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Research Article

Determinants of AI Use in University Teachers: The Role of Leadership, Teaching Concerns, and Constructivist Pedagogical Beliefs

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This study examines the determinant factors influencing artificial intelligence (AI) adoption among university teachers and its impact on teacher leadership and concerns. Through a quantitative cross-sectional study involving 452 professors from six public and private universities in northern Peru, the research tested six hypotheses regarding the relationships between attitudes toward AI, constructivist pedagogical beliefs, facilitating conditions, and teaching modality. Data were collected via validated instruments and analyzed via structural equation modeling (PLS-SEM). The results revealed that attitudes toward AI ($\beta = 0.529$, $p < 0.001$) and constructivist pedagogical beliefs ($\beta = 0.253$, $p < 0.01$) significantly influence AI adoption, whereas facilitating conditions have no significant effect. The study also revealed that AI use strongly impacts teacher leadership ($\beta = 0.711$, $p < 0.001$) and teacher concerns ($\beta = 0.597$, $p < 0.001$). However, teaching modality did not significantly moderate the relationship between attitudes and AI use. The model showed robust explanatory power, with AI use explaining 50.5% of the variance in teacher leadership and 35.6% in teacher concerns. These findings contribute to understanding the complex dynamics of AI adoption in higher education and provide valuable insights for developing effective institutional strategies for AI integration in educational settings.

Keywords: artificial intelligence; educational technology; higher education; pedagogical beliefs; teacher leadership; teaching concerns; technology adoption; university teachers

1. Introduction

The adoption of artificial intelligence (AI) in higher education has significantly transformed teaching and learning processes on a global scale. This technological advancement poses substantial challenges for university educators, who must adapt to new tools and innovative pedagogical methods [1, 2]. Integrating AI into the academic sphere not only requires the development of new technical skills but also calls for a reassessment of traditional educator roles and a restructuring of established educational practices [2, 3]. This phenomenon has sparked growing interest within

the international academic community, reflected in an increase in research addressing this issue from diverse perspectives [4, 5].

Despite heightened interest in educational AI, current research reveals significant gaps in understanding faculty adoption patterns. Recent studies have approached this issue in fragmented ways: Lu et al. [6] and Shahid et al. [7] examined perceived utility and ease of use but focused primarily on individual cognitive factors without contextualizing them within institutional frameworks. Ghamrawi et al. [8], Nagy et al. [5], and Acosta-Enriquez et al. [9] investigated leadership implications of AI integration but failed to explore the fundamental mechanisms driving adoption. While Nagy et al. [5] and Shahid et al. [7] identified resource availability as crucial for implementation, they overlooked the critical role of pedagogical beliefs in adoption decisions [10]. This fragmented literature points to three critical research gaps: (1) limited exploration of the dynamic interplay between personal attitudes and institutional conditions that shapes adoption decisions, (2) insufficient investigation of how constructivist pedagogical beliefs (CPBs) specifically influence AI integration choices, and (3) inadequate examination of the potentially bidirectional relationship between AI adoption and teacher leadership (TL) development. The present study addresses these gaps through a comprehensive approach examining how attitudes, institutional conditions, and pedagogical beliefs collectively influence AI adoption among university faculty, while simultaneously investigating its impact on TL and pedagogical concerns. This integrated perspective is especially significant given the rapid evolution of AI capabilities and their transformative potential in higher education contexts.

At the national level, implementing AI in higher education faces additional challenges related to technological infrastructure, faculty training, and institutional policies. The existing digital divide and resistance to change within certain academic sectors may hinder the widespread adoption of these innovative technologies [9, 11]. Studies by Dyubele et al. [12] and Hardi et al. [13] emphasize the importance of considering local contextual factors to effectively implement advanced educational technologies.

Recent studies, such as Acosta-Enriquez et al. [10], have examined attitudes toward ChatGPT among Generation Z university students, highlighting the importance of perceived ethics and student concerns in AI acceptance. Additionally, Acosta-Enriquez et al. [9] investigated how factors such as frequency of use, information verification, and responsible usage affect attitudes toward ChatGPT, providing evidence on ethical practices and student behavior. In a broader analysis, Acosta-Enriquez et al. [14] explore the cognitive, affective, and behavioral components of student attitudes toward ChatGPT, revealing how these aspects influence AI usage in educational contexts. Similarly, Solórzano Solórzano et al. [15] examine the relationship between AI acceptance and entrepreneurial intention among international trade students, underscoring the impact of hedonic motivation, habits, and performance expectations on entrepreneurial behavior. Another recent study by Arbulú Pérez Vargas et al. [16] analyzed how digital skills and mobile self-efficacy mediate the relationship between stress and academic engagement in postpandemic virtual environments, providing a framework for understanding how technological factors affect education in digital learning settings. Finally, Acosta-Enriquez et al. [17], utilizing the UTAUT2 model, identified key factors such as performance expectancy and hedonic motivation as significant predictors of AI adoption in the university context, noting differences across disciplines and institution types.

The primary objective of this study is to analyze the factors influencing AI use (USEAI) among university faculty and its impact on educational leadership and teaching concerns. This research is aimed at addressing the current knowledge gap by examining the interaction between attitudes toward AI (ATAs), facilitating conditions (FCs), and CPBs in relation to AI adoption. The novelty of this study lies in the inclusion of constructs such as educational leadership and teaching concerns in the research model, as well as the formulation of hypotheses that explore the relationships among these factors [18, 19]. This multidimensional approach provides a deeper understanding of the complexity of this phenomenon, addressing aspects that have been less explored in previous research.

From a theoretical perspective, this research contributes to understanding technological adoption processes in higher education by expanding existing models, such as the unified theory of acceptance and use of technology (UTAUT), to include factors specific to the educational context [4, 7]. In practical terms, the findings of this study will offer valuable insights for higher education institutions in developing effective strategies for AI implementation, faculty training, and the creation of innovative learning environments [4, 20]. Additionally, the findings will assist educational policymakers in addressing educators' concerns and needs regarding the integration of AI into their teaching practices [8, 11]. This study will not only advance knowledge in the field of educational technology but also provide critical perspectives for the digital transformation of higher education in an AI-driven world.

2. Literature Review

2.1. Impact of AI on Teaching in Higher Education. AI is significantly transforming teaching practices in higher education. Singh and Hiran [21] and Mukhammadsidiqov et al. [22] highlighted how AI enables personalized learning experiences and individualized feedback, enhancing student engagement and outcomes. Raja et al. [23] emphasized the positive impact of AI on students' learning lives, whereas González Campos et al. [24] noted that AI automates repetitive tasks, allowing educators to focus more on individualized support. Amado-Salvatierra et al. [25] explore educators' perceptions of AI integration in higher education, and Lu et al. [26] discuss how AI-generated content (AIGC) supports innovative teaching practices. Kumar et al. [27] analyze the transformation of higher education under the influence of AI, and Téllez et al. [28] provide an overview of AI applications in university administration. Samman [29] presents a meta-analysis on AI integration in higher education, whereas

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Kallunki et al. [30] examine faculty and staff perceptions of the shifts brought about by AI. Finally, Lee et al. [31] investigated the impact of generative AI from educators' perspectives. Collectively, these studies underscore the transformative impact of AI on higher education, highlighting both its benefits and the challenges it presents.

2.2. A Review of Teacher Perceptions on the USEAI. The integration of AI in education generates mixed perceptions among teachers. On the one hand, its potential to improve learning outcomes and educational efficiency is recognized [21, 32]. However, there are concerns about the changing role of the teacher, the transparency of AI systems, and the potential loss of the human element in education [33, 34]. The effective implementation of AI requires significant training and adaptation by teachers [35]. To address these challenges, specific training programs [36] and the development of ethical guidelines to ensure responsible implementation [37] are recommended. Thus, while AI offers significant opportunities for education, it also presents challenges that require careful management and a balanced approach to its integration into educational settings.

2.3. Theoretical Research Model and Hypothesis Formulation. While the UTAUT model provides a comprehensive framework for understanding technology adoption, this study adopts a selective approach by incorporating only the FCs' construct due to its focus on institutional enablers rather than individual motivations. This deliberate selection enabled the integration of FCs with pedagogical beliefs and attitudes—constructs that previous research [7, 17] has identified as particularly relevant for AI adoption in educational contexts. Unlike standard UTAUT applications that emphasize performance expectancy, effort expectancy, and social influence—which primarily address individual perceptions of technology utility—this research prioritizes understanding how constructivist pedagogical orientations interact with institutional support in shaping AI adoption decisions. Regarding moderating factors, teaching modality (TM) was specifically selected over traditional UTAUT moderators (age, gender, experience) because recent literature [38, 39] suggests that instructional delivery format uniquely shapes technology implementation practices in educational environments, particularly for AI tools that may be deployed differently across face-to-face, hybrid, and fully online settings. This specific adaptation of UTAUT elements facilitates the development of a more contextualized model that addresses the unique characteristics of AI adoption in higher education while maintaining theoretical connections to established technology acceptance frameworks. The proposed conceptual model is presented in Figure 1.

2.4. The Influence of Attitudes on USEAI. ATAs are defined as evaluative predispositions that reflect teachers' overall positive or negative orientation toward implementing AI in educational contexts. These attitudes comprise cognitive components (beliefs about AI's effectiveness), affective components (emotional responses to AI), and behavioral intentions regarding its use [6]. As conceptualized by Jaffar et al. [40], these attitudes represent relatively stable evaluative judgments that significantly influence adoption behaviors and implementation practices.

AI is significantly transforming teaching practices in higher education. Positive ATAs, including perceptions of usefulness and ease of use, are strongly correlated with higher adoption rates of AI tools in teaching [26, 40]. Factors such as experience, AI training [41], age, digital competence [42, 43], and gender [44] influence these attitudes and, consequently, AI usage. Although educators recognize the benefits of AI for personalized learning and improved instructional systems, they also face challenges related to technical competency and ethical concerns [45–47]. On the basis of the above, the following hypothesis is formulated:

Hypothesis 1. *ATAs significantly influence the USEAI by university teachers.*

2.5. FCs for USEAI. FCs for USEAI refer to the organizational, technical, and resource-related factors that support or constrain the implementation of AI in educational environments. As defined by Ahmed et al. [48], these conditions include institutional infrastructure, technical support, training opportunities, resource availability, and policy frameworks. Rizvi [49] conceptualizes these conditions as the objective environmental factors that remove barriers to adoption and enable effective integration of AI technologies in educational settings.

Studies have shown that integrating AI into higher education can optimize resources, personalize learning, and improve academic performance [48, 50]. However, successful AI implementation requires careful consideration of ethical issues and effective integration into existing educational systems [49]. FCs, such as training and support for teachers, play a crucial role in addressing challenges such as unfamiliarity and technical difficulties [48]. Notably, Helmiatin et al. [47] reported that while FCs positively influence effort expectancy, they may negatively impact the behavioral intention to adopt AI. The potential benefits of AI in education are significant and include enhanced student engagement, improved academic outcomes, and personalized learning experiences [22, 51, 52]. However, challenges such as plagiarism risks and the gap between teachers' perceptions and students' actual AI skills require attention [53, 54]. To maximize the benefits of AI, institutions must provide adequate support, training, and resources while addressing ethical considerations and potential risks [55, 56]. Thus, the following hypothesis is proposed:

Hypothesis 2. *FCs for USEAI significantly influence the USEAI by university teachers.*

2.6. CPBs and AI Adoption. CPBs represent teachers' epistemological orientations that view learning as an active process wherein students construct knowledge through experience, inquiry, and social interaction rather than passive reception of information. According to Almerich et al. [57], these beliefs emphasize student-centered approaches, collaborative learning environments, and authentic problem-solving

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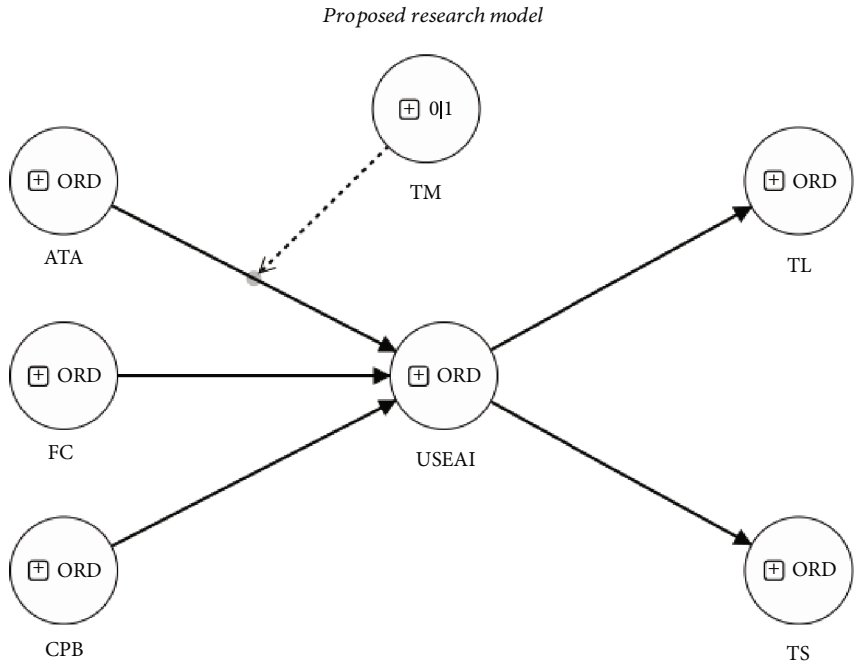


FIGURE 1: Proposed research model. Note: ATAs = attitudes toward AI; FC = facilitative conditions for AI use; USEAI = use of IA; TL = teacher leadership; TS = teachers' concern; CPB = constructivist pedagogical belief; TM = teaching modality.

activities. Marra [58] conceptualizes constructivist pedagogy as encompassing beliefs about knowledge construction, learner autonomy, and contextual learning—principles that potentially align with adaptive and personalized capabilities of AI technologies.

Studies indicate that teachers with constructivist beliefs are more likely to integrate technological resources into their teaching [57] and that technology-based constructivist learning environments can influence instructors' epistemological beliefs [58]. These constructivist practices have a positive effect on the self-efficacy of preservice teachers [59], with a preference for constructivist-based strategies observed among teacher trainees [60]. However, it is important to note that the practical implementation of these beliefs can vary due to external factors such as curriculum demands and student behavior [61]. These findings suggest a significant relationship between CPBs and the adoption of interactive applications in higher education. Therefore, the following hypothesis is proposed:

Hypothesis 3. *CPBs significantly influence the USEAI by university teachers.*

2.7. USEAI and TL. TL in the context of AI integration refers to educators' capacity to influence, inspire, and guide educational innovation through the strategic implementation of AI technologies. As conceptualized by Ghamrawi et al. [8], this form of leadership encompasses curriculum development, instructional innovation, professional development facilitation, and change management within educational institutions. Miao and Yao [2] define TL as the ability to leverage technological innovations to enhance educational effectiveness while guiding colleagues through transformational processes.

Ghamrawi et al. [8] suggested that AI can expand TL by facilitating personalization and curriculum development, although it may also challenge traditional roles. Luo and Wang [62] highlight the impact of intelligent learning management systems on teachers' digital leadership, whereas Miao and Yao [2] emphasize the need to develop new competencies for leadership in the AI era. Alam [63] and Lin et al. [64] reported that AI applications enhance instructional quality and learning outcomes, indirectly supporting TL. Collectively, these studies suggest that AI is transforming university TL, requiring adaptation to new roles and competencies in an evolving educational environment. Thus, the following hypothesis is formulated:

Hypothesis 4. *The USEAI significantly influences TL by university teachers.*

2.8. USEAI and Teachers' Concerns (TSs). TSs regarding AI encompass the apprehensions, uncertainties, and questions that educators experience when confronted with integrating AI into their professional practice. Angeles et al. [65] define these concerns as multidimensional constructs that include ethical considerations, pedagogical implications, professional identity questions, and technical uncertainties. According to Guillén-Yparrea and Hernández-Rodríguez [66], these concerns represent legitimate professional considerations rather than mere resistance to change and significantly influence implementation decisions.

Studies indicate that AI integration in higher education generates significant concerns among teachers, primarily

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related to academic integrity and unintentional plagiarism [65, 66]. Additionally, there is evidence of a lack of preparation and the need for training to use AI tools effectively [31, 67]. Teachers recognize the potential of AI to enhance teaching practices but also express concerns about its impact on their professional roles [8, 26, 54]. Further concerns arise regarding privacy and surveillance in online learning environments [45, 68]. There is a consensus on the need for clear policies and ethical frameworks to regulate USEAI in education [69]. Collectively, these findings underscore that USEAI significantly influences university TSs, covering ethical, pedagogical, and professional aspects that require comprehensive solutions. On this basis, the following hypothesis is proposed:

Hypothesis 5. *The USEAI significantly influences TSs among university teachers.*

2.9. TM as a Moderator. TM refers to the instructional delivery format through which educational content is presented to students, including face-to-face instruction, fully online learning, hybrid/blended approaches, or synchronous/asynchronous digital formats. As conceptualized by Cabellos et al. [38], modality represents a contextual variable that shapes how technologies are implemented and experienced in educational settings. Chen et al. [39] define TM as a multidimensional construct encompassing temporal, spatial, and interactional dimensions of the educational experience, potentially moderating how attitudinal factors influence technology adoption decisions.

Studies have shown that positive attitudes toward ICTs are positively associated with their use and that institutional FCs significantly affect technology adoption [38]. Technological pedagogical content knowledge (TPACK) and attitudes toward technology play crucial mediating roles in the intention to use technology [39, 70]. In some contexts, learning management system competency may be more influential than attitudes [71]. Additionally, the language modality used by educators affects pedagogical communication [72]. Factors such as perceived usefulness and FCs are essential for the successful adoption of online teaching [73]. These findings suggest that TM can effectively moderate the relationship between ATAs and its use, highlighting the importance of considering multiple factors in implementing educational technologies. Therefore, the following hypothesis is proposed:

Hypothesis 6. *TM moderates the effect of the relationship between ATAs and the USEAI by university teachers.*

3. Method

To evaluate the proposed research hypotheses, a survey-based quantitative research approach was implemented, following the best methodological practices for empirical studies in the field of educational technology [19]. This method allowed the collection of systematic data on university teachers' attitudes toward the USEAI in their pedagogical practices.

3.1. Participants. The study involved 452 university instructors from six public and private universities in northern Peru. A nonprobabilistic convenience sampling method was employed, a technique commonly used in exploratory research on technology adoption in higher education [10]. This sampling method facilitates efficient data collection in contexts where access to participants may be limited, although it is acknowledged that it may impact the representativeness of the sample.

The choice of this sampling approach is justified by its ability to provide valuable preliminary insights into trends in instructors' ATAs while also recognizing limitations in terms of generalizability. Importantly, the lack of statistical representativeness may affect the study's statistical power and ability to extrapolate findings to the broader population of university instructors within the Peruvian higher education context.

Table 1 provides a detailed breakdown of the sample's sociodemographic characteristics. Among the participants, 53.54% ($n = 242$) were female, and 46.46% ($n = 210$) were male. In terms of age distribution, the majority of participants were between 41 and 50 years old (29.65%, $n = 134$), followed by those aged 31–40 years (26.77%, $n = 121$) and 51–60 years (21.68%, $n = 98$). Smaller percentages were in the 25–30 years' age range (11.95%, $n = 54$) and were aged 61 years or older (9.95%, $n = 45$).

In terms of university type, 51.55% ($n = 233$) of the participants were from public universities, whereas 48.45% ($n = 219$) were from private universities. In terms of faculty affiliation, 28.32% ($n = 128$) of the participants were from the faculty of education; 18.14% ($n = 82$) were from social sciences; 11.50% ($n = 52$) were from health sciences and medicine; 9.51% ($n = 43$) were from engineering and architecture; 7.74% ($n = 35$) were from law and political science; 7.74% ($n = 35$) were from physical sciences, mathematics, statistics, and computer science; 6.86% ($n = 31$) were from business sciences; 5.31% ($n = 24$) were from economics and accounting; and 4.87% ($n = 22$) were from agricultural sciences. Finally, regarding prior experience with AI in university settings, 100% of the respondents reported having experience.

3.2. Instruments. For this study, a data collection instrument was developed on the basis of an exhaustive review of the literature on the adoption of AI by university instructors and its implications for leadership and educational concerns. The questionnaire was carefully constructed, integrating theoretical frameworks and relevant empirical findings for each evaluated construct.

The survey was administered via Google Forms and organized into three main sections. The first section presented informed consent, followed by sociodemographic data collection. The third and most extensive section contained the scale for attitudes and perceptions toward AI, comprising six fundamental constructs.

The first construct, ATAs, was based on Alnasib's [18] research and assessed instructors' general perceptions through five items. CPBs were measured with three items grounded in the work of Cabero-Almenara et al. [19], who

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TABLE 1: Sociodemographic details of the sample ($n = 452$).

Sociodemographic variable	fi	%
Gender		
Female	242	53.54
Male	210	46.46
Age		
[25–30]	54	11.95
[31–40]	121	26.77
[41–50]	134	29.65
[51–60]	98	21.68
[61 or more]	45	9.95
Type of university		
Private	219	48.45
Public	233	51.55
Faculty of origin		
Education	128	28.32
Health sciences and medicine	52	11.50
Engineering and architecture	43	9.51
Social sciences	82	18.14
Business science	31	6.86
Law and political science	35	7.74
Economics and accounting	24	5.31
Agricultural sciences	22	4.87
Physical sciences, mathematics, statistics, and computer science	35	7.74
Do you have previous experience using AI at university?		
Yes	452	100.0
No	0	0

Note: Own elaboration.

explored instructors' views on student-centered learning in the context of AI.

FC for USEAI were assessed with three items on the basis of Alnasib's [18] study, which examined institutional support and available resources. TL was measured with five items inspired by Ghamrawi et al. [8], who analyzed how AI might impact educators' leadership roles.

TSs were measured through five items grounded in the findings of Acosta-Enriquez et al. [10], which address instructors' concerns about USEAI. Finally, the USEAI was assessed with seven items on the basis of Alnasib's [18] work, which measured the frequency and type of USEAI in educational practices.

In total, the instrument comprises 28 items distributed among these six constructs, all of which are evaluated on a 5-point Likert scale, where 1 indicates "*strongly disagree*" and 5 indicates "*strongly agree*." To ensure validity and reliability, the instrument underwent a rigorous validation process, including confirmatory factor analysis (CFA). Strict criteria were applied to factor loadings (> 0.70) and average variance extracted (AVE > 0.50), ensuring the robustness of the instrument in accurately measuring university instructors' attitudes, perceptions, and practices related to AI in the educational domain.

3.3. Procedure and Data Analysis. The data collection process spanned 6 months, from April to September 2024, and focused exclusively on public and private universities in the northern region of Peru. Prior to initiating the study, the necessary ethical approvals were obtained from the participating institutions, ensuring adherence to ethical research standards.

The survey was distributed primarily through two digital channels: institutional emails and WhatsApp messages. To maximize participation, valuable support was provided by academic coordinators in each faculty, who facilitated the study's dissemination among instructors.

Additionally, a standardized protocol was implemented to ensure consistency in data collection across the various participating institutions. This protocol included uniform training for survey administrators and provided clear, concise guidelines for participants, ensuring homogeneity in the survey's administration.

The data analysis followed a systematic approach across multiple stages. Initially, meticulous data cleaning and preprocessing were conducted via Microsoft Excel, removing incomplete or invalid responses to ensure data quality. A descriptive analysis was subsequently performed to characterize the sample, and the results are presented in Table 1.

The measurement model evaluation began with exploratory factor analysis (EFA) via SmartPLS v.4.0 to identify the underlying internal structure of the items and factors. A CFA was subsequently conducted via the same software. During the CFA, three items (ATA4—0.476: "AI tools are easy to integrate into my teaching"; TS3—0.489: "I worry about technical difficulties with AI"; and FC2—0.492: "The IT support staff is helpful when I use AI") had factor loadings below 0.50 and were consequently removed. This elimination did not affect construct validity, as each remaining construct retained more than three items, maintaining convergent validity criteria. The model fit indices were evaluated via the goodness-of-fit measures available in SmartPLS v.4.0, specifically standardized root mean square residual (SRMR), d_ULS, d_G, χ^2/df, and normed fit index (NFI). Notably, traditional fit indices such as RMSEA, CFI, or TLI were not included, as they are not computed in SmartPLS, which uses different criteria for assessing model fit in partial least squares structural equation modeling (PLS-SEM) analyses.

PLS-SEM was chosen over covariance-based SEM (CB-SEM) because of three main considerations: the study's predictive focus, the presence of both reflective and formative constructs in our theoretical model, and the inclusion of moderating variables (TM in this case). Analysis was conducted via SmartPLS v.4.0 software [74]. Bootstrapping procedures with 5000 resamples were employed to obtain confidence intervals for the beta values and p values, enhancing the robustness of our hypothesis testing results.

Instrument reliability was assessed via Cronbach's alpha and composite reliability (CR), with both measures exceeding the 0.70 threshold. Discriminant validity was examined

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via the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT < 0.85) ratio, ensuring adequate distinction between the constructs. Additionally, a common method bias test using Harman's single-factor test revealed that no single factor accounted for more than 50% of the variance, suggesting minimal common method bias.

4. Results

4.1. Results of the Measurement Model. Table 2 presents the results of the CFA, demonstrating robust psychometric properties for all measurement items. The outer loadings range from 0.706 to 0.937, exceeding the threshold of 0.70 recommended by Hair [75], thus confirming satisfactory indicator reliability. Standard deviations for all items range between 0.008 and 0.092, indicating minimal dispersion from their means and supporting the stability of the measurement model. The factor structure aligns with the theoretical foundations drawn from prior research by Alnasib [18], Cabero-Almenara et al. [19], Ghamrawi et al. [8], and Acosta-Enriquez et al. [10], confirming the construct validity of the instrument in the present educational context.

Table 3 presents the reliability and convergent validity indices for all constructs in the measurement model. Cronbach's alpha (α) values range from 0.758 to 0.968, exceeding the minimum threshold of 0.70 recommended by Nunnally and Bernstein [76]. Similarly, CR measures—both rho_a (0.791–0.969) and rho_c (0.860–0.974)—surpass the 0.70 benchmark established by Hair et al. [77], confirming excellent internal consistency reliability across all constructs. The highest reliability is observed for the USEAI construct ($\alpha = 0.968$, rho_a = 0.969, rho_c = 0.974), while FCs demonstrate the lowest, though still adequate, reliability values ($\alpha = 0.758$, rho_a = 0.791, rho_c = 0.860). AVE values range from 0.646 to 0.841, all exceeding the 0.50 threshold, thus establishing convergent validity. These results collectively confirm that the measurement scales possess strong psychometric properties, establishing a solid foundation for subsequent structural model analysis.

Table 4 presents the results of the Fornell–Larcker criterion assessment for discriminant validity. According to this criterion [78], a measurement model exhibits adequate discriminant validity when the square root of the AVE for each construct (values on the diagonal) exceeds its correlations with all other constructs (off-diagonal values in the corresponding rows and columns). Analysis of the table reveals that all constructs meet this criterion. For instance, the value for ATAs is 0.826, which is greater than its correlations with other constructs (ranging from 0.473 to 0.700). Similarly, TL shows a value of 0.892, exceeding its correlations with other variables (ranging from 0.444 to 0.711). The highest correlation observed is between USEAI and TL at 0.711, but this remains below both constructs' respective diagonal values (0.917 and 0.892). These results confirm that each construct captures unique phenomena that are empirically distinct from other constructs in the model, thereby establishing discriminant validity.

Table 5 displays the HTMT values for assessing discriminant validity. The HTMT approach represents a more stringent assessment of discriminant validity compared to the Fornell–Larcker criterion. According to Rasoolimanesh [79], HTMT values below 0.85 indicate adequate discriminant validity between construct pairs. Examination of Table 5 reveals that all HTMT values range from 0.048 to 0.793, remaining below the critical threshold of 0.85. The highest HTMT value (0.793) is observed between ATAs and TSs, suggesting some conceptual overlap yet still maintaining discriminant validity. Notably, the lowest HTMT values are observed between TL and TSs at 0.081, and between TL and USEAI at 0.048, indicating these constructs are highly distinct. These results provide additional confirmation of discriminant validity among all constructs in the measurement model, complementing the Fornell–Larcker analysis and further strengthening confidence in the measurement model's validity.

Table 6 presents the variance inflation factor (VIF) values for all structural model paths, enabling assessment of multicollinearity among predictor variables. VIF values range from 1.000 to 2.757, all well below the critical threshold of 5.0 established by Hair et al. [77], indicating absence of problematic multicollinearity. The highest VIF value is observed for FC → USEAI (2.757), followed closely by CPB → USEAI (2.623), suggesting some correlation among these predictors but not at levels that would compromise the structural model estimates. ATAs (ATA → USEAI) demonstrate a moderate VIF value (2.031), while the moderating variable (TM → USEAI) shows low collinearity (1.025). The paths from USEAI to outcome variables (USEAI → TL and USEAI → TS) both exhibit perfect VIF values of 1.000, confirming complete absence of collinearity concerns. The interaction term (TM × ATA → USEAI) shows minimal collinearity (1.810), indicating independence from its component variables. These results collectively establish that multicollinearity does not pose a threat to the validity of path coefficient estimates in the structural model, thus providing confidence in the robustness of hypothesis testing results.

The goodness-of-fit indices of a measurement model are relevant for determining convergent validity [80]; therefore, these criteria provide a reference for researchers to determine to what extent the values obtained fit well with the expected values [75]. Table 7 presents the values of the goodness-of-fit indices of the measurement model, where the SRMR presented a value of 0.064, satisfying the threshold proposed by [81]. The value of chi-square/gl (χ^2/df) shows that the model has an acceptable fit because it has an adequate value between 1 and 3, as proposed by [82]. Finally, the value of the NFI is 0.978, which satisfies the threshold of [82].

4.2. Testing the Research Hypotheses. Table 8 and Figure 2 show the main results of the analysis performed via standardized path coefficients (β), together with the p values, confidence intervals, standard deviations, effect sizes (f^2), and decisions. Path analysis makes it possible to determine β between the relationships of the exogenous and endogenous variables of the study, as well as the direction of these effects [75, 83]. Hypothesis 1 (H1) revealed a significant effect between ATAs and USEAI, with a path coefficient of $\beta =$

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TABLE 2: Results of the confirmatory factor analysis (CFA).

Items		Outer loadings	Construct	Support
AI can enhance the quality of my teaching	ATA1	0.762	Attitudes toward AI (ATAs)	[18]
Using AI in education makes teaching more efficient	ATA2	0.732		
AI tools help me provide better feedback to students	ATA3	0.875		
AI can help personalize learning experiences for students	ATA5	0.880		
Using AI in teaching improves student engagement	ATA6	0.870		
Students should construct their own knowledge through technology-enhanced learning	CPB1	0.825	Constructivist pedagogical beliefs (CPBs)	[19]
Technology should support student-centered learning approaches	CPB2	0.836		
AI tools should facilitate active learning and knowledge construction	CPB3	0.849		
My institution provides adequate technical support for AI implementation	FC1	0.748	Facilitative conditions for AI use (FC)	[18]
I have access to necessary resources for using AI in teaching	FC3	0.829		
My institution offers training opportunities for AI integration	FC4	0.879		
AI helps me take initiative in improving teaching practices	TL1	0.882	Teacher leadership (TL)	[8]
Using AI enables me to lead educational innovation	TL2	0.917		
AI integration enhances my role as an educational leader	TL3	0.894		
AI tools support my curriculum development leadership	TL4	0.926		
Using AI strengthens my instructional leadership capabilities	TL5	0.838		
I am concerned about maintaining academic integrity with AI use	TS1	0.706	Teachers' concerns (TSs)	[10]
I worry about the impact of AI on student learning autonomy	TS2	0.835		
I am concerned about privacy issues related to AI use	TS4	0.840		
I worry about the changing role of teachers with AI integration	TS5	0.767		
I am concerned about ethical implications of AI in education	TS6	0.860		
I use AI tools for lesson planning and preparation	USEAI1	0.890	Use of AI (USEAI)	[18]
I implement AI for student assessment and feedback	USEAI2	0.906		
I utilize AI for content creation and curation	USEAI3	0.930		
I employ AI tools for administrative tasks	USEAI4	0.933		
I use AI for personalizing student learning experiences	USEAI5	0.937		
I integrate AI in classroom activities	USEAI6	0.918		
I apply AI tools for student progress monitoring	USEAI7	0.902		

Note: Own elaboration.

TABLE 3: Reliability and convergent validity.

Construct	α	CR (rho_a)	CR (rho_c)	AVE
ATA	0.882	0.894	0.915	0.683
CPB	0.790	0.809	0.875	0.700
FC	0.758	0.791	0.860	0.673
TL	0.935	0.936	0.951	0.795
TS	0.862	0.872	0.901	0.646
USEAI	0.968	0.969	0.974	0.841

Note: Own elaboration.

TABLE 4: Fornell–Larcker criterion.

Construct	ATA	CPB	FC	TL	TS	USEAI
ATA	0.826					
CPB	0.473	0.837				
FC	0.492	0.776	0.820			
TL	0.638	0.466	0.444	0.892		
TS	0.700	0.469	0.536	0.646	0.804	
USEAI	0.699	0.531	0.493	0.711	0.597	0.917

0.529 $***$ and a p value of $p < 0.001$, with a substantial effect size ($f^2 = 0.302$) indicating a medium to large practical significance according to Cohen's [84] guidelines. Hypothesis 3 (H3) shows a significant effect between CPBs and USEAI, with a path coefficient $\beta = 0.253$ $**$ and a p value < 0.01, with a medium effect size ($f^2 = 0.153$), demonstrating the meaningful contribution of pedagogical beliefs to AI

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TABLE 5: Heterotrait–monotrait (HTMT) ratio criterion.

Construct	ATA	CPB	FC	TL	TS	USEAI
ATA						
CPB	0.572					
FC	0.588	0.432				
TL	0.702	0.528	0.513			
TS	0.793	0.552	0.657	0.081		
USEAI	0.751	0.594	0.565	0.445	0.647	

TABLE 6: Multicollinearity report.

	VIF
ATA → USEAI	2.031
CPB → USEAI	2.623
FC → USEAI	2.757
TM → USEAI	1.025
USEAI → TL	1.000
USEAI → TS	1.000
TM × ATA → USEAI	1.810

adoption. Hypothesis 2 (H2) shows a nonsignificant effect between FCs and USEAI, with a path coefficient $\beta = 0.012$ and a p value of 0.885, with a negligible effect size ($f^2 = 0.000$), resulting in the rejection of this hypothesis. Hypothesis 4 (H4) confirms a significant effect between USEAI and TL, with a path coefficient $\beta = 0.711$ *** and a p value < 0.001, with a large effect size ($f^2 = 0.553$), highlighting the substantial practical significance of AI adoption in transforming leadership capabilities. Hypothesis 5 (H5) shows a significant effect between USEAI and TSs, with a path coefficient $\beta = 0.597$ *** and a p value < 0.001, with a large effect size ($f^2 = 0.422$), emphasizing the meaningful influence of AI adoption on raising pedagogical and ethical concerns. Finally, Hypothesis 6 (H6) shows a nonsignificant moderating effect of TM on the relationship between attitudes and USEAI, with a path coefficient $\beta = 0.101$ and a p value of 0.371, with a negligible effect size ($f^2 = 0.002$), resulting in the rejection of this hypothesis.

Table 9 presents the coefficients of determination (R^2) and adjusted R^2 values for the endogenous constructs in the structural model. The results demonstrate that the exogenous variables ATAs, FCs, and CPBs collectively explain 54.3% of the variance in USEAI ($R^2 = 0.543$, adjusted $R^2 = 0.531$), indicating substantial explanatory power according to Hair et al. [77], who suggest that R^2 values of 0.75, 0.50, and 0.25 represent substantial, moderate, and weak explanatory power, respectively. In the subsequent relationships, USEAI as a predictor explains 50.5% of the variance in TL ($R^2 = 0.505$, adjusted $R^2 = 0.503$), demonstrating moderate-to-substantial explanatory capability for this endogenous variable. Similarly, USEAI explains 35.6% of the variance in TSs ($R^2 = 0.356$, adjusted $R^2 = 0.353$), representing moderate explanatory power. The minor differences between R^2 and adjusted R^2 values indicate that the model maintains robust explanatory power while accounting for the number of predictor variables.

5. Discussion

The results of this research provide significant evidence regarding the factors that influence USEAI among university instructors and its impact on TL and concerns. The main findings are discussed below in relation to each proposed hypothesis.

For the first hypothesis, the results confirm that ATAs significantly influence its use by university instructors ($\beta = 0.529$, $p < 0.001$), with a medium-to-large effect size ($f^2 = 0.302$). This finding aligns with those of previous studies, such as those of Jaffar et al. [40], Lu et al. [6], and Hassan [41], which identified a strong correlation between positive attitudes and the adoption of AI tools in teaching. The magnitude of the coefficient and substantial effect size further support the arguments of Villegas-José and Delgado-García [43] and Galindo-Domínguez et al. [42] on the critical role of digital competence and positive attitudes in AI implementation. Additionally, this result validates observations by Dincer and Bal [45], Hidayat et al. [47], and Fakhar et al. [46] on the importance of teacher perceptions in technology adoption.

With respect to CPBs (H3), a significant but moderate influence on USEAI was observed ($\beta = 0.253$, $p < 0.01$), with a medium effect size ($f^2 = 0.153$). This result complements the findings of Almerich et al. [57] and Marra [58], who reported that instructors with constructivist orientations tend to integrate more technological resources into their teaching. The effect size supports Ledoux and McHenry's [59] observations on the positive impact of constructivist practices on teacher self-efficacy and aligns with preferences identified by Machado and Wang [60]. However, the moderate strength of the relationship suggests, as noted by Savasci and Berlin [61], that practical implementation may be affected by external factors.

The nonsignificant effect of FCs on AI adoption ($\beta = 0.012$, $p > 0.05$), with a negligible effect size ($f^2 = 0.000$), represents a particularly intriguing finding that challenges the conventional understanding of technology adoption in education [48, 49]. This unexpected result can be explained through several theoretical and contextual factors. First, the increasing availability of user-friendly AI tools through cloud-based platforms has reduced dependence on institutional technical infrastructure, as noted by Watanabe [55] and Zhang and Zhang [56]. Tools such as ChatGPT and other AI applications are readily accessible through standard web browsers, requiring minimal institutional support for implementation, a phenomenon documented by Lu et al. [6] and Shahid et al. [7]. Second, the proliferation of online learning communities and resources has created alternative support structures outside traditional institutional frameworks, enabling teachers to learn and troubleshoot independently [47, 54]. Third, the rapid evolution of AI technology may have outpaced traditional institutional

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TABLE 7: Model fit.

Criteria	Estimated model	Threshold	Author	Decision
SRMR	0.055	< 0.85	Sun and Ge [81]	Acceptable
d_ULS	1.298			
d_G	0.852			
χ^2/df	1.764	Entre 1 y 3	Escobedo Portillo et al. [82]	Acceptable
NFI	0.954	> 0.90	Escobedo Portillo et al. [82]	Acceptable

Note: Own elaboration.

TABLE 8: Path, p value, confidence intervals, standard deviation, and decision coefficients.

Hypothesis		β	p value	Confidence interval 2.50%	Confidence interval 97.50%	SD	F^2	Decision
H1	ATA ➔ USEAI	0.529***	$p \leq 0.001$	0.364	0.688	0.083	0.302	Accepted
H3	CPB ➔ USEAI	0.253*	0.003	0.091	0.422	0.084	0.153	Accepted
H2	FC ➔ USEAI	0.012	0.885	−0.150	0.175	0.083	0.000	Rejected
H4	USEAI ➔ TL	0.711***	$p \leq 0.001$	0.624	0.791	0.042	0.553	Accepted
H5	USEAI ➔ TS	0.597***	$p \leq 0.001$	0.474	0.719	0.063	0.422	Accepted
H6	TM × ATA ➔ USEAI	0.101	0.371	−0.121	0.316	0.112	0.002	Rejected

Note: Path = path coefficient. In column β for H2 and H6, p values that are greater than 0.05 are considered not significant.
Abbreviation: SD = standard deviation.
*$p < 0.05$; ***$p < 0.001$.

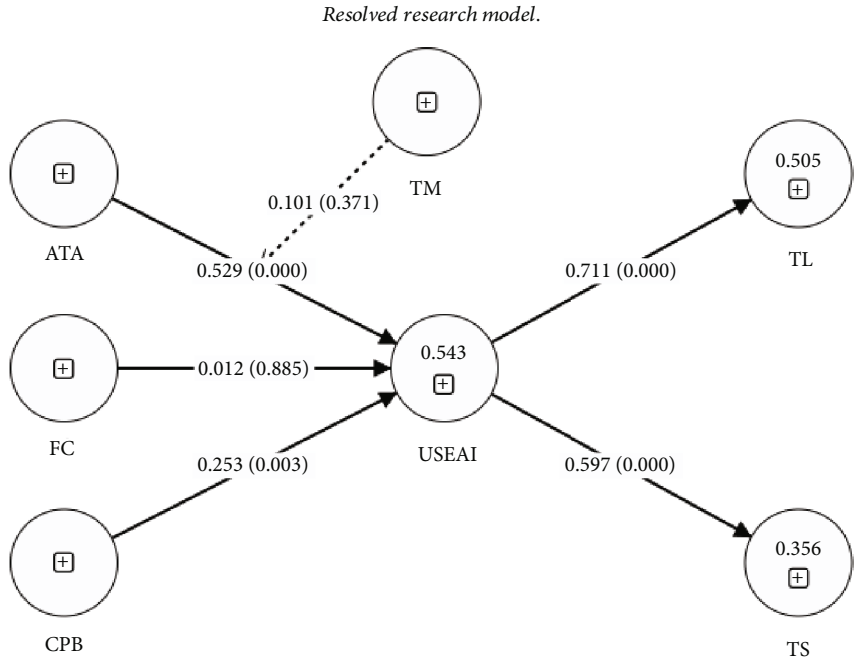


FIGURE 2: Resolved research model. Note: At the intersections of the relationship lines are the path coefficients on the left and the p values on the right (inside the parentheses).

support mechanisms, leading teachers to rely more on peer networks and self-directed learning, as observed by Ali et al. [52] and Al Daraai et al. [51]. This finding suggests that the relationship between institutional support and technology adoption may be evolving, particularly for emerging technologies such as AI, which are characterized by high accessibility and rapid change [22]. Furthermore, this result indicates that traditional models of technology adoption in

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TABLE 9: Coefficients of determination.

	R^2	R^2 adjusted
TL	0.505	0.503
TS	0.356	0.353
USEAI	0.543	0.531

education may need revision to account for the unique characteristics of AI tools and their implementation patterns [5, 8]. The lack of significance in FCs also suggests that barriers to AI adoption may be more psychological and pedagogical than technical or resource-based, reinforcing the importance of addressing attitudes and beliefs in professional development programs [45–47].

The study revealed a strong impact of USEAI on TL (H4: $\beta = 0.711$, $p < 0.001$), with a large effect size ($f^2 = 0.553$), supporting observations by Ghamrawi et al. [8] and Luo and Wang [62] on the transformation of educational leadership. This substantial effect size underscores the practical significance of AI adoption in reshaping leadership capabilities in educational settings. This finding validates Miao and Yao's [2] predictions regarding the need to develop new leadership competencies in the AI era and confirms observations by Alam [63] and Lin et al. [64] on how AI applications improve instructional quality and support TL.

With respect to TSs (H5), USEAI was found to have a significant influence ($\beta = 0.597$, $p < 0.001$), with a large effect size ($f^2 = 0.422$). This result aligns with findings by Angeles et al. [65], Delello et al. [67], and Lee et al. [31] concerning concerns related to academic integrity and teacher preparedness. The substantial effect size highlights the meaningful practical impact of AI adoption on generating pedagogical, ethical, and professional concerns among educators. The effect size supports observations by Perez-Alvarez et al. [54] and Lu et al. [6] on the impact on professional roles and validates concerns raised by Seo et al. [68] and Dincer and Bal [45] about privacy and surveillance. Additionally, it underscores the need for clear policies and ethical frameworks, as noted by Flores-Vivar and García-Peñalvo [69].

Finally, the hypothesis regarding the moderating effect of TM (H6) was not supported by the data ($\beta = 0.101$, $p > 0.05$), with a negligible effect size ($f^2 = 0.002$). This result contrasts with expectations based on studies such as those by Cabellos et al. [38], Bai et al. [70], and Chen et al. [39]. It also diverges from findings by Alharbi et al. [71] concerning the importance of learning management system competence and Nguyen's [73] observations on online teaching adoption.

These findings make significant contributions to understanding AI adoption in higher education, highlighting the critical importance of teacher attitudes and pedagogical beliefs while challenging certain assumptions about the role of FCs and teaching modalities. Practical implications suggest the need to focus on fostering positive ATAs and addressing TSs as key elements for successful implementation.

5.1. Theoretical and Practical Implications. This research offers significant contributions to both the theoretical understanding and practical implementation of AI in higher education. From a theoretical perspective, the study extends existing technology adoption models by empirically validating the role of psychological and pedagogical factors in AI adoption. The findings demonstrate that ATAs and CPBs significantly predict USEAI in university teaching, reinforcing the theoretical foundations established by Shahid et al. [7] and Liu et al. [4] regarding the psychological dimensions of technology adoption.

The unexpected finding regarding FCs challenges established theoretical assumptions in technology adoption models. The lack of a significant effect of institutional support mechanisms on USEAI suggests a need to reconceptualize traditional adoption frameworks, particularly in educational contexts where teacher autonomy and technology accessibility may have greater influence than previously theorized. This finding contributes to the evolution of technology adoption theory, particularly in understanding how emerging technologies such as AI may require different theoretical frameworks than those developed for earlier educational technologies.

The research also advances educational leadership theory by establishing an empirical connection between USEAI and TL development ($\beta = 0.711$, $p < 0.001$). This relationship, as initially proposed by Miao and Yao [2], suggests that technology adoption transcends mere tool use and actively shapes leadership capacities in higher education. The significant influence of USEAI on TSs ($\beta = 0.597$, $p < 0.001$) further enriches the theoretical understanding of how technological innovation affects professional identity and practice.

These theoretical insights have substantial practical implications for higher education institutions. The strong relationship between attitudes and AI adoption suggests that institutions should prioritize initiatives that foster positive perceptions of AI among faculty. This requires moving beyond traditional technical training to address underlying beliefs and concerns about AI's role in education. Professional development programs should incorporate both technical skills and pedagogical applications, emphasizing how AI can enhance rather than replace existing teaching practices.

The significance of CPBs in AI adoption indicates that institutions should align AI implementation with student-centered learning approaches. This alignment can be achieved through professional development programs that demonstrate how AI tools can support active learning, collaborative knowledge construction, and personalized education experiences. The nonsignificant effect of FCs suggests that institutions should reconsider their resource allocation strategies. Rather than focusing primarily on technical infrastructure, institutions might benefit from investing in collaborative learning environments where teachers can share experiences and develop innovative applications of AI in teaching.

The strong relationship between USEAI and TL development presents opportunities for institutional transformation. Educational institutions should develop comprehensive leadership programs that integrate AI competency with pedagogical leadership. This could involve establishing mentorship

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programs, creating specialized leadership roles focused on educational technology innovation, and developing recognition systems that acknowledge teachers who successfully implement AI-enhanced pedagogical approaches.

Furthermore, the significant effect of USEAI on TSs necessitates the development of robust institutional frameworks for ethical AI implementation. These frameworks should address issues of academic integrity, privacy protection, and appropriate use guidelines. Institutions should establish clear policies while maintaining flexibility to accommodate emerging AI applications and evolving pedagogical needs.

5.2. Limitations and Future Studies. This study has several limitations that should be considered when interpreting its results. The use of nonprobabilistic convenience sampling limits the generalizability of the findings to the broader context of Peruvian universities. Its cross-sectional nature prevents observations of changes in teacher attitudes and behaviors over time. Additionally, the exclusive reliance on quantitative, self-reported data may have limited the depth of understanding of teacher experiences. The geographical concentration on six universities in northern Peru also restricts the representativeness of the findings, as regional differences in technological infrastructure, resources, and cultural context may influence AI adoption patterns.

Building upon these limitations, we propose four specific directions for future research. First, a 1-year longitudinal study tracking a cohort of 100 university teachers from different disciplines could examine how attitudes and practices toward AI evolve during the implementation of specific AI tools such as ChatGPT or Google Bard. This approach addresses the current study's cross-sectional limitations while providing insights into adoption patterns over time, following the methodological guidelines proposed by Shahid et al. [7] for longitudinal technology adoption studies.

Second, future research should employ a mixed-methods design incorporating semistructured interviews ($n = 20$) and classroom observations ($n = 10$) alongside quantitative surveys. This methodology provides deeper insights into teachers' experiences and challenges with AI implementation, addressing the current study's limitation of relying solely on self-reported quantitative data. The qualitative component could specifically explore how teachers integrate AI tools into their pedagogical practices and how this integration affects their teaching approaches, as suggested by Ghamrawi et al. [8].

Third, we recommend a comparative study of universities in different regions of Peru, specifically comparing three geographical areas: coastal (Lima), highland (Cusco), and jungle (Iquitos) regions. This study is aimed at examining how regional technological infrastructure and cultural factors influence AI adoption patterns, addressing the geographical limitations of the current study. This comparative approach could utilize the validated instruments from our study while incorporating region-specific variables identified by Nagy et al. [5].

Fourth, future research should investigate the relationship between teacher AI adoption and student learning outcomes through a quasiexperimental design. This could involve comparing student academic performance, engagement, and satisfaction in courses with varying levels of AI integration. The study should include pre- and posttests of student learning outcomes, controlling for variables such as prior academic performance and technology familiarity, following the experimental design framework proposed by Lu et al. [6].

6. Conclusions

This research makes substantial contributions to understanding the factors that influence AI adoption in higher education and its implications for teaching practices. The findings reveal that ATAs are a critical predictor of its use in university teaching, with a more substantial impact ($f^2 = 0.302$) than institutional FCs ($f^2 = 0.000$). This insight challenges traditional views on technology implementation in higher education, suggesting that the success of AI adoption depends more on individual than institutional factors.

CPBs play a relevant, albeit moderate, role in AI adoption ($f^2 = 0.153$), indicating a connection between innovative pedagogical orientations and the willingness to integrate new technologies. This finding establishes a conceptual bridge between contemporary pedagogical theories and technological innovation in higher education.

The study reveals a strong relationship between USEAI and TL development ($f^2 = 0.553$), providing empirical evidence on how emerging technologies redefine leadership roles in higher education. This substantial effect size indicates the practical significance of AI adoption in transforming educational leadership. This transformation suggests an evolution in the conceptualization of educational leadership, where technological competence becomes an essential component of leadership capacity.

TSs emerge as a notable consequence of USEAI ($f^2 = 0.422$), highlighting the need to address ethical, pedagogical, and professional aspects in the implementation of these technologies. The large effect size demonstrates the meaningful practical impact of AI adoption on generating concerns among educators. This finding underscores the importance of developing ethical frameworks and institutional policies to guide the responsible integration of AI in higher education.

The absence of a moderating effect of TM on the relationship between attitudes and USEAI ($f^2 = 0.002$) contradicts previous expectations, suggesting that the influence of attitudes on technology adoption transcends that of specific teaching modalities. This discovery invites a reconsideration of technology implementation models across various educational contexts.

The results of this research extend the theoretical base of technology adoption in higher education and provide practical guidance for institutions seeking to implement AI effectively. Emphasizing teacher attitudes and pedagogical beliefs as key factors suggests a need for more professional development and cultural change–focused approaches rather than an exclusive focus on technological infrastructure.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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