Artificial Intelligence Adoption in Human Talent Management among SMEs in Emerging Economies: Evidence from Ecuador

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Abstract

This study analyzes the adoption of Artificial Intelligence (AI) in Human Talent Management (HTM) among small and medium-sized enterprises (SMEs), using Ecuador as the empirical case and articulating the results with evidence reported for other emerging economies in Latin America, Asia, and Africa. Despite accelerated global technological advancement, SMEs in emerging economies face structural, financial, and human capital barriers that constrain digital transformation. Drawing on the integration of the Technology–Organization–Environment (TOE) and Ability–Motivation–Opportunity (AMO) frameworks, the study adopts a quantitative, cross-sectional, and descriptive design with a comparative discussion, based on a sample of 250 Ecuadorian SMEs. Data were collected through a validated Likert-scale questionnaire and analyzed using descriptive statistics, non-parametric tests, and Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate a moderate level of AI adoption (M = 2.94) and no statistically significant differences by firm size or sector. The AMO construct exhibited the strongest direct effect ($\beta = 0.52$) and a partial mediating role between TOE dimensions and AI adoption, explaining 63% of the variance ($R^2 = 0.63$). Although AMO scores are relatively low, their variability explains adoption differences, underscoring the central role of competencies, motivation, and organizational opportunities in fostering inclusive and sustainable digital transformation.

Keywords: Artificial Intelligence; Human Talent; SMEs; Innovation; Digital Transformation.

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Introduction

Contemporary business organizations operate in highly competitive environments characterized by rapid technological transformation processes that directly influence labor dynamics. Human talent management, in particular, has undergone a significant transformation through the incorporation of technological tools that have reshaped organizational processes, boosting productivity, optimizing business models, and generating new opportunities for growth and competitiveness (Barrera-Gómez & Flórez-Romero, 2024; OECD, 2023).

Among these innovations, artificial intelligence (AI) has become firmly established as a key driver of innovation, with increasingly broad applications across sectors such as industry, education, healthcare, security, and finance areas in which its current and future impact is undeniable (Mendoza et al., 2024). In recent years, the development of intelligent tools has strengthened AI's capacity to emulate human abilities and enhance personnel management within organizations. As noted by Garg (2021), its use has expanded from engineering into human resource management, while Biradar et al. (2024) emphasize that its integration into personnel administration processes has become a topic of growing academic interest. Similarly, Canossa-Montes de Oca & Peraza-Villarreal (2024) argue that global technological changes have facilitated the incorporation of tools that support critical human talent management functions, ranging from recruitment to employee offboarding. These advances reinforce the notion that technology constitutes a transformative force within organizations, through which strategic actions are articulated to achieve institutional objectives (OECD, 2021; OECD, CAF, & SELA, 2024).

Nevertheless, despite global advances in artificial intelligence, small and medium-sized enterprises (SMEs) in intermediate-development economies continue to face structural and cultural limitations that hinder its effective adoption. Among the main obstacles identified are insufficient knowledge for managing technological tools, resistance to change, inadequate training, high implementation costs, and concerns related to information security (Murillo et al., 2024; CEPAL, 2024; Pozo-Benites et al., 2025).

Empirical evidence from different national contexts reveals converging patterns regarding these challenges. Cases such as Ecuador, India, Brazil, Vietnam, and South Africa reflect a growing awareness of the potential of artificial intelligence in human talent management processes, albeit with adoption levels that remain incipient and uneven. In Ecuador, SMEs exhibit moderate progress in digitalization, accompanied by persistent gaps in human and financial capital (Programa de las Naciones Unidas para el Desarrollo, 2025). In India, adoption is largely concentrated in large corporations, while medium-sized

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enterprises still lack adequate digital infrastructure (Rajkumar et al., 2024). In Brazil, although public policies have promoted digital transformation and the use of advanced technologies, implementation among micro, small, and medium-sized enterprises remains limited due to low levels of digital maturity (Regis et al., 2025). Similarly, in Vietnam and Indonesia, emerging digital ecosystems face challenges related to technological integration, cybersecurity, and workforce training, particularly within the SME segment (Flaminiano, 2025).

These patterns suggest that emerging and intermediate-development economies share constraints associated with their productive structures, organizational capabilities, and levels of digital maturity. At the same time, the adoption of artificial intelligence in human talent management is increasingly recognized as a strategic factor for reducing productivity gaps, strengthening competitiveness, and promoting more inclusive digital transformation processes (Schwaeke et al., 2025). However, the scientific literature continues to focus predominantly on developed countries or large technology corporations, thereby limiting empirical understanding of how SMEs incorporate AI into their labor and management practices under different institutional and economic conditions.

Within this context, the present study focuses on an empirical analysis of artificial intelligence adoption in human talent management among Ecuadorian SMEs, with the aim of providing a context-sensitive understanding of this phenomenon within a Latin American economy of intermediate development. Based on this empirical evidence, the findings are interpreted in light of prior studies conducted in other emerging economies and comparable contexts, allowing for the identification of regularities, contrasts, and common explanatory factors in technological adoption processes. Therefore, this research seeks to contribute to closing the existing gap in the literature by examining the level of artificial intelligence adoption in human talent management within SMEs, identifying the factors that condition its implementation, the opportunities it generates, and the barriers that limit its use. By articulating localized empirical evidence with a broader comparative framework, the study expands the understanding of digital transformation processes from a global perspective, providing relevant insights for both academia and the design of policies and strategies aimed at technological development and business sustainability in intermediate-development contexts.

Literature Review

Human Talent Management (HTM) has been consolidated as a strategic axis within organizations, aimed at attracting, developing, and retaining the most suitable personnel in alignment with institutional objectives. This process involves ensuring job satisfaction through equity, recognition, and the appreciation of individual competencies (Farro Díaz & Santos Nauca Torres, 2022). Aguirre et al. (2024) point out that HTM not only focuses on attracting and retaining talent but also on strengthening employees' skills and motivation so that their performance aligns with organizational goals. Consequently, HTM emerges as an essential component of business sustainability and competitiveness, particularly in environments characterized by innovation and continuous change.

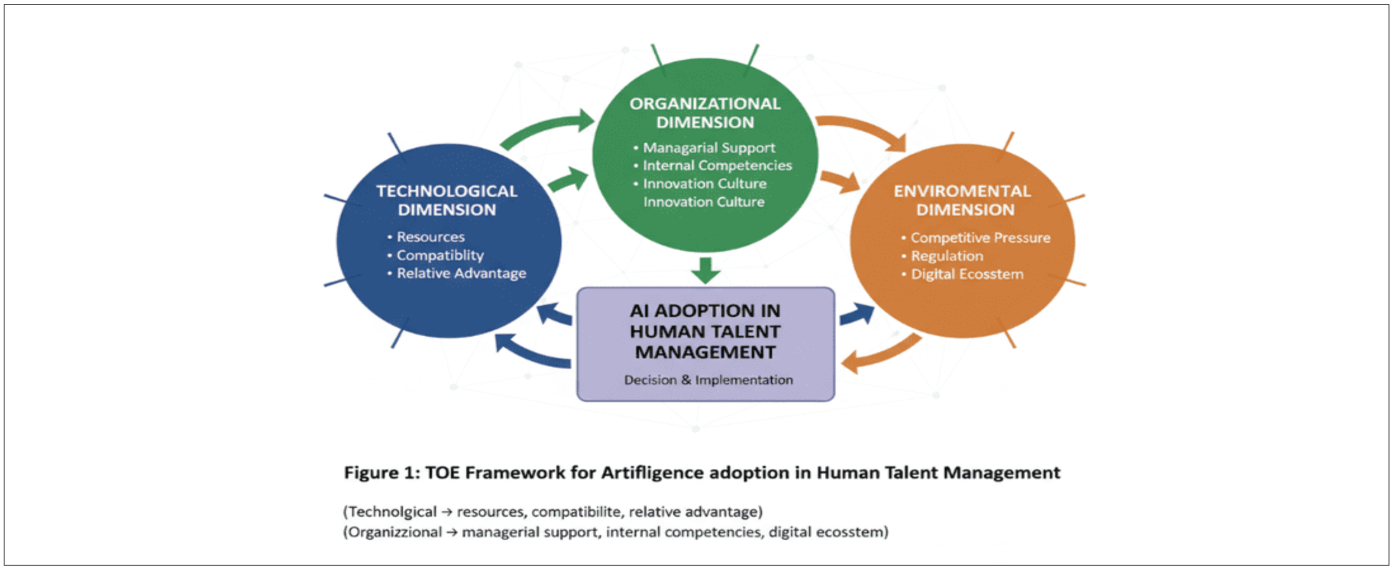
Digital transformation understood as the strategic integration of digital technologies into business processes has profoundly modified the way organizations operate and create value (Kraus et al., 2022). This transformation goes beyond mere task automation, as it involves redefining business models, organizational structures, and work competencies. However, small and medium-sized enterprises (SMEs) face significant barriers to its implementation due to a lack of financial and training resources, limiting their ability to compete in increasingly digitalized environments (Murillo et al., 2024). As a result, digitalization progresses unevenly, with the availability of resources and technological maturity determining each organization's capacity for innovation.

In this context, Artificial Intelligence (AI) is recognized as a strategic tool that enables the processing of large volumes of data, task automation, and decision-making support. McCarthy (2022) defines AI as the science and engineering of creating programs capable of imitating human cognitive processes, while Granados (2022) highlights its purpose of replicating human functions in artificial systems. Nevertheless, its implementation faces recurring challenges such as insufficient infrastructure, lack of technical knowledge, security risks, and resistance to change (Vera Ortega et al., 2024). These limitations are more pronounced in emerging economies, where labor exposure to AI is lower and opportunities for technological adaptation are limited.

To explain these variations, the Technology–Organization–Environment (TOE) framework provides an appropriate theoretical model for analyzing the factors influencing AI adoption in SMEs. This model argues that technological adoption depends on three interrelated dimensions: Technological, encompassing innovation characteristics and resource availability; Organizational, including firm size, structure, digital competencies, and managerial support; and Environmental, involving competitive pressures, institutional forces, and public policies (Schwaeke et al., 2025). The classic TOE framework was first articulated by Tornatzky and Fleischer (1990) in The Processes of Technological Innovation, where they emphasised how three dimensions: technological context, organizational context and environmental context influence the adoption of innovations at the firm level. This foundational model remains widely used in technology adoption research, particularly in small and medium-sized enterprises, as a lens to examine how internal resources, structures and external pressures shape digital transformation. Complementarily, the AMO model proposed by Appelbaum et al. (2000) introduces a behavioural perspective for human resource management research by focusing on how employees' Ability, Motivation and Opportunity to participate in work systems mediate performance outcomes. Integrated into an AI-adoption context, the combined TOE–AMO framework allows the examination of structural, organisational and behavioural factors affecting AI uptake in human talent management processes.

Figure 1 illustrates the TOE framework for AI adoption in human talent management. It conceptually integrates the technological dimension (resources, compatibility, and relative advantage), the organizational dimension (managerial support, internal competencies, and innovation culture), and the environmental dimension (competitive pressure, regulation, and digital ecosystem).

Figure 1. TOE Framework for AI Adoption in Talent Management



Source: Developed by the authors based on Tornatzky and Fleischer (1990) and literature review.

Several studies agree that AI provides significant opportunities in HTM processes, particularly in recruitment, performance evaluation, and training. In recruitment, task automation such as résumé screening and candidate identification has increased efficiency and accuracy (Tursunbayeva et al., 2025) emphasize that AI integration has become a strategic factor accelerating selection stages and reducing human bias. Garg (2021) adds that AI has evolved from an experimental innovation into an essential tool in personnel management, improving decision quality and optimizing human resources.

AI is also applied in competency assessment through automated testing, virtual interviews, and real-time performance analytics, facilitating the identification of skill gaps and the implementation of improvement plans (Percy-Zayas & Martínez-Delgado, 2023). In the field of training, Canossa-Montes de Oca & Peraza-Villarreal (2024) emphasize AI's ability to foster personalized and collaborative learning, promoting continuous improvement of human capital. Complementarily, Villarreal and Flor (2023) highlight the predictive role of algorithms in anticipating staff turnover and detecting dissatisfaction factors, thus reinforcing talent retention. Moreover, AI contributes to diversity and inclusion policies by identifying biases in selection and promotion processes and enhances strategic decision-making through the analysis of large datasets. However, Horodyski (2023) warns that the reliability of such systems depends on data quality, which may reproduce structural inequities, while Torres (2023) and Larson (2022) argue that although AI increases efficiency, it does not replace human judgment in strategic decision-making.

Within the Latin American context, studies by CEPAL (2025), the Inter-American Development Bank (Hirs & Vargas, 2023), and the OECD (2023, 2024) show that digital transformation and AI adoption among SMEs exhibit persistent structural gaps. In Mexico and Colombia, AI has been gradually incorporated into recruitment and training processes, although it remains concentrated in large corporations (≈ 35%). In Peru and Chile, public policies have promoted digital skills, yet integration in SMEs does not exceed 25%. Argentina and Brazil show notable technological progress that coexists with regulatory and labor barriers (≈ 40%), while OECD countries surpass 70% adoption in productive and administrative processes.

The reviewed literature demonstrates that AI adoption in human talent management represents an organizational transformation process influenced by technological, organizational, and environmental factors. Its success depends not only on the availability of digital tools but also on institutional capacity to integrate them into business strategies and organizational culture. For SMEs, this relationship is particularly sensitive to budget constraints, employees' digital skills, and openness to innovation. From this perspective, artificial intelligence constitutes a core component of firms' digital maturity and long-term competitive sustainability, as its effective integration with human talent management and sustainability-oriented practices strengthens employee performance and enhances organizational resilience.

Methodology

This study adopts a quantitative, descriptive–comparative, and cross-sectional design to examine the level of artificial intelligence (AI) adoption in human talent management (HTM) processes among small and medium-sized enterprises (SMEs). Ecuador is analyzed as the empirical case due to its representativeness as an emerging Latin American economy characterized by structural constraints, limited digital infrastructure, and heterogeneous levels of technological maturity (Páez Egüez & Cumbal Simba, 2024). This case-based approach enables the identification of behavioral, technological, and organizational factors shaping AI integration in SMEs. The findings derived from the Ecuadorian context are subsequently interpreted in light of evidence reported for other emerging economies, allowing for a comparative understanding of digital transformation dynamics within broader development settings (OECD, 2023; CEPAL, 2025).

Research Design

The methodological structure was grounded in the Technology–Organization–Environment (TOE) framework, complemented by the Ability–Motivation–Opportunity (AMO) model (Tornatzky & Fleischer, 1990; Appelbaum et al., 2000), enabling an integrated analysis of technological, organizational, environmental, and behavioral factors influencing AI adoption in SMEs. The TOE framework provided the analytical foundation to examine technological factors (infrastructure, compatibility, and digital maturity), organizational factors (structure, digital competencies, leadership, and innovation culture), and environmental factors (competitive pressure, regulation, and institutional support). The AMO model incorporated a behavioral dimension, emphasizing employees' abilities, motivation, and opportunities to engage in technological innovation within HRM processes (Schwaeke et al., 2025).

This theoretical integration guided the operationalization of variables and the construction of the measurement instrument, structured into six dimensions corresponding to the TOE–AMO framework: Human Talent Management, Digital Transformation, Use of Artificial Intelligence in HRM, Opportunities and Challenges of AI, Human Factors (Ability–Motivation–Opportunity), and Environmental and Institutional Factors. The design thus contributes to understanding AI not only as a technological innovation but as a sociotechnical process of organizational transformation linking structural and behavioral determinants (Murillo et al., 2024; Pozo-Benites et al., 2025). The descriptive–comparative approach provided a diagnostic view of AI adoption levels among Ecuadorian SMEs and allowed comparisons with patterns observed in other emerging economies across Asia, Africa, and Latin America (OECD, 2023; OECD, CAF, & SELA, 2024; Banerjee, Martínez, & Puentes, 2023).

Population and Sample

The study population consisted of human resources managers and executives from companies that had initiated digital transformation processes. A non-probabilistic convenience sampling method was used, selecting 250 SMEs that voluntarily agreed to participate and had available information on their digital management practices. The sample included firms from manufacturing (28%), services (31%), commerce (24%), and technology or innovation-related sectors (17%), reflecting the productive structure of Ecuadorian SMEs as reported by the National Institute of Statistics and Census (INEC, 2025). This sectoral distribution strengthens the external and comparative validity of the study, facilitating analytical comparisons with findings from countries such as Mexico, Chile, Peru, and Colombia, where AI adoption patterns display similar characteristics (CEPAL, 2025).

Inclusion and Exclusion Criteria

(i) Legally registered and operational SMEs in Ecuador;

(ii) classified as small or medium-sized according to Ecuadorian legislation;

(iii) possessing a formal HRM department or designated responsible person;

(iv) having initiated digitalization processes in administrative or HR operations; and

(v) expressing willingness to participate in the research.

Exclusion criteria: single-person businesses without employees and companies showing no evidence of technological adoption were excluded. These criteria ensured that respondents represented organizations with sufficient structure and digital maturity to evaluate both technological and human-factor dimensions of the TOE–AMO model.

Instrument and Validation

Data were collected using a structured questionnaire with a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument was developed based on an extensive literature review on Artificial Intelligence (AI), Human Resource Management (HRM), and digital transformation, and was structured according to the Technology–Organization–Environment (TOE) and Ability–Motivation–Opportunity (AMO) theoretical frameworks (Tornatzky & Fleischer, 1990; Appelbaum et al., 2000). It included six dimensions: (i) Human Talent Management, (ii) Digital Transformation in HRM, (iii) Use of Artificial Intelligence in HRM, (iv) Opportunities and Challenges of AI, (v) Human Factors in AI Adoption (Ability, Motivation, and Opportunity), and (vi) Environmental and Institutional Factors.

The questionnaire was validated through expert judgment by five specialists in business management and digital technologies, ensuring content validity and conceptual coherence with the TOE–AMO model. A pilot test was conducted with 38 companies (15% of the total sample) to verify clarity, reliability, and internal consistency. The overall Cronbach's Alpha coefficient reached 0.92, demonstrating excellent internal consistency (George & Mallery, 2019). Reliability coefficients by dimension were: Human Talent Management ($\alpha = 0.89$), Digital Transformation ($\alpha = 0.87$), Artificial Intelligence in Business Management ($\alpha = 0.90$), Opportunities and Challenges of AI in HRM ($\alpha = 0.88$), Human Factors AMO ($\alpha = 0.91$), and Environmental and Institutional Factors ($\alpha = 0.86$). These values exceed the minimum reliability threshold ($\alpha \geq 0.70$) recommended by Hair et al. (2021) and align with findings from previous studies on AI adoption in SMEs and HRM (Chikwendu et al., 2025; Wahyudi et al., 2023).

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The questionnaire was designed as a self-administered instrument to ensure uniformity in responses and facilitate data collection from geographically dispersed SMEs. This approach minimized interviewer bias and allowed participants to provide perceptions about organizational and behavioral constructs such as motivation and digital competence that are inherently subjective and best captured through self-reported measures. Although qualitative methods (e.g., interviews or focus groups) could have offered deeper insights, the study prioritized quantitative comparability and statistical modeling (PLS-SEM) across a large sample. Future research may complement these findings through qualitative exploration to contextualize the behavioral mechanisms underlying AI adoption.

Operationalization of Variables

The study variables were structured according to the TOE–AMO framework to capture the interrelationships among technological, organizational, environmental, and human-behavioral factors influencing AI adoption in HRM processes. The model incorporated six dimensions corresponding to the validated questionnaire, integrating the three classical TOE domains with the AMO components: Ability, Motivation, and Opportunity representing employees' digital skills, commitment to innovation, and organizational opportunities for participation (See table 1).

Table 1. Operationalization of Variables and Hypotheses

Dimension	Variable	Operational Definition	Measurement Indicators	Scale	Hypothesis
Technological	AI Adoption Level	Degree of integration of AI tools in HRM processes	Use of AI in recruitment, evaluation, and training	Likert (1–5)	H1: The level of AI adoption is positively related to the firm's digital maturity.
Organizational	Employee Digital Competence	Capability of employees and managers to use digital tools	Training, autonomy, and managerial support	Likert (1–5)	H2: Employee digital competence positively influences AI adoption.
Environmental	Institutional and External Support	Availability of incentives, policies, and innovation ecosystems	Access to public programs and technological networks	Likert (1–5)	H3: Institutional support facilitates AI adoption.
AMO – Ability	Employees' Digital Skills	Mastery of digital and AI tools in HR processes	Technical proficiency, training, and learning opportunities	Likert (1–5)	—
AMO – Motivation	Organizational Motivation	Employees' and firms' willingness to innovate and adopt technology	Attitude toward change, recognition, and engagement	Likert (1–5)	H4: Organizational motivation mediates the relationship between digital competence and AI adoption.
AMO – Opportunity	Opportunities for Innovation	Organizational support for experimentation and participation	Leadership support, innovation culture, and decision autonomy	Likert (1–5)	

Source: Own elaboration (2025)

Data Collection and Analysis

Data collection took place between April and May 2025 through the electronic distribution of the questionnaire to HR managers and company executives. The data were analyzed using descriptive statistics (frequencies, means, and standard deviations) to characterize AI adoption levels, and non-parametric tests (Kruskal–Wallis and Chi-square) to identify differences by firm size and sector. Reliability was verified using Cronbach's Alpha, with all constructs exceeding the recommended threshold (George & Mallery, 2019; Hair et al., 2021).

Additionally, a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was applied to validate the hypothesized relationships within the TOE–AMO framework. This multivariate technique enables simultaneous evaluation of the measurement and structural models, suitable for medium-sized samples and non-normal data (Hair et al., 2021). The analysis, conducted in SmartPLS 4, assessed composite reliability, AVE, discriminant validity, and estimated path coefficients (β), R^2, and bootstrapped t-values.

Results were interpreted according to the TOE–AMO model, integrating descriptive, inferential, and structural findings to explain technological, organizational, environmental, and behavioral determinants of AI adoption in SMEs (OECD, 2023; CEPAL, 2025). The inclusion of PLS-SEM enhanced the study's explanatory and predictive rigor, aligning it with current standards for empirical research on digital transformation and business sustainability.

Results

Descriptive Analysis

Descriptive results indicate a moderate level of artificial intelligence (AI) adoption among Ecuadorian small and medium-sized enterprises (SMEs). The overall AI adoption index reached a mean of 2.94 (SD = 0.28) on a five-point scale, suggesting that the integration of intelligent tools into human talent management (HTM) processes remains at an initial stage. As shown in Table 2, the highest mean values were found in Human Talent Management (M = 3.12) and Digital Transformation (M = 3.05), followed by Environmental and

Institutional Factors (M = 2.97). The lowest scores corresponded to Human Factors (AMO) (M = 2.85) and Opportunities and Challenges of AI (M = 2.91), reflecting existing gaps in digital skills, motivation, and cultural readiness for AI adoption in SMEs.

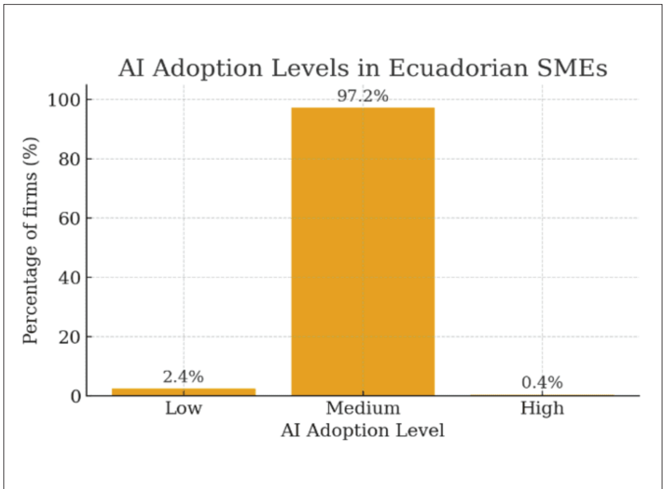
Table 2. Descriptive and Inferential Results by Dimension

Dimension	Mean	SD	Min	Max	Kruskal–Wallis (H)	p-value	ρ Spearman with AI Adoption
Human Talent Management	3.12	0.41	2.00	4.00	3.26	0.071	0.46**
Digital Transformation	3.05	0.37	2.10	3.90	2.98	0.082	0.52**
Use of AI in HTM	2.94	0.28	2.00	3.68	—	—	—
Opportunities and Challenges of AI	2.91	0.32	2.00	3.60	3.08	0.084	0.49**
Human Factors (AMO)	2.85	0.35	1.90	3.70	3.42	0.065	0.55**
Environmental and Institutional Factors	2.97	0.30	2.10	3.80	3.22	0.069	0.43**

Note. N = 250 SMEs. Non-parametric Kruskal–Wallis tests (by firm size and sector) and Spearman correlations (ρ).
$p < 0.01$.

Figure 2 presents the distribution of AI adoption levels. It reveals that 97.2% of firms are positioned at a medium level, 2.4% at a low level, and only 0.4% at a high level, confirming that technological penetration in HTM processes is still limited among Ecuadorian SMEs.

Figure 2. AI Adoption Levels in Ecuadorian SMEs



Source: Authors' elaboration based on survey data from 250 Ecuadorian SMEs (2025), processed in Python 3.11 using matplotlib.

Inferential Analysis

According to the Kruskal–Wallis non-parametric contrasts (see Table 3), differences in AI adoption levels across firm size (small vs. medium) and economic sector (commerce, industry, services, construction, and others) were not statistically significant ($p > 0.05$). This indicates a generalized homogeneity in adoption levels among the groups analyzed, suggesting that the degree of AI integration into HTM processes is not determined by firm size or sectoral category.

However, Spearman correlations revealed positive and significant associations between Digital Transformation ($\rho = 0.52$, $p < 0.01$), Human Factors – AMO ($\rho = 0.55$, $p < 0.01$) and AI Adoption, indicating that firms with higher digital maturity and stronger management of employees' abilities, motivations, and opportunities exhibit greater levels of intelligent technology integration. Overall, these results confirm the internal consistency of the data and reinforce the relevance of the TOE–AMO framework for explaining AI adoption patterns among Ecuadorian SMEs.

Measurement Model (PLS-SEM)

The measurement model was assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM). As displayed in Table 3, all constructs achieved satisfactory levels of internal reliability (α and CR > 0.80) and convergent validity (AVE > 0.50). Furthermore, the square roots of the AVE values exceeded the inter-construct correlations, thus meeting the Fornell–Larcker criterion for discriminant validity.

Table 3. TOE–AMO Measurement Model Results

Construct	α	CR	AVE	Highest Loading	√AVE (Fornell–Larcker)
Human Talent Management	0.89	0.91	0.67	0.84	0.82
Digital Transformation	0.87	0.90	0.65	0.79	0.81
Use of AI in HTM	0.90	0.92	0.69	0.85	0.83
Opportunities and Challenges of AI	0.88	0.90	0.66	0.80	0.81
Human Factors (AMO)	0.91	0.93	0.70	0.88	0.84
Environmental and Institutional Factors	0.86	0.89	0.62	0.77	0.79

Note. All loadings > 0.70. Convergent and discriminant validity confirmed (Hair et al., 2021).

Structural Model (PLS-SEM)

The structural model results (see Table 4 and Figure 3) confirmed all hypothesized relationships within the TOE–AMO framework. The path coefficients (β) ranged between 0.28 and 0.52, all statistically significant ($p < 0.05$). The Human Factors (AMO) construct demonstrated a partial mediating effect, linking the technological, organizational, and environmental dimensions with the AI Adoption construct.

Table 4. Structural Model Results with AMO Mediation

Path	β	t	p	f²	VIF	Supported
HTM → AI Adoption	0.41	5.21	0.000	0.18	2.10	Yes
Digital Transformation → AI Adoption	0.36	4.58	0.000	0.15	1.94	Yes
Environmental Factors → AI Adoption	0.28	3.72	0.001	0.11	1.88	Yes
AMO → AI Adoption	0.52	6.34	0.000	0.24	2.03	Yes
Digital Transformation → AMO	0.47	5.87	0.000	0.20	2.05	Yes
HTM → AMO	0.44	5.63	0.000	0.19	2.09	Yes
Environmental Factors → AMO	0.39	4.92	0.000	0.16	2.01	Yes

Mediation effects:

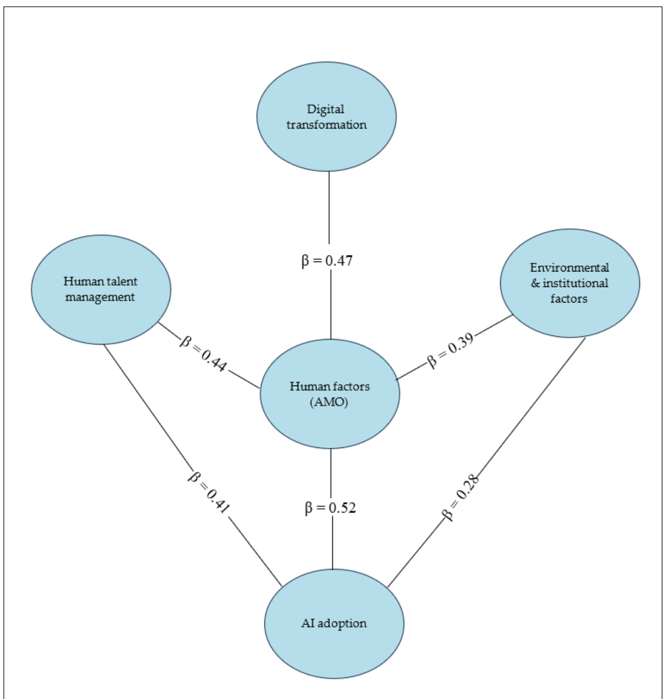
Digital Transformation → AMO → AI Adoption = 0.24 ($p < 0.01$)

HTM → AMO → AI Adoption = 0.23 ($p < 0.01$)

Environmental Factors → AMO → AI Adoption = 0.20 ($p < 0.01$)

The model demonstrates strong explanatory power, with R^2 (AI Adoption) = 0.63 and R^2 (AMO) = 0.58, while collinearity statistics (VIF < 3) confirm the absence of multicollinearity.

Figure 3. TOE–AMO Structural Path Diagram (PLS-SEM)



Source: Created by the author in Python 3.11 (networkx and matplotlib libraries).

Discussion

The results confirm that the adoption of artificial intelligence (AI) in Human Talent Management (HTM) among Ecuadorian SMEs remains at an incipient yet consolidating stage, with an average index of 2.94 out of 5 and 97.2% of firms positioned at a medium level of use. This pattern is consistent with evidence reported for other emerging economies in Latin America, where most SMEs continue to operate with low digital maturity and persistent limitations in connectivity, financing, and access to specialized talent (Pozo-Benites et al., 2025). Accordingly, the Ecuadorian case does not represent an exception, but rather exemplifies the structural gap that characterizes SMEs across the region.

A relevant finding is the homogeneity of AI adoption levels across firm size and economic sector, with no statistically significant differences. This suggests that AI integration in HTM is not driven by sectoral "frontiers," but constrained by shared structural barriers such as capital limitations, incipient digital capabilities, and an evolving institutional environment. Similar dynamics have been observed across Latin America, where SMEs systematically lag behind large firms and OECD economies regardless of sectoral orientation (OECD, CAF, & SELA, 2024; Hirs & Vargas, 2023), reflecting a pattern of slow and horizontal technological diffusion.

From a comparative perspective, this pattern contrasts with evidence from Africa and emerging Asia, where sectoral differentiation in AI adoption is beginning to emerge. Manufacturing SMEs in South Africa and Tanzania have shown earlier progress in AI-enabled services and data analytics, albeit from low baselines (Akoh, 2024), while export-oriented and digital-service sectors in India and Southeast Asia display relatively higher adoption levels (Flaminiano, 2025). These differences indicate that, unlike Asia and parts of Africa, Ecuador remains at an earlier stage characterized by transversal constraints that limit strategic differentiation.

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Beyond descriptive patterns, the structural model provides deeper insight into the mechanisms underlying AI adoption. The significant relationships between AI adoption and Digital Transformation, Human Talent Management, and Human Factors (AMO) confirm that adoption in emerging economies cannot be understood as a purely technological decision (Obaid et al., 2022). Rather, it constitutes a sociotechnical process shaped by the interaction of digital maturity, organizational capabilities, and innovation culture (Alkhalaf & Al-Tabbaa, 2023).

Within this framework, the AMO dimension emerges as the most relevant mediator, showing the strongest association with adoption ($\rho = 0.55$) and the highest direct effect ($\beta = 0.52$). This finding underscores that, in resource-constrained contexts, human capital represents a more critical bottleneck than technological infrastructure. In emerging economies, the relatively high costs of AI implementation, combined with limited internal digital competencies and uneven absorptive capacity, mean that the availability of technology alone is insufficient to drive adoption. Instead, firms' ability to develop skills, sustain motivation for change, and create organizational spaces for participation and experimentation becomes decisive, as these human and cultural factors determine whether technological potential can be effectively internalized and translated into HRM practices. Effective AI integration therefore depends on the development of digital skills, motivation toward change, and genuine organizational opportunities for participation in innovation (Starke & Ludviga, 2025), positioning AMO as a transmission mechanism linking technological and environmental conditions with concrete HTM outcomes (Alkhalaf & Al-Tabbaa, 2023).

This interpretation aligns with recent evidence from Ibero-American SMEs. Studies based on large firm samples highlight digital skills and leadership as decisive factors for advancing digital maturity, while technological and financial barriers dominate only at initial stages (Gutiérrez Navas et al., 2025). The Ecuadorian results reflect this pattern: although moderate progress in digital transformation is observed (M = 3.05), the human dimension remains the weakest link (M = 2.85), revealing a misalignment between digitalization processes and HTM practices.

Similar constraints are documented in Africa and emerging Asia. Digital transformation among Sub-Saharan African SMEs is limited by low digital literacy, infrastructural deficits, and weak alignment between technology and business objectives (Achieng & Malatji, 2022), while organizational preparedness and managerial commitment explain AI adoption more strongly than competitive pressure (African Leadership University, 2025; Sechabe & Malatji, 2025). In Asia, low adoption rates persist despite high awareness, primarily due to implementation costs, infrastructure gaps, and skill shortages. Regional reports emphasize that AI-driven productivity gains require coordinated investments in technology, training, and public policy (ERIA/OECD, 2024; World Economic Forum, 2025).

From a theoretical standpoint, the empirical validation of the integrated TOE–AMO model represents a significant contribution to AI adoption research in emerging economies (Zhang, Wu & Yin, 2024). The findings reaffirm the relevance of TOE dimensions while demonstrating that infrastructure and policy alone are insufficient without parallel investments in skills, motivation, and participation opportunities. In Latin America, moderate adoption, limited sectoral differentiation, and the dominant role of human factors suggest a low digital maturity equilibrium (Vera-Ortega & Yong Amaya, 2025; Pozo-Benites et al., 2025), shaped more by human capital constraints than by technological availability (OECD, CAF, & SELA, 2024; Hirs & Vargas, 2023).

For SME managers in emerging economies, the results indicate that human-capital-centered strategies should be prioritized over purely technological investments when promoting AI adoption in HTM. In practical terms, this implies implementing scalable and low-cost training initiatives aimed at strengthening digital competencies, such as internal or external micro-credentials, short bootcamps focused on applied AI use in HR processes, train-the-trainer schemes, and mentoring programs that leverage internal early adopters as knowledge multipliers (Dao et al., 2025). To reinforce motivation, incentive structures linked to learning and experimentation can be deployed through mechanisms such as recognition for certification attainment, protected time allocated to digital upskilling, or the inclusion of AI-related objectives within performance management and OKR systems, thereby aligning individual incentives with organizational digital transformation goals (Zhang et al., 2024). Finally, enhancing opportunity requires organizational arrangements that create space for participation and experimentation, including cross-functional teams, the designation of "AI champions" within HR units, and the implementation of short-cycle pilot or sandbox projects that allow firms to test AI applications in recruitment, evaluation, or training under controlled conditions, even in resource-constrained environments.

From a public policy perspective, the mediating role of AMO suggests that institutional interventions should extend beyond infrastructure provision toward strengthening human and organizational capabilities. In this regard, targeted digital training subsidies for SMEs, the promotion of public–private partnerships with universities, vocational centers, and technology hubs, and sector-specific capacity-building programs can help close persistent skill gaps and enhance absorptive capacity (Kahveci, 2025). Additionally, policy instruments that incentivize continuous learning and managerial development such as co-financed certification programs, support for SME participation in innovation networks, or pilot-based funding schemes for AI experimentation can amplify digital transformation outcomes by reinforcing the ability, motivation, and opportunity conditions necessary for sustainable AI adoption, particularly in emerging economies characterized by limited organizational readiness.

Limitations and Future Research

Despite its contributions, this study has limitations. Its cross-sectional design restricts analysis of dynamic adoption trajectories, while non-probabilistic sampling and self-reported data may limit generalizability and introduce perceptual bias. Future research should extend the TOE–AMO framework through longitudinal and multi-country studies, sectoral analyses, and qualitative approaches to deepen understanding of how AI reshapes HTM practices and employee experiences in diverse institutional contexts.

Conclusions

This study examined the adoption of artificial intelligence (AI) in Human Talent Management (HTM) among SMEs in an emerging Latin American economy, using Ecuador as a representative case and situating the findings within a broader comparative framework that includes Latin America, Africa and Asia. The results show that AI adoption in HTM remains at an incipient but consolidating stage: the overall adoption index is moderate, with the vast majority of firms located at an intermediate level of integration and no significant differences across firm size or sector. These findings confirm that structural and cultural constraints rather than sectoral specialization shape the trajectory of AI adoption in SMEs in emerging economies.

By integrating the Technology–Organization–Environment (TOE) and Ability–Motivation–Opportunity (AMO) frameworks, the study provides robust empirical evidence that AI adoption is best understood as a sociotechnical process. Digital transformation, HTM practices, environmental and institutional factors, and especially human factors (AMO) all exhibit significant and positive relationships with AI adoption. The AMO construct emerges as the strongest predictor and a partial mediator between the technological, organizational, and environmental dimensions and AI use in HTM, underscoring the central role of employees' skills, motivation, and opportunities in enabling effective AI uptake. The explanatory power of the structural model ($R^2 = 0.63$ for AI adoption) reinforces the relevance of the TOE–AMO integration for analyzing digital transformation in SMEs.

The comparative discussion with evidence from Africa and Asia confirms that SMEs in emerging economies share common patterns: low initial digital maturity, dependence on human capabilities, evolving institutional ecosystems, and uneven progress in AI integration. The study contributes to the literature by providing empirically grounded, cross-regional insights on AI adoption in HTM and by identifying clear levers for action particularly investment in digital skills, leadership development, and targeted institutional support. These findings offer a useful basis for designing public policies and organizational strategies that foster an inclusive and sustainable digital transformation of SMEs in emerging economies.

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