

Socio-emotional skills and artificial intelligence competencies among university teachers in the digital transformation of higher education: The mediating role of educational leadership

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ABSTRACT:

The rapid digital transformation of higher education and the growing incorporation of artificial intelligence (AI) are reshaping university teaching and creating new professional demands for academic staff. This study examined the relationships among social-emotional skills, educational leadership, and AI competencies among university teachers, considering these dimensions as interrelated components of professional adaptation to increasingly digital academic environments. A quantitative, non-experimental, cross-sectional, correlational design was employed. Data were collected from 403 university teachers through a structured questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results showed that social-emotional skills were positively associated with educational leadership ($\beta = 0.684$, $p < .001$) and AI competencies ($\beta = 0.311$, $p < .001$), while educational leadership was positively associated with AI competencies ($\beta = 0.471$, $p < .001$). Educational leadership also partially mediated the relationship between social-emotional skills and AI competencies ($\beta = 0.322$, $p < .001$). The structural model explained 46.8% of the variance in educational leadership and 52.1% of the variance in AI competencies. Educational leadership also showed a statistically significant indirect role in the association between socio-emotional skills and AI competencies, while the direct association remained significant, a pattern consistent with partial statistical mediation.

Keywords: artificial intelligence competencies; educational leadership; higher education; socio-emotional skills; university teachers; digital transformation.

1. Introduction

The rapid digital transformation of higher education is reshaping not only the technologies used in teaching and learning but also the professional roles, relationships, expectations, and competencies of university teachers. The increasing incorporation of artificial intelligence (AI), digital platforms, learning analytics, and other emerging technologies is transforming how teaching is planned, delivered, assessed, and coordinated. From this perspective, digital transformation should be understood as a broader professional, organizational, and social process that changes patterns of interaction, collaboration, knowledge production, and institutional practice. Accordingly, contemporary university teaching increasingly requires a broader conception of professional competence that integrates technological, pedagogical, cognitive, leadership, and socio-emotional dimensions [1,2]. Effective participation in digitally transformed educational environments therefore depends not only on technological proficiency but also on teachers' capacity to respond to social and organizational change, collaborate with others, and sustain meaningful educational relationships amid evolving professional demands [3,4].

Within this transformation, the integration of AI represents a particularly relevant socio-technical process. University teachers are not merely users of emerging technologies but also interpreters, evaluators, and agents of pedagogical change. The increasing presence of AI has expanded opportunities for personalized learning, instructional support, assessment, feedback, and other educational practices [5]. At the same time, its adoption introduces new professional responsibilities involving the critical evaluation of AI-generated outputs, ethical and pedagogical decision-making, continuous learning, and adaptation to changing expectations. Consequently, AI-related transformation is shaped by the interaction between technological possibilities and the social, professional, and organizational contexts in which teachers work. From this perspective, AI competencies are embedded in broader processes of professional judgment, collaboration, institutional learning, and responsible educational practice.

AI competence in university teaching encompasses knowledge of AI capabilities and limitations, the critical evaluation of AI-generated outputs, the pedagogically meaningful integration of AI into teaching and assessment, ethical reasoning, and responsible professional decision-making [6,7]. Recent competency-oriented approaches similarly emphasize combinations of AI literacy, pedagogical knowledge, adaptability, professional learning, and reflective judgment as necessary for effective engagement with AI-mediated educational environments [7]. This multidimensional conception is particularly important because teachers encounter technological transformation under different professional and organizational conditions. Thus, AI competencies involve not only knowledge and use of technological tools but also the professional capacities required to evaluate, adapt to, and responsibly incorporate AI into educational practice [6,7].

Among these professional capacities, socio-emotional skills may play an important role in teachers' adaptation to digitally transformed environments. Technological and organizational change can generate uncertainty, new interpersonal demands, continuous learning requirements, and modifications to established professional practices. Socio-emotional competencies can help teachers regulate emotions, communicate effectively, develop constructive relationships, adapt to changing circumstances, manage professional challenges, and sustain collaborative environments [8]. These competencies include emotional self-awareness, self-regulation, empathy, communication, resilience, adaptability, and responsible decision-making. Their relevance extends beyond individual well-being, as they are also associated with the quality of teacher-student interactions, classroom environments, collaboration, and professional functioning [9,10]. Consequently, socio-emotional development has increasingly been recognized as an important component of teacher education and professional practice [11].

Educational leadership constitutes another relevant dimension of teachers' professional participation in digital transformation. Contemporary approaches conceptualize teacher leadership beyond formal administrative

positions, emphasizing educators' capacity to influence colleagues, foster collaborative cultures, support professional learning, contribute to institutional improvement, and facilitate pedagogical innovation. This perspective is particularly relevant in AI-mediated educational environments, where technological change requires collective interpretation, shared learning, ethical deliberation, and coordinated responses rather than isolated individual adoption. Research examining AI and teacher leadership suggests that the development and use of AI may reshape teachers' leadership roles and create new opportunities and challenges for professional agency and collaboration [12]. Educational leadership can therefore be understood as a professional capacity through which university teachers contribute to collective responses to technological and organizational change.

Previous research provides theoretical and empirical grounds for considering relationships among socio-emotional skills, educational leadership, and AI competencies. Leadership in educational settings involves interpersonal processes requiring communication, collaboration, emotional regulation, trust building, and the capacity to respond constructively to different perspectives and sources of resistance. Similarly, teachers' socio-emotional resources may facilitate productive relationships, collaborative learning, and adaptive responses to professional challenges [8–11]. Research on AI in education has also emphasized the relevance of professional learning, adaptability, ethical considerations, and contextual conditions for the development of teachers' AI competence [6,7,13,15]. In parallel, emerging work on AI and teacher education highlights the importance of integrating technological and pedagogical development with broader human and professional capabilities [16,17]. Taken together, this literature suggests that socio-emotional skills and educational leadership may be relevant to teachers' capacity to engage with AI, although the relationships among these dimensions have not been sufficiently examined empirically.

Despite the growing literature on socio-emotional competencies, educational leadership, and artificial intelligence in higher education,

empirical evidence concerning their interrelationships remains fragmented. Previous studies have frequently examined these dimensions as distinct areas of professional development [13–15], providing valuable insights into individual constructs but offering limited evidence about how they may operate together within contexts of rapid technological change. Despite these advances, limited empirical evidence has examined socio-emotional skills, educational leadership, and AI competencies within a single structural framework. In particular, it remains unclear whether educational leadership constitutes an intermediate statistical pathway linking teachers' socio-emotional resources with their AI competencies. Moreover, although existing conceptual and systematic approaches identify technological knowledge, pedagogical expertise, professional learning, adaptability, ethical reasoning, and contextual influences as relevant to AI competence [6,7,13,15], integrative empirical models connecting human, relational, and technological dimensions among university teachers remain scarce. This gap is particularly relevant because AI-related professional adaptation involves not only technological knowledge but also relational, collaborative, and organizational capacities through which teachers respond to institutional change [16–18].

Addressing this gap, the present study examined the direct relationships among the three constructs and tested the mediating role of educational leadership in the association between socio-emotional skills and AI competencies. By integrating these dimensions within a single structural model, the study contributes empirical evidence for understanding AI-related professional adaptation as a socio-technical process in which technological competencies are connected with human, relational, and leadership capacities. The study further contributes evidence from teachers in participating higher education institutions in Guayas, Ecuador, a context that remains comparatively underrepresented in this literature.

The contribution of this study is therefore threefold. First, it integrates socio-emotional skills, educational leadership, and AI competencies within a single empirical model

rather than examining them as separate dimensions of teacher professional development. Second, it examines educational leadership as an intermediate statistical pathway through which socio-emotional resources may be associated with AI-related professional competencies, thereby connecting individual human capacities with relational and organizational processes. Third, it provides evidence from higher education institutions in Guayas, Ecuador, contributing a Latin American perspective to an emerging literature on teacher AI competence that remains geographically uneven.

The study was guided by the following research question: How are socio-emotional skills, educational leadership, and AI competencies related among university teachers, and to what extent does educational leadership mediate the relationship between socio-emotional skills and AI competencies? Based on the proposed conceptual model, the following hypotheses were formulated:

H1. Socio-emotional skills are positively associated with educational leadership.

H2. Socio-emotional skills are positively associated with AI competencies.

H3. Educational leadership is positively associated with AI competencies.

H4. Educational leadership mediates the relationship between socio-emotional skills and AI competencies.

2. Methodology

• Research design

This study adopted a quantitative approach to examine the relationships among socio-emotional skills, educational leadership, and artificial intelligence (AI) competencies among university teachers. This approach was appropriate because the study sought to measure latent constructs through multiple indicators and estimate their relationships within a theoretically specified structural model.

A non-experimental, cross-sectional design was employed. No intervention, treatment, or technological training was implemented. Instead, the study examined university teachers' self-

reported competencies as they occurred within their professional and institutional contexts. Data were collected during a defined period, allowing the hypothesized relationships among socio-emotional skills, educational leadership, and AI competencies to be examined at a specific point in time.

The study followed a cross-sectional correlational design with a theory-driven structural model. The analytical framework was designed to examine the magnitude and direction of the hypothesized associations among the constructs and to assess the indirect association between socio-emotional skills and AI competencies through educational leadership. Given the non-experimental and cross-sectional nature of the study, the estimated relationships were interpreted as statistical associations rather than evidence of causal effects. Accordingly, the proposed relationships were examined as statistical associations within a theoretically specified structural model and should not be interpreted as evidence of temporal or causal effects.

The conceptual model was grounded in the premise that the digital transformation of university teaching involves more than the acquisition of technological skills. The incorporation of AI into teaching and other academic activities also requires professional capacities related to emotional regulation, interpersonal communication, adaptability, collaborative work, ethical judgment, and educational leadership. Contemporary approaches to AI integration emphasize that technological competence should be accompanied by human and professional capacities that enable educators to evaluate emerging technologies critically, manage educational innovation, and make responsible pedagogical decisions [7,8]. Accordingly, the proposed model considers socio-emotional skills and educational leadership as relevant human dimensions associated with university teachers' AI competencies within digitally transforming higher education environments.

Given the multidimensional nature of the proposed framework and the use of latent constructs measured through multiple reflective indicators, Partial Least Squares Structural

Equation Modeling (PLS-SEM) was employed to estimate the proposed relationships among the constructs. PLS-SEM allows the measurement and structural models to be assessed within a single analytical framework and is appropriate for explanatory and predictive research involving multiple latent variables and theoretically specified relationships. In the present study, PLS-SEM was used to evaluate the reliability and validity of the measurement model and to examine the hypothesized direct and indirect statistical associations among socio-emotional skills, educational leadership, and AI competencies.

• **Participants and sampling**

The target population comprised university teachers employed in public and private higher education institutions in Ecuador. The study was conducted in eight higher education institutions located in the province of Guayas, including six public and two private institutions in the cities of Guayaquil and Milagro. Participants were actively engaged in undergraduate or postgraduate teaching during the data collection period, regardless of academic discipline or professional specialization.

Participants were selected using a non-probability convenience sampling strategy. This procedure was appropriate because the study required access to university teachers who met predefined eligibility criteria and were available during the data collection period. Although convenience sampling limits the statistical generalizability of the findings to the broader population of university teachers, it was considered suitable for the explanatory purpose of the study, which focused on examining theoretically grounded relationships among latent constructs rather than estimating population parameters (Hernández et al., 2014).

Data collection was conducted between January and February 2026. A total of 500 invitations were distributed among eligible university teachers through the participating institutions. Of these, 412 questionnaires were returned, representing a response rate of 82.4% (412/500). Following the data-quality screening procedure, nine questionnaires were excluded because they contained substantial missing information or

response patterns indicating insufficient engagement. Consequently, 403 questionnaires were retained as valid cases, representing 97.8% of the returned questionnaires (403/412) and 80.6% of the total invitations distributed (403/500).

The participant flow can therefore be summarized as follows: 500 teachers were invited to participate, 412 questionnaires were returned, 9 responses were excluded during data-quality screening, and 403 valid cases were retained for the final analysis.

Participants were eligible when they met the following criteria: (a) they were currently employed as university teachers at one of the participating higher education institutions; (b) they had at least one year of teaching experience in higher education; (c) they voluntarily agreed to participate by providing informed consent; and (d) they completed the questionnaire. Responses were excluded when they contained substantial missing information or invariant response patterns across substantive items that suggested insufficient engagement.

The final sample comprised 403 university teachers. Of these, 221 were female (54.8%), 177 were male (43.9%), and 5 identified as non-binary or preferred not to answer (1.3%). Regarding age, 83 participants (20.6%) were under 35 years, 141 (35.0%) were between 35 and 44 years, 116 (28.8%) were between 45 and 54 years, and 63 (15.6%) were 55 years or older. Regarding academic qualifications, 196 participants (48.6%) held a master's degree, 180 (44.7%) held a doctorate, and 27 (6.7%) held another postgraduate degree. In terms of teaching experience, 68 participants (16.9%) had between 1 and 5 years of experience, 129 (32.0%) between 6 and 10 years, 142 (35.2%) between 11 and 20 years, and 64 (15.9%) more than 20 years. Regarding previous AI training, 238 participants (59.1%) reported having received AI-related training, whereas 165 (40.9%) had not. Concerning the frequency of AI use, 170 participants (42.2%) reported using AI frequently, 171 (42.4%) occasionally, and 62 (15.4%) rarely.

• Variables and research model

The study examined three latent constructs derived from contemporary literature on university teacher education, educational leadership, socio-emotional competencies, and artificial intelligence in higher education.

The independent variable, socio-emotional skills, refers to the set of competencies that enable university teachers to recognize, regulate, and appropriately manage their emotions while establishing constructive interpersonal relationships and responding adaptively to professional challenges. Consistent with contemporary perspectives on teacher competencies, this construct encompasses emotional self-regulation, empathy, communication, collaborative work, resilience, adaptability, and responsible decision-making [3,9,8]. Within the present study, these competencies were considered relevant to teachers' ability to respond to uncertainty and changing professional expectations associated with digital transformation.

The mediating variable, educational leadership, represents university teachers' capacity to influence educational improvement, promote collaborative professional environments, guide pedagogical innovation, facilitate organizational change, and encourage continuous professional development within higher education institutions [12]. Rather than restricting leadership to formal administrative positions, the study conceptualizes it as a professional capacity through which educators can influence colleagues, foster collaborative practices, support innovation, and contribute to institutional responses to emerging educational challenges.

The dependent variable, artificial intelligence competencies, encompasses university teachers' knowledge, skills, and attitudes concerning the pedagogically appropriate, ethically responsible, and effective use of AI within higher education. Consistent with recent international competency frameworks, this construct includes AI literacy, pedagogical integration of AI tools, ethical awareness, critical evaluation of AI-generated content, AI-supported educational decision-making, and continuous professional learning related to emerging technologies [7]. These

competencies are conceptualized as part of the professional capacities required for university teachers to participate effectively in the digital transformation of higher education.

The proposed model assumes that socio-emotional skills are positively associated with educational leadership and AI competencies. Educational leadership is also expected to be positively associated with AI competencies and to mediate the association between socio-emotional skills and AI competencies. The model therefore considers AI competence not solely as a technological attribute but as a professional capacity that may be associated with broader human competencies relevant to teachers' adaptation to digitally transforming academic environments.

• Instrument development

Data were collected through a structured self-administered questionnaire designed to measure the three latent constructs included in the proposed conceptual model: socio-emotional skills, educational leadership, and artificial intelligence (AI) competencies. The questionnaire was developed through a theory-informed adaptation process rather than by reproducing a single previously validated scale for each construct. Indicators were derived from the conceptual dimensions consistently identified in the literature and competency frameworks reviewed for socio-emotional skills, educational leadership, and AI competencies [3,7,8,9,11,12]. The adaptation process sought to preserve the conceptual meaning of the original dimensions while contextualizing the indicators to university teaching and the digital transformation of higher education.

Instrument development involved four sequential stages: (1) identification of construct dimensions and candidate indicators from the relevant literature and competency frameworks; (2) contextual adaptation of indicator wording to university teaching; (3) qualitative content review by five experts; and (4) pilot testing with 30 university teachers prior to the evaluation of the measurement properties in the main sample. Rather than developing entirely new measurement scales, the questionnaire integrated conceptually established indicators whose

wording was adapted to the professional context of university teachers. The operationalization of each construct was defined before data collection, and each indicator was assigned a specific code to ensure traceability throughout the measurement and data-analysis procedures.

The final measurement model comprised 18 substantive reflective indicators, with six indicators for each latent construct: socio-emotional skills (SES1–SES6), educational leadership (EL1–EL6), and artificial intelligence competencies (AI1–AI6).

Table 1. Constructs, indicators, and sources of the measurement instrument

Construct	Code	Indicator/Item	Original source/adaptation basis
Socio-emotional skills	SES1	I can recognize and understand my emotional responses when facing demanding teaching situations.	Adapted from the socio-emotional competence dimensions reported by Lozano et al. [3] and Molina et al. [4].
Socio-emotional skills	SES2	I can regulate my emotions effectively when experiencing pressure or unexpected situations in my teaching work.	Adapted from emotional self-regulation dimensions reported by Lozano et al. [3], Olayiwola and Naidoo [8], and Sánchez et al. [9].
Socio-emotional skills	SES3	I communicate effectively and respectfully with students and colleagues, including when disagreements arise.	Adapted from interpersonal communication and relational competence dimensions reported by Lozano et al. [3] and Sánchez et al. [9].
Socio-emotional skills	SES4	I am able to understand and consider the emotions and perspectives of others in professional interactions.	Adapted from empathy and interpersonal competence dimensions reported by Olayiwola and Naidoo [8] and Sánchez et al. [9].
Socio-emotional skills	SES5	I adapt constructively to changes in teaching practices, institutional demands, or educational technologies.	Adapted from adaptability and professional competence dimensions reported by Molina et al. [4] and Sologuren et al. [10].
Socio-emotional skills	SES6	I remain resilient and make responsible decisions when facing complex professional situations.	Adapted from resilience and responsible decision-making dimensions reported by Sánchez et al. [9], Sologuren et al. [10], and Quiroz et al. [11].
Educational leadership	EL1	I encourage colleagues to participate in initiatives aimed at improving teaching practices.	Adapted from teacher leadership dimensions discussed by Ghamrawi et al. [12].
Educational leadership	EL2	I contribute to the development and implementation of innovative pedagogical practices within my institution.	Adapted from teacher leadership and pedagogical innovation dimensions reported by Ghamrawi et al. [12].
Educational leadership	EL3	I promote collaboration and knowledge sharing among colleagues.	Adapted from collaborative and distributed leadership dimensions reported by Ghamrawi et al. [12].
Educational leadership	EL4	I support colleagues when they face changes in teaching practices or the adoption of emerging technologies.	Adapted from teacher leadership and professional support dimensions reported by Ghamrawi et al. [12].
Educational leadership	EL5	I encourage continuous professional learning related to new educational practices and technologies.	Adapted from teacher leadership and professional learning dimensions reported by Ghamrawi et al. [12] and Zhou et al. [15].
Educational leadership	EL6	I contribute to institutional improvement by promoting responsible and collaborative responses to educational change.	Adapted from teacher leadership and institutional change perspectives reported by Ghamrawi et al. [12].

Construct	Code	Indicator/Item	Original source/adaptation basis
AI competencies	AI1	I understand the basic capabilities and limitations of artificial intelligence tools used in higher education.	Adapted from AI competency dimensions identified by Fu and Weng [7] and Zhou et al. [6].
AI competencies	AI2	I can integrate AI tools into teaching activities in ways that are pedagogically meaningful.	Adapted from AI-supported teacher competency and pedagogical integration dimensions reported by Fu and Weng [7] and Aljemely [13].
AI competencies	AI3	I can critically evaluate the accuracy, relevance, and limitations of AI-generated information.	Adapted from critical AI literacy and evaluation dimensions reported by Zhou et al. [6,15].
AI competencies	AI4	I consider ethical, academic integrity, privacy, and responsible-use issues when incorporating AI into teaching.	Adapted from the ethical and responsible AI dimensions reported by Fu and Weng [7], Aljemely [13], and Zhou et al. [15].
AI competencies	AI5	I can use AI-supported information to inform instructional decisions while maintaining professional judgment.	Adapted from AI-supported educational decision-making dimensions reported by Fu and Weng [7] and Zhou et al. [15].
AI competencies	AI6	I actively engage in professional learning to update my knowledge and skills regarding emerging AI applications in education.	Adapted from continuous professional learning dimensions reported by Fu and Weng [7], Aljemely [13], and Zhou et al. [15].

Note. The indicators were adapted to the context of university teaching. The wording was revised for contextual relevance and clarity while preserving the conceptual meaning of the dimensions identified in the cited literature. No indicator was reproduced as a direct quotation from the original sources.

The socio-emotional skills construct was operationalized through six reflective indicators representing emotional self-awareness, emotional self-regulation, interpersonal communication, empathy, adaptability, and resilience and responsible decision-making. These dimensions are consistent with evidence on socio-emotional competencies in teacher education and professional practice [3,8–11]. The construct was therefore designed to capture the human and relational capacities through which university teachers manage emotional responses, interact constructively with others, and adapt to changing professional circumstances.

The educational leadership construct comprised six reflective indicators addressing influence on colleagues, pedagogical innovation, collaboration and knowledge sharing, professional support, continuous professional learning, and institutional improvement. Its operationalization

was informed primarily by research on teacher leadership and the changing role of educators in technology-intensive educational environments [12]. Educational leadership was conceptualized as a professional capacity through which university teachers influence collaborative processes, support colleagues, promote innovation, and contribute to institutional improvement, rather than as a function restricted to formally appointed administrators.

The artificial intelligence competencies construct comprised six reflective indicators covering understanding of AI capabilities and limitations, pedagogical integration, critical evaluation of AI-generated information, ethical and responsible use, AI-supported instructional decision-making, and continuous professional learning. These dimensions were aligned with recent AI competency frameworks and research emphasizing that teachers' AI competence encompasses technological, pedagogical, ethical, critical, and professional dimensions [6,7,13,15].

The questionnaire consisted of four sections. The first collected demographic and professional information, including gender, age, academic degree, years of teaching experience, institutional affiliation, disciplinary field, previous AI training,

and frequency of AI use in teaching activities. The remaining three sections measured the latent constructs using the 18 reflective indicators presented in Table 1. All substantive items were evaluated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher perceived levels of the corresponding competency.

Prior to large-scale administration, the questionnaire underwent a qualitative content review by five experts. The experts were selected based on their academic and professional experience in higher education, educational research, socio-emotional competencies, educational leadership, and digital or AI-related competencies. The expert review was used as a qualitative content-assessment stage intended to evaluate item relevance, clarity, coherence, and correspondence with the intended constructs. Their qualitative observations were used to refine item wording and improve the correspondence between the indicators and their respective constructs prior to pilot testing. No indicator was removed during this process, and the three-construct structure was retained.

A pilot study was subsequently conducted with 30 university teachers who met the general eligibility criteria established for the main study. The pilot assessment examined item comprehension, questionnaire completion, response consistency, and preliminary internal consistency. The overall instrument yielded a Cronbach's alpha coefficient of 0.79, indicating acceptable preliminary internal consistency. Because the questionnaire comprised three conceptually distinct latent constructs, the overall Cronbach's alpha was reported only as an indicator of the preliminary internal consistency of the instrument as a whole, rather than as evidence of unidimensionality. The three constructs were treated as separate dimensions, and their measurement properties were subsequently assessed independently in the main sample through the PLS-SEM measurement model. Thus, the pilot alpha of 0.79 was intended as a global preliminary reliability estimate, while construct-specific reliability was evaluated in the main study using the corresponding reliability and validity criteria for each dimension. Based on feedback from the pilot participants, minor

linguistic adjustments were made to improve item comprehension without altering the conceptual structure or the number of indicators.

Following the expert review and pilot assessment, the final questionnaire containing 18 substantive indicators was administered to the participants included in the main study. The resulting measurement structure was subsequently evaluated empirically through the PLS-SEM measurement-model assessment described in the data-analysis procedures. PLS-SEM was selected because the study sought to estimate a theoretically specified model involving multiple latent constructs measured through reflective indicators while simultaneously examining direct and indirect associations and the explanatory performance of the endogenous constructs.

• Data collection procedure

Data collection was conducted during the academic period from January to February 2026 using a structured online questionnaire administered through a secure digital survey platform. The online modality facilitated access to university teachers from the participating higher education institutions while maintaining standardized administration procedures and supporting efficient data management.

Institutional authorization for participant recruitment was obtained from the participating institutions prior to data collection, in accordance with their respective institutional procedures. Invitations explaining the purpose of the study, the voluntary nature of participation, and the expected completion requirements were distributed through institutional email lists, academic networks, and professional communication platforms used by university faculty members. No financial, academic, or other incentives were offered for participation.

Before accessing the questionnaire, participants were presented with an electronic informed consent form describing the study objectives, the voluntary nature of participation, the approximate completion requirements, confidentiality procedures, and the researchers' contact information. Only participants who explicitly provided informed consent were granted access to the questionnaire. Participants

were informed that they could discontinue their participation at any time without academic or professional consequences.

Several procedures were implemented to support data quality. Substantive questionnaire items were configured as mandatory responses to minimize missing data. Duplicate submissions were restricted using the controls available on the survey platform. After data collection, all returned questionnaires were screened for completeness and response quality. The screening process included examination of completion patterns, response consistency, and unusually short completion times in conjunction with other indicators of insufficient engagement. Questionnaires exhibiting substantial incompleteness or invariant response patterns across substantive items were excluded from the final dataset. These procedures resulted in the exclusion of nine questionnaires from the 412 returned responses, leaving 403 valid questionnaires for the final analysis.

Following completion of the data collection and screening process, the valid responses were exported to Microsoft Excel for preliminary organization and verification and subsequently transferred to IBM SPSS Statistics for data cleaning and descriptive analysis. The final validated dataset was then imported into SmartPLS version 4 for estimation of the measurement and structural models.

• Data analysis

Data analysis was conducted in two sequential stages, combining descriptive statistics with multivariate analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM). IBM SPSS Statistics was used for data screening and descriptive analysis, whereas SmartPLS version 4 was used to estimate the measurement and structural models. PLS-SEM was selected because the study sought to examine theoretically specified relationships among multiple latent constructs measured through reflective indicators and to assess both direct and indirect associations within the proposed structural model (Hair et al., 2022).

First, descriptive analyses were conducted to characterize the final sample. Frequencies and

percentages were calculated for categorical demographic and professional variables, while means and standard deviations were calculated for the principal study constructs and other continuous variables. Prior to structural analysis, the dataset was screened for missing data, duplicate responses, and response patterns indicative of insufficient engagement. Only the 403 questionnaires that met the established eligibility and data-quality criteria were included in the final analysis.

The measurement model was evaluated before testing the structural relationships. Indicator reliability was assessed through standardized outer loadings, with values of 0.70 or higher considered desirable. Indicators with somewhat lower loadings were considered for retention when theoretically justified and when their inclusion did not compromise the overall reliability and validity of the corresponding construct. Internal consistency reliability was assessed using Cronbach's alpha (α), Composite Reliability (CR), and rho_A. Values above 0.70 were considered indicative of satisfactory internal consistency, while CR values between 0.70 and 0.95 were considered appropriate for the reflective constructs.

Convergent validity was assessed using the Average Variance Extracted (AVE), with values of 0.50 or higher considered indicative of satisfactory convergent validity. Discriminant validity was examined using both the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). For the HTMT assessment, values below 0.85 were considered evidence of adequate discriminant validity among the constructs.

After establishing the adequacy of the measurement model, the structural model was assessed. Collinearity among predictor constructs was examined using Variance Inflation Factor (VIF) values. Standardized path coefficients (β), t-values, p-values, and bootstrapped confidence intervals were estimated for the hypothesized direct relationships. Statistical inference was based on a non-parametric bootstrapping procedure using 5,000 resamples. A significance level of 5% was adopted, with $p < .05$ considered statistically significant.

The explanatory capacity of the structural model was evaluated using the coefficient of determination (R^2) for the endogenous constructs. Predictive relevance was assessed using Stone–Geisser's Q^2 , and effect sizes (f^2) were calculated to determine the contribution of predictor constructs to the explained variance of the endogenous variables. These statistics were interpreted jointly with the estimated path coefficients to assess the explanatory and predictive performance of the proposed model.

The mediating role of educational leadership was assessed through the indirect association between socio-emotional skills and AI competencies via educational leadership. The indirect effect was evaluated using the bootstrapped estimate, t -value, p -value, and corresponding confidence interval. Mediation was interpreted based on the statistical significance and direction of the indirect effect, together with the pattern of the corresponding direct and total effects. Given the cross-sectional and non-experimental nature of the study, mediation was interpreted as an indirect statistical association within the proposed theoretical model rather than as evidence of a causal mechanism.

Hypotheses H1–H4 were evaluated based on the magnitude and direction of the standardized path coefficients, statistical significance, confidence intervals, and, for H4, the estimated indirect effect. The interpretation also considered the explanatory power (R^2), predictive relevance (Q^2), and effect sizes (f^2) of the structural model.

• **Ethical considerations**

The study was conducted in accordance with internationally recognized ethical principles for research involving human participants. Throughout the research process, the principles of respect for participants, voluntary participation, informed consent, confidentiality, anonymity, and scientific integrity were observed.

Before accessing the questionnaire, all participants received clear information about the purpose of the study, the nature of their participation, the expected completion requirements, the voluntary nature of participation, and the procedures implemented to protect the confidentiality of their responses.

Electronic informed consent was obtained from all participants before questionnaire access was granted. Participants were informed that participation was voluntary and that they could discontinue their participation at any point without academic or professional consequences.

No personally identifiable information was collected through the questionnaire. Responses were treated confidentially, and the resulting dataset was stored in secure electronic files accessible only to the research team. The data were used exclusively for research purposes, and findings were reported in aggregate form to prevent the identification of individual participants or participating institutions.

The study involved an anonymous, self-administered questionnaire concerning university teachers' professional competencies and perceptions and did not involve clinical interventions, experimental manipulation, or procedures that altered participants' professional activities. Ethical procedures were implemented throughout the study to minimize potential risks and protect participants' rights, privacy, and autonomy.

In accordance with the applicable institutional regulations, this study did not require formal ethics committee review because it involved an anonymous, non-interventional questionnaire concerning professional perceptions and did not collect personally identifiable or sensitive information. The research procedures nevertheless followed applicable ethical standards for research involving human participants.

3. Results

• **Sample characteristics**

A total of 500 eligible university teachers were invited to participate across the participating higher education institutions. Of these, 412 questionnaires were returned, corresponding to a response rate of 82.4%. Following data-quality screening, nine questionnaires were excluded because of incomplete responses or response patterns indicative of insufficient engagement. The final analytical sample therefore comprised 403 valid questionnaires, representing 97.8% of

the returned questionnaires and 80.6% of the initial invitations.

Participants represented different academic disciplines and higher education institutions and

showed variation in previous AI-related training and frequency of AI use. This variation provided descriptive context for the subsequent analysis of socio-emotional skills, educational leadership, and AI competencies.

Table 2. Sociodemographic and professional characteristics of the participants (n = 403)

Variable	Category	n	%
Gender	Female	221	54.8
	Male	177	43.9
	Non-binary / Prefer not to answer	5	1.3
Age	Under 35 years	83	20.6
	35–44 years	141	35.0
	45–54 years	116	28.8
	55 years or older	63	15.6
Academic degree	Master's degree	196	48.6
	Doctorate	180	44.7
	Other postgraduate degree	27	6.7
Teaching experience	1–5 years	68	16.9
	6–10 years	129	32.0
	11–20 years	142	35.2
	More than 20 years	64	15.9
Previous AI training	Yes	238	59.1
	No	165	40.9
Frequency of AI use	Frequently	170	42.2
	Occasionally	171	42.4
	Rarely	62	15.4

The sample was predominantly female (54.8%), while 43.9% of participants were male and 1.3% identified as non-binary or preferred not to report gender. The largest age group was 35–44 years (35.0%), followed by participants aged 45–54 years (28.8%). Regarding academic qualifications, 48.6% held a master's degree, 44.7% held a doctorate, and 6.7% reported another postgraduate qualification. Most participants had more than six years of teaching experience. Previous AI-related training was reported by 59.1% of respondents, and 84.6% reported using AI frequently or occasionally in teaching activities.

AI use and previous AI-related training were therefore heterogeneous across the sample, indicating varying levels of professional exposure to artificial intelligence.

• Descriptive statistics

Descriptive statistics were calculated for the three latent constructs before estimating the structural model. Mean scores for socio-emotional skills, educational leadership, and AI competencies were all above the midpoint of the five-point response scale.

Table 3. Descriptive statistics of the latent constructs

Construct	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Socio-emotional skills	4.18	0.51	2.31	5.00	−0.61	0.42
Educational leadership	4.05	0.58	2.14	5.00	−0.47	0.15

Construct	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
AI competencies	3.87	0.64	1.92	5.00	-0.32	-0.41

Socio-emotional skills showed the highest mean score ($M = 4.18$, $SD = 0.51$), followed by educational leadership ($M = 4.05$, $SD = 0.58$), whereas AI competencies showed the lowest mean ($M = 3.87$, $SD = 0.64$). These results indicate comparatively higher self-reported levels of socio-emotional and leadership capacities than of AI competencies.

The distributions showed moderate negative skewness across the three constructs, ranging from -0.61 to -0.32 , while kurtosis values ranged from -0.41 to 0.42 . These values did not indicate substantial distributional irregularities. Although PLS-SEM does not require multivariate

normality, the descriptive distributions did not reveal extreme departures from symmetry or kurtosis.

• Assessment of the measurement model

The measurement model was assessed before testing the hypothesized structural relationships. Indicator reliability, internal consistency reliability, and convergent validity were examined through standardized outer loadings, Cronbach's alpha, rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 4. Reliability and convergent validity of the measurement model

Construct	Indicator	Outer loading	Cronbach's α	rho_A	CR	AVE
Socio-emotional skills	SES1	0.801	0.918	0.921	0.936	0.708
	SES2	0.842				
	SES3	0.851				
	SES4	0.824				
	SES5	0.846				
	SES6	0.819				
Educational leadership	EL1	0.794	0.907	0.910	0.928	0.684
	EL2	0.836				
	EL3	0.861				
	EL4	0.844				
	EL5	0.827				
	EL6	0.813				
AI competencies	AI1	0.823	0.927	0.930	0.943	0.734
	AI2	0.847				
	AI3	0.866				
	AI4	0.872				
	AI5	0.838				
	AI6	0.854				

Standardized outer loadings ranged from 0.794 to 0.872, exceeding the recommended minimum criterion of 0.70 for reflective indicators. All 18 indicators therefore demonstrated satisfactory indicator reliability and were retained in the final measurement model.

Internal consistency reliability was satisfactory across all constructs. Cronbach's alpha ranged from 0.907 to 0.927, rho_A from 0.910 to 0.930, and Composite Reliability from 0.928 to 0.943. All values exceeded 0.70, while CR values remained below 0.95, supporting adequate reliability without evidence of excessive indicator redundancy.

Convergent validity was supported, with AVE values ranging from 0.684 to 0.734, all exceeding the 0.50 criterion. The measurement model therefore demonstrated satisfactory indicator reliability, internal consistency, and convergent validity.

• Discriminant validity

Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT) to determine whether the three latent constructs were empirically distinguishable

Table 5. Fornell–Larcker criterion

Construct	SES	EL	AIC
Socio-emotional skills (SES)	0.841		
Educational leadership (EL)	0.684	0.827	
AI competencies (AIC)	0.612	0.703	0.857

Note. Diagonal values in bold represent the square root of the AVE.

For each construct, the square root of the AVE exceeded its correlations with the other constructs. Diagonal values ranged from 0.827 to 0.857, whereas inter-construct correlations ranged from 0.612 to 0.703, satisfying the Fornell–Larcker criterion.

Table 6. Heterotrait–Monotrait Ratio (HTMT)

Construct pair	HTMT
SES - EL	0.742
SES - AIC	0.661
EL - AIC	0.781

All HTMT values were below the conservative threshold of 0.85, ranging from 0.661 to 0.781. The highest value was observed between educational leadership and AI competencies (HTMT = 0.781). Together with the Fornell–Larcker results, these findings supported discriminant validity among the three constructs.

• Assessment of common method bias

Because the predictor, mediator, and outcome constructs were measured using the same self-

administered questionnaire and obtained from the same respondents, common method bias was statistically assessed in addition to the procedural measures implemented during questionnaire administration. Full collinearity VIF values were calculated for the three latent constructs. Values ranged from 1.742 to 2.116, remaining below the conservative threshold of 3.30. These results did not indicate problematic levels of common method variance.

Table 7. Full collinearity assessment for common method bias

Construct	Full collinearity VIF
Socio-emotional skills	1.742
Educational leadership	2.116
AI competencies	1.963

The full-collinearity VIF values did not indicate problematic levels of common method variance according to the criterion applied. Nevertheless, because all principal constructs were assessed using self-reported responses collected within the

same questionnaire, the possibility of residual common-method effects cannot be completely excluded.

• Structural model assessment

Following confirmation of measurement reliability, validity, and the absence of problematic common method variance, the structural model was evaluated to test the

hypothesized relationships among socio-emotional skills, educational leadership, and AI competencies. Predictor collinearity was assessed before estimating the structural paths.

Table 8. Structural model collinearity assessment

Structural relationship VIF	
SES → EL	1.000
SES → AIC	1.879
EL → AIC	1.879

Structural-model VIF values ranged from 1.000 to 1.879, remaining below the adopted threshold of 3.30 and indicating no problematic predictor collinearity.

Table 9. Structural path coefficients and hypothesis testing

Hypothesis	Relationship	β	t	p	95% CI	f^2	Decision
H1	SES - EL	0.684	18.73	<0.001	[0.612, 0.748]	0.878	Supported
H2	SES - AIC	0.311	5.62	<0.001	[0.201, 0.418]	0.117	Supported
H3	EL - AIC	0.471	8.96	<0.001	[0.365, 0.572]	0.273	Supported

Socio-emotional skills were positively associated with educational leadership ($\beta = 0.684$, $t = 18.73$, $p < .001$; 95% CI [0.612, 0.748]), supporting H1.

Socio-emotional skills were also positively associated with AI competencies ($\beta = 0.311$, $t = 5.62$, $p < .001$; 95% CI [0.201, 0.418]), supporting H2.

Educational leadership showed a positive association with AI competencies ($\beta = 0.471$, $t = 8.96$, $p < .001$; 95% CI [0.365, 0.572]), supporting H3.

Notably, educational leadership showed a stronger direct association with AI competencies than socio-emotional skills within the proposed model. This pattern suggests that AI-related professional competence may be particularly connected with the relational and organizational practices through which teachers share knowledge, support colleagues, participate in collective learning, and respond to technological change.

Effect-size estimates indicated a large contribution of socio-emotional skills to

educational leadership ($f^2 = 0.878$), a moderate contribution of educational leadership to AI competencies ($f^2 = 0.273$), and a comparatively smaller contribution of socio-emotional skills to AI competencies ($f^2 = 0.117$).

• Coefficient of determination and predictive relevance

The explanatory capacity of the structural model was evaluated using the coefficient of determination (R^2) and adjusted R^2 . Predictive relevance was assessed using Stone–Geisser's Q^2 .

Table 10. Explanatory and predictive power of the structural model

Endogenous construct	R^2	Adjusted R^2	Q^2
Educational leadership	0.468	0.467	0.312
AI competencies	0.521	0.519	0.389

The model explained 46.8% of the variance in educational leadership ($R^2 = 0.468$; adjusted $R^2 = 0.467$). For AI competencies, the model explained 52.1% of the variance ($R^2 = 0.521$; adjusted $R^2 = 0.519$). Q^2 values were positive for both endogenous constructs (0.312 for educational leadership and 0.389 for AI competencies), supporting predictive relevance within the estimated model.

• Mediation analysis

The statistical mediating role of educational leadership was assessed through the indirect association between socio-emotional skills and AI competencies using bootstrapping with 5,000 resamples.

Table 11. Indirect effect and mediation analysis

Indirect relationship β	t	p	95% CI	Mediation
SES $\rightarrow$ EL $\rightarrow$ AIC	0.322 7.81	<0.001	[0.243, 0.401]	Partial mediation

The indirect association between socio-emotional skills and AI competencies through educational leadership was positive and statistically significant ($\beta = 0.322$, $t = 7.81$, $p < .001$; 95% CI [0.243, 0.401]). Because the direct association also remained significant, the observed pattern was consistent with partial statistical mediation. The bootstrapped confidence interval did not include zero. The direct association between socio-emotional skills and AI competencies also remained significant after including educational leadership ($\beta = 0.311$, $p < .001$), indicating partial statistical mediation. Given the cross-sectional and non-experimental design, this result should be interpreted as evidence of a statistically significant indirect association within the proposed model rather than as evidence of a temporal or causal mediating mechanism.

Conceptually, educational leadership may function as an intermediate pathway because socio-emotional skills such as self-regulation, communication, collaboration, and adaptability can facilitate leadership behaviors that support innovation, collective learning, and the management of technological change. In this context, leadership may help translate teachers' socio-emotional resources into practices that facilitate the development and application of AI competencies. Accordingly, H4 was supported at the statistical level. However, given the cross-sectional, non-experimental design, these findings should be interpreted as evidence of a statistically significant indirect association rather than a causal mechanism.

4. Discussion

This study examined the relationships among socio-emotional skills, educational leadership, and artificial intelligence (AI) competencies among teachers from the participating higher education institutions in Guayas, Ecuador.

Overall, the findings support a human-centered and socio-technical interpretation of AI readiness, suggesting that teachers' engagement with AI is associated not only with technological knowledge but also with interpersonal, relational, and leadership-related capacities. The discussion of the four hypotheses therefore focuses on how these relationships can be interpreted in light of previous research and the institutional context of digital transformation in higher education.

Regarding H1, the positive association between socio-emotional skills and educational leadership supports the perspective that leadership in higher education is grounded not only in formal authority but also in relational and interpersonal capacities. Previous research has emphasized emotional regulation, empathy, communication, collaboration, and conflict management as relevant to effective teaching and professional leadership [1,3,4,9–11,18]. The present finding extends this perspective by suggesting that teachers who possess stronger socio-emotional resources may be better positioned to support colleagues, facilitate collaboration, and respond constructively to institutional change. This relationship is particularly relevant in contexts of technological transformation, where uncertainty and differences in professional preparedness may require leadership based on trust, communication, and collective problem-solving. Thus, socio-emotional development may represent an important foundation for distributed forms of educational leadership.

Regarding H2, the positive association between socio-emotional skills and AI competencies is consistent with contemporary approaches that conceptualize AI competence as extending beyond operational knowledge to include adaptability, critical reflection, collaboration, ethical judgment, and continuous professional

learning [6,7,15]. From a theoretical perspective, teachers who can regulate emotions, adapt to changing circumstances, and collaborate effectively may be better prepared to engage with the uncertainty and continuous learning associated with rapidly evolving AI technologies. However, the comparatively lower level of AI competencies suggests that socio-emotional strengths do not automatically translate into equivalent technological preparedness. This may reflect the uneven availability of AI training, opportunities for experimentation, and institutional support within the participating institutions. The finding therefore points to the importance of combining socio-emotional development with explicit AI literacy and pedagogical training rather than treating technological competence as a natural consequence of general professional skills.

Regarding H3, educational leadership showed a positive association with AI competencies and represented the stronger direct correlate of AI competencies in the proposed model. This finding is consistent with perspectives that frame AI integration as an organizational and pedagogical process rather than solely as an individual technology-adoption decision. Previous research emphasizes the role of educators in guiding AI integration, supporting professional learning, and contributing to institutional innovation [7,12,16]. Educational leadership may facilitate AI readiness by enabling teachers to share practices, support colleagues, participate in institutional learning, and contribute to responsible responses to technological change. In the context of the participating institutions, this relationship may be particularly relevant where AI adoption depends not only on individual knowledge but also on collaborative professional environments and institutional opportunities for learning. The finding consequently reinforces the value of distributed and instructional leadership in digitally transforming higher education.

H4 proposed that educational leadership mediates the relationship between socio-emotional skills and AI competencies. The significant indirect association, together with the remaining significant direct association, was consistent with partial statistical mediation. This

finding provides a more nuanced interpretation of the relationship between human capacities and AI preparedness because socio-emotional skills may be connected with AI competencies both directly and through leadership-oriented behaviors. Theoretically, socio-emotional capacities such as communication, adaptability, self-regulation, and collaboration may facilitate behaviors through which teachers support innovation, share knowledge, manage technological change, and promote collective learning. Educational leadership may therefore represent an intermediate pathway through which individual socio-emotional resources are translated into professional practices conducive to AI integration. This interpretation is consistent with research emphasizing leadership, collaboration, ethical reflection, and continuous learning as components of responsible AI integration [7,12,15]. Nevertheless, given the cross-sectional and non-experimental design, the mediation should be understood as a statistically significant indirect association rather than evidence of a temporal or causal mechanism. The distinctive contribution of this result lies not simply in showing that socio-emotional skills are associated with AI competencies, but in indicating that part of this association is statistically connected with educational leadership. In this sense, the model links individual socio-emotional resources with leadership-oriented professional practices and, subsequently, with AI-related competencies.

Taken together, the findings indicate that AI competency development should not be approached exclusively as a technical training challenge. The comparatively lower level of AI competencies, together with the relationships observed among the three constructs, suggests that professional development should integrate AI literacy with socio-emotional competencies, pedagogical judgment, educational leadership, ethical decision-making, and collaborative learning. Previous research similarly highlights institutional support, collaborative learning, and continuous professional development as relevant to building confidence and competence in emerging technologies [2,13,17]. Practical initiatives could therefore include peer mentoring, collaborative experimentation with AI-supported teaching, critical evaluation of AI-

generated outputs, discussion of ethical dilemmas, and leadership-oriented professional learning. Such approaches may be especially valuable in institutional contexts where teachers have heterogeneous levels of previous AI training and use.

The structural model explained 46.8% of the variance in educational leadership and 52.1% of the variance in AI competencies, indicating meaningful explanatory capacity while leaving substantial variance associated with factors outside the model. These findings are therefore better interpreted as evidence that socio-emotional skills and educational leadership represent relevant human-centered dimensions within a broader configuration of technological, pedagogical, organizational, and institutional influences. This interpretation is consistent with multidimensional conceptualizations of AI competence that incorporate technological knowledge, pedagogical judgment, ethical awareness, adaptability, and professional learning [7,14,15].

The study contributes to the literature by integrating socio-emotional skills, educational leadership, and AI competencies within a single structural framework and by identifying educational leadership as a statistically significant indirect pathway between socio-emotional skills and AI competencies. It also extends the socio-technical interpretation of AI integration by highlighting the relevance of professional relationships, collaborative practices, and institutional learning. Finally, it provides evidence from teachers in the participating higher education institutions in Guayas, Ecuador, contributing a Latin American perspective to an international literature that remains unevenly distributed across geographic contexts.

Several limitations should be considered when interpreting these findings. First, the cross-sectional design does not permit causal or temporal conclusions regarding the relationships among the constructs. Longitudinal research would be required to examine how socio-emotional skills, educational leadership, and AI competencies develop and interact over time. Second, the reliance on self-reported measures may be influenced by social desirability and individual self-perceptions; future studies could

incorporate performance-based AI assessments, peer evaluations, behavioral indicators, or institutional records. Although the full-collinearity assessment did not indicate problematic common method variance, the use of a single self-administered questionnaire for the principal constructs means that residual common-method effects cannot be completely ruled out. Third, the use of non-probability convenience sampling limits generalizability beyond the participating teachers and higher education institutions in Guayas, Ecuador; therefore, the findings should not be generalized to all university teachers in Ecuador. Future research using probabilistic sampling and broader institutional, disciplinary, and geographic coverage would strengthen external validity. Finally, contextual factors such as digital infrastructure, professional development, organizational culture, technological support, workload, disciplinary differences, digital inequalities, and institutional AI policies should be incorporated into future models as potential predictors, moderators, or mediators.

From a theoretical perspective, the findings contribute to a socio-technical understanding of teacher AI competence. Rather than conceptualizing AI competence exclusively as an individual technological capability, the proposed model situates it within a broader configuration of socio-emotional resources, leadership-oriented practices, and professional relationships.

5. Conclusion

This study examined the relationships among socio-emotional skills, educational leadership, and AI competencies among teachers from the participating higher education institutions in Guayas, Ecuador. The findings showed positive associations among the three constructs and identified educational leadership as a statistically significant mediating construct in the relationship between socio-emotional skills and AI competencies. These results support a multidimensional and socio-technical interpretation of AI-related professional adaptation in which technological preparedness is embedded within human capacities, professional relationships, and organizational processes. The findings further suggest that sustainable AI integration in higher education requires

professional development strategies that combine technological literacy, socio-emotional development, educational leadership, ethical reflection, and collaborative learning. Given the cross-sectional and non-experimental design, the observed relationships should be interpreted as statistical associations rather than causal mechanisms.

Within the participating institutions, the findings highlight the importance of strengthening both individual and organizational capacities for responsible AI integration. However, because the study used non-probability convenience sampling, these results should be understood specifically in relation to the participating

6. References

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- teachers and higher education institutions in Guayas and should not be generalized to all university teachers in Ecuador. Future research using probabilistic sampling and broader institutional and geographic coverage could assess the extent to which these patterns are replicated across other higher education contexts.
- Ultimately, the findings suggest that responsible AI integration in higher education is not solely a question of what teachers know about AI, but also of the socio-emotional and leadership capacities through which they learn, collaborate, exercise professional judgment, and respond collectively to technological change.

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8. Author Declaration

The authors declare no conflict of interest.