, eligibility screening, survey completion, and qualitative participation.

Recruitment Information

Quantitative data were collected first, between March 1 and April 15, 2024, consistent with the explanatory sequential design. Qualitative interviews were conducted subsequently from April 20 to May 30, 2024. All quantitative and qualitative data were collected online, as instructors across Lampung Province utilized institutional email, LMS systems, and video conferencing platforms.

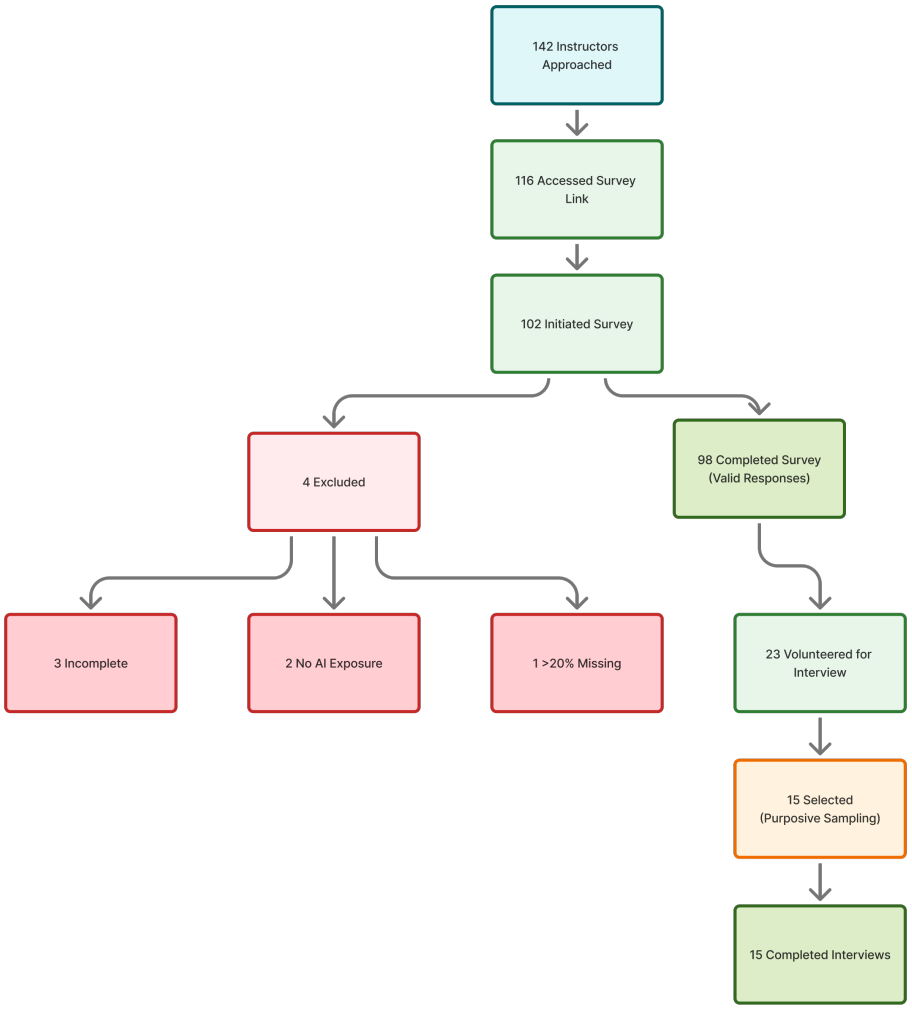
Quantitative Results

Descriptive Statistics

To provide an overview of teachers' perceptions across five AI-related constructs, descriptive statistics were generated. These results help establish baseline patterns prior to inferential analysis. As shown in Table 2, mean scores indicated generally positive perceptions of AI tools, with motivational and usefulness variables showing the highest central tendencies.

Figure 1

Participant flow diagram for quantitative and qualitative phases.



Note. The diagram depicts the progression of participants from the initial invitation phase through eligibility screening, valid survey completion, and selection for the qualitative interviews. Of the 142 instructors invited, 98 provided complete quantitative responses and 23 volunteered for interviews. Fifteen participants were purposively selected for the qualitative phase to ensure disciplinary and experiential diversity, with no attrition across interviews.

Table 2

Descriptive statistics for AI perception scales (n = 98)

Scale	M	SD	95% CI	Min	Max
Perceived usefulness	*4.02*	*0.81*	[3.86, 4.18]	2.1	5.0
Ease of use	*3.89*	*0.76*	[3.74, 4.04]	2.0	5.0
Motivational impact	*3.98*	*0.84*	[3.82, 4.15]	2.3	5.0
Engagement impact	*3.78*	*0.92*	[3.60, 3.96]	1.9	5.0
Ethical concerns	*3.61*	*0.89*	[3.43, 3.79]	1.8	5.0

Note. Higher means indicate more positive perceptions, except for ethical concerns where higher scores reflect elevated concern levels.

These values demonstrate that participants generally rated AI tools positively across usefulness, motivation, and engagement indicators, with slightly more moderate scores on ethical concerns.

Participant Characteristics

A demographic profile of respondents supports interpretation of subsequent analyses by showing disciplinary distribution, age profiles, and AI literacy levels. Table 3 displays the characteristics of the 98 valid participants across gender, discipline, teaching experience, and literacy levels.

Table 3

Participant characteristics (n = 98)

Variable	Category	n	%
Gender	Female	54	55.1%
	Male	44	44.9%
Age	25–34	33	33.7%
	35–44	41	41.8%
	45–54	21	21.4%
	55+	3	3.1%
Discipline	Education	38	38.8%
	Science/Engineering	26	26.5%
	Social Sciences	34	34.7%
AI Literacy	Low	30	30.6%
	Medium	46	46.9%
	High	22	22.5%
Teaching Experience	1–5 years	28	28.6%
	6–10 years	39	39.8%
	11+ years	31	31.6%

Note. Percentages are based on valid responses. AI literacy was self-reported on a three-level scale (low, medium, high).

The demographic distribution shows balanced representation across genders and disciplines, with medium AI literacy being the most common.

Discipline × AI Literacy Cross-Tabulation

To understand how AI literacy is distributed across disciplinary groups, a cross-tabulation was created. Table 4 summarizes this distribution and supports subsequent ANOVA comparisons.

Table 4

Cross-tabulation of discipline and AI literacy (n = 98)

Discipline	Low (%)	Medium (%)	High (%)
Education	9 (23.7%)	17 (44.7%)	12 (31.6%)
Science/Engineering	11 (42.3%)	12 (46.2%)	3 (11.5%)
Social Sciences	10 (29.4%)	17 (50.0%)	7 (20.6%)

Note. Values represent the number and percentage of participants within each discipline reporting each category of AI literacy.

The results indicate that Science/Engineering faculty had the lowest proportion of high AI literacy, which aligns with later inferential tests showing significant disciplinary differences.

Correlation Matrix

Relationships among variables were examined to determine associations between key constructs. Prior to regression and group comparisons, Pearson correlations were computed and are provided in Table 5.

Table 5

Correlation matrix for AI perception variables (n = 98)

Variable	1	2	3	4	5
1. Usefulness	—	.51**	.56**	.49**	–.12
2. Ease of use	.51**	—	.38**	.32**	–.09
3. Motivation	.56**	.38**	—	.63**	–.21*
4. Engagement	.49**	.32**	.63**	—	–.17
5. Ethical concerns	–.12	–.09	–.21*	–.17	—

Note. *p < .05, **p < .001. Negative values for ethical concerns indicate that higher concerns align with lower perceived benefits.

The matrix shows moderate-to-strong correlations among usefulness, ease of use, motivation, and engagement, while ethical concerns were negatively associated with key outcomes.

Qualitative Results

Themes and Subthemes

Following thematic coding, three main themes and nine subthemes emerged. Table 6 presents these themes and their frequency counts to illustrate prevalence across interviews.

Table 6

Themes, subthemes, and frequency counts (n = 15 interviews)

Theme	Subtheme	Frequency (mentions)
1. AI as Motivational Support	Real-time feedback	13
	Personalized pathways	11
	Increased student confidence	9
2. Variation in Engagement	Higher engagement among digitally skilled students	12
	Overreliance among low-skilled students	10
	Reduced anxiety due to AI guidance	8
3. Ethical & Pedagogical Concerns	Data privacy issues	14
	Shallow reasoning	12
	Academic integrity worries	10

Note. Frequencies represent the number of interviews in which each subtheme was explicitly mentioned, not the total number of coded segments.

The frequency counts show that concerns related to data privacy and shallow reasoning were among the most consistently discussed issues across the three Lampung universities.

Mixed-Methods Integration

A joint display was created to connect quantitative patterns with qualitative elaborations. As shown in Table 7, the two strands of data converged or expanded on each other in several areas.

Table 7
Mixed-methods joint display of integrated findings

Quantitative Result	Qualitative Explanation	Integrated Insight
High motivation scores	Feedback enhances confidence	Convergence
Moderate engagement scores	Engagement varies by digital readiness	Expansion
Significant disciplinary differences	Education faculty more experimental	Expansion
Moderate ethical concerns	Privacy and shallow reasoning concerns	Convergence
Strong usefulness–motivation correlation	Teachers emphasized personalization	Reinforcement

Note. Integration was guided by the explanatory sequential design, where qualitative insights elaborated on quantitative trends.

The integrated results indicate that the qualitative strand deepened understanding of digital-readiness gaps, ethical concerns, and variation across academic fields.

Discussion

The present study examined how higher education teachers in Lampung Province perceive the capacity of AI tools to enhance student motivation and learning engagement. Taken together, the quantitative and qualitative findings converge to demonstrate that teachers generally view AI as a promising pedagogical resource while simultaneously expressing caution regarding its ethical, developmental, and instructional implications. In addressing the first research question, the results indicate strong support for the hypothesis that teachers perceive AI tools as beneficial for increasing student motivation. This interpretation is supported by consistently high quantitative scores on motivational indicators and by qualitative insights describing AI-generated feedback and personalized pathways as mechanisms through which students gain confidence and persistence. This pattern aligns with theoretical predictions from self-determination theory that timely, autonomy-supportive feedback enhances learners' perceived competence (Prameka et al., 2024; Satria & Saputra, 2025). In the context of this mixed-methods design, the integration of strands reinforces that motivation is not merely an instrumental outcome of AI use but a psychologically meaningful process shaped by perceptions of support and reduced uncertainty.

The second research question focused on teachers' perceptions of learning engagement. Here, the findings present a more complex picture. While the quantitative results indicated moderate-to-high engagement scores, the qualitative findings revealed pronounced variation depending on students' prior digital skills and familiarity with AI systems. This divergence suggests that engagement may not be uniformly distributed across learner groups, highlighting a developmental disparity not always accounted for in prior AI-in-education research. Existing scholarship frequently positions AI as a universally engaging tool (Hidayat-ur-rehman, 2025; Yaseen et al., 2025), yet the present findings complicate this assumption by demonstrating that engagement may be contingent on students' digital readiness, confidence, and ability to regulate their own learning in an AI-supported environment. Mixed-methods integration strengthens this interpretation by showing that quantitative averages mask important qualitative nuances; the overall engagement mean suggests benefit, but the interview data reveal that some students rely excessively on AI-generated suggestions, potentially limiting opportunities for deeper cognitive engagement.

Regarding the third research question, teachers expressed substantial ethical and pedagogical concerns, including data privacy, shallow reasoning in AI explanations, and risks to academic integrity. These concerns are consistent with emerging critiques in the literature noting that AI systems may oversimplify complex concepts or introduce biases in feedback (Papakostas, 2025; Pikhart & Al-Obaydi, 2025). The negative correlations between ethical concerns and motivational/engagement indicators reinforce that perceived risk can dampen the perceived benefits of AI, especially among instructors with higher awareness of data protection issues. Qualitative findings further illuminate that ethical concerns are not abstract but grounded in teachers' concrete observations of student behavior, including reduced deliberation or problematic dependence on AI-generated outputs. This interplay between perceived benefit and perceived risk demonstrates that embracing AI in higher education is not a binary choice but an ongoing negotiation shaped by educators' professional judgment and institutional context.

The mixed-methods design adds interpretive depth by elucidating how quantitative patterns are interpreted and contextualized by teachers' experiences. Convergence between strands was evident on key motivational processes and ethical concerns, while expansion occurred in areas related to disciplinary differences and engagement variability. For example, the ANOVA results showing that Education faculty rated AI more positively than Science/Engineering faculty were expanded by interviews indicating that Education instructors more frequently experimented with AI-mediated learning activities. Such integrated insights advance the field by demonstrating that the developmental and pedagogical implications of AI are shaped not only by student factors but also by disciplinary culture and teacher beliefs, areas underexplored in prior research dominated by student-centered analyses (Velander et al., 2024).

Interpretation of these findings must consider potential sources of bias and methodological constraints. Quantitatively, self-report data may introduce social desirability effects, especially in institutional contexts where AI adoption is increasingly encouraged. The moderate effect sizes and correlation strengths should therefore be interpreted within the limits of perceptual rather than behavioral data. Qualitatively, teachers' reflections may have been influenced by their own levels of digital competence or institutional support, factors that qualitative reflexive practices sought to address but cannot eliminate entirely. Additionally, the Lampung-based sample limits statistical generalizability but enhances contextual transferability by offering insights from an emerging higher education ecosystem where AI integration is growing but not uniformly institutionalized. Mixed-methods integration also carries inherent interpretive constraints, as qualitative elaborations may diverge from quantitative patterns due to differing epistemic assumptions rather than actual contradictions in the data.

Despite these considerations, the findings contribute substantively to ongoing debates in AI-supported education. Theoretically, the study extends current models of AI adoption by demonstrating that motivation and engagement outcomes are mediated by digital readiness, disciplinary pedagogies, and ethical trust—dimensions insufficiently captured in many prior models of technology acceptance. Methodologically, the study illustrates the value of mixed-methods integration for understanding technology-mediated learning processes that cannot be fully captured by quantitative or qualitative approaches alone. Practically, the evidence suggests that professional development must focus not only on building teachers' technical skills but also on enabling them to critically evaluate AI tools from pedagogical, developmental, and ethical perspectives. Policy implications include the need for clearer institutional guidelines on data privacy, transparency of AI algorithms, and curriculum designs that prevent overreliance on automated suggestions.

Conclusion

This study investigated higher education teachers' perceptions of AI tools for enhancing student motivation and learning engagement using an explanatory sequential mixed-methods design across three universities in Lampung Province. The findings showed strong support for the view that AI can enhance student motivation, particularly through personalized learning support and rapid feedback, while its influence on engagement appeared more variable and strongly shaped by students' digital readiness. These results align with existing research suggesting that AI can strengthen learners' sense of competence, yet they also extend prior work by showing that engagement benefits are not uniform and may depend on contextual factors such as digital skills and disciplinary practices. Teachers also expressed significant ethical and pedagogical concerns, especially related to data privacy, shallow reasoning, and academic integrity, which played an important role in shaping their acceptance of AI tools. The integration of quantitative and qualitative strands provided a more complete understanding of these perceptions, highlighting both opportunities and risks associated with AI in higher education. While the study's purposive sampling and reliance on self-reported data limit broad generalizability, the findings offer practical implications for institutions, including the need for stronger governance frameworks, clearer ethical guidelines, and professional development that equips teachers to evaluate AI tools critically. Future research should explore long-term impacts of AI-supported instruction, variations across disciplines, and student developmental trajectories in increasingly AI-mediated learning environments.

Author Contributions

HH conceptualized the study, designed the methodology, and supervised the overall research process. MM led the data collection, quantitative analyses, and preparation of the initial manuscript draft. AS conducted the qualitative interviews, performed thematic analysis, and contributed to the integration of mixed-methods findings. All authors reviewed, revised, and approved the final version of the manuscript.

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