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| RESEARCH ARTICLE

The Mediating Role of AI Adoption in Talent Management in the Relationship Between TOE Factors and Perceived Talent Management Effectiveness in Metro Manila Organizations

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| ABSTRACT
This study explored how Artificial Intelligence (AI) adoption mediates the relationship between Technology–Organization–Environment (TOE) factors and perceived talent management effectiveness among HR professionals in Metro Manila organizations. Anchored on the TOE framework and supplemented by the Ability–Motivation–Opportunity (AMO) framework, the study explains both the adoption of AI and the capability stage through which AI may enhance talent management outcomes. A quantitative, cross-sectional research design was employed, with data collected from 137 HR professionals in Metro Manila using purposive and snowball sampling. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the relationships among constructs. The results indicated that technological and organizational contexts serve as the primary engines of AI adoption, whereas external environmental pressures did not drive any influence in AI adoption. The findings on mediation analysis suggested that while AI enhanced talent management effectiveness, it was not a prerequisite for achieving strong HR outcomes. Instead, AI functioned as an enabling capability that amplified organizational readiness through improved decision support, process efficiency, and more consistent talent management practices. Ultimately, this study contributes to the literature by clarifying the role of AI as a performance-enhancing mechanism and highlighting the importance of internal readiness over external pressure in driving adoption and providing insights to researchers, HR professionals, industry leaders, into leveraging AI for organizational success.

| KEYWORDS

Artificial Intelligence, AI Adoption, Human Resource Management, Talent Management, TOE Framework

| ARTICLE INFORMATION

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1. Introduction
Many organizations are increasingly integrating digital technologies to improve efficiency and support decision-making. As digital transformation accelerates, these technologies are also being leveraged to improve both operational efficiency and strategic decision-making (Rožman et al., 2022).

Among these technologies, Artificial Intelligence (AI) has gained significant attention due to its ability to process large volumes of data, identify patterns, and support complex decision-making, which increasingly shapes how organizations operate. Rather than functioning as a standalone innovation, AI is being integrated across various organizational functions, including Human Resource Management (HRM), where it contributes to more data-driven and systematic approaches to managing people and processes.

Within HRM, Talent Management (TM) is widely associated with processes for retaining top talent, encompassing the processes through which organizations attract, develop, and retain employees who contribute to long-term organizational success (Lewis

& Heckman, 2006). However, traditional TM approaches are often constrained by administrative inefficiencies, subjectivity, and limited use of analytics. The integration of AI into talent management offers significant opportunities to address these limitations by improving recruitment accuracy, enabling personalized learning, and enhancing performance management through data-driven insights. Empirical evidence suggests that AI-enabled HR systems can improve employee engagement, productivity, and decision-making quality when effectively implemented (Rožman et al., 2022; Asif et al., 2025).

Despite these potential benefits, the adoption of AI remains uneven across organizations, particularly in developing economies such as the Philippines. While digital infrastructure is increasingly accessible, adoption at the organizational level remains limited. According to Quimba et al. (2024), only approximately 14.9% of firms in the Philippines have adopted AI technologies, with adoption concentrated in larger organizations and urban regions. This highlights a gap between technological availability and actual implementation, suggesting that organizational readiness plays a critical role in determining whether AI can be effectively adopted and utilized.

This context is especially relevant in highly urbanized regions such as Metro Manila, which serves as the country's primary economic and technological hub. Given its concentration of businesses, digital infrastructure, and talent, Metro Manila provides a suitable setting for examining how firms engage with AI-driven solutions. However, despite this advantage, adoption remains inconsistent, indicating the presence of underlying organizational and environmental constraints.

To better understand these dynamics, this study adopts the Technology–Organization–Environment (TOE) framework, which explains technology adoption as a function of technological conditions, organizational readiness, and external environmental factors that shape whether organizations adopt innovation. Complementing this, the study draws on the Ability–Motivation–Opportunity (AMO) framework to explain the capability and performance stage, or how AI adoption may enhance TM effectiveness by strengthening employee ability, motivation, and opportunity through HR systems and processes.

In response to this gap, this study aims to examine the influence of TOE factors on AI adoption in HR functions and to determine whether AI adoption enhances perceived Talent Management effectiveness among organizations in Metro Manila.

Specifically, the study seeks to:

1. Examine the influence of technological, organizational, and environmental factors on AI adoption in talent management;
2. Determine the effect of AI adoption on perceived talent management effectiveness; and
3. Test the mediating role of AI adoption in the relationship between TOE factors and talent management effectiveness.

By addressing these objectives, the study contributes to both theory and practice by clarifying the role of AI as an enabling capability in HR and providing insights for organizational leaders on whether investments in AI-driven talent management systems are necessary or primarily performance-enhancing.

2. Literature Review

2.1 Artificial Intelligence

Artificial Intelligence (AI) is no longer regarded as a futuristic concept but a foundational component of modern organizations. Early conceptualizations and definitions of AI emphasized the possibility that machines could simulate aspects of human intelligence, including learning, problem-solving, and language use (McCarthy et al., 1955), while modern viewpoints describe it as a set of technologies that enable systems to analyze data, recognize patterns, and support decision-making processes (Trunk et al., 2020; Nilsson, 2010).

Key AI capabilities include machine learning (ML), which enables systems to learn from data, deep learning (DL), which utilizes layered neural networks to process complex and unstructured information, and natural language processing (NLP), which allows machines to understand and generate human language. These capabilities underpin applications such as chatbots, predictive analytics, and intelligent automation (Janiesch et al., 2021; Nillson, 2010).

In organizational contexts, AI enhances efficiency and supports data-driven decision-making by automating routine tasks and processing large volumes of information. Within human resource management (HRM), AI is increasingly applied across various functions contributing to improved recruitment, learning and development, performance management, workforce planning, and

employee engagement. These applications illustrate the evolving role of AI from administrative task automation toward supporting more strategic decision-making processes (Petre et al., 2024).
Adopting AI in HR practices automates repetitive, data-intensive tasks such as candidate screening, learning personalization, and performance tracking. This enables faster and more consistent decision-making while reducing administrative burden. As a result, HR professionals can shift their focus from transactional activities to more strategic responsibilities, positioning themselves as key business partners who contribute to organizational planning and value creation

2.2 Evolution of Human Resource Management
Human Resource Management has evolved significantly over time, transitioning from a transactional and administrative function into a strategic role that contributes to organizational performance (Yilmaz, 2023). In modern organizations, HRM is increasingly supported by digital technologies that enhance efficiency, decision-making, and workforce management.

The integration of AI into HRM represents a major advancement in this evolution. AI technologies enable organizations to automate repetitive tasks, analyze large datasets, and generate insights that support strategic HR decisions (Aydın & Karaarslan, 2023). This transformation allows HR professionals to shift their focus from administrative tasks to value-adding activities, strengthening their role as strategic partners within organizations.

2.3 Talent Management
As industries evolve and workforce expectations shift, organizations are compelled to adopt more systematic and strategic approaches to managing talent. Although there is no single, universally accepted definition of talent management and the concept remains inconsistently defined in terms of its scope and meaning (Lewis & Heckman, 2006; Cappelli & Keller, 2014), it is generally understood as an integrated and strategic approach to attracting, developing, managing, and retaining employees who contribute to organizational performance–one of the biggest difficulties many organizations face in today's talent-hungry market (Boštjančič & Slana, 2018).

Wandhe (2016) describes talent management as encompassing planning, recruiting, developing, managing, and compensating employees throughout the organization, positioning it as a core HR function. These functions collectively support the broader objective of ensuring organizational success through effective talent utilization (Cizmic & Ahmic, 2021; Singh, 2021). The concept itself, although relatively recent, builds on long-standing HR practices aimed at placing the right individuals in the right roles at the right time, including workforce planning, succession planning, and career development (Cappelli & Keller, 2014). The term gained prominence following McKinsey's (1998) "war for talent" report highlighting the strategic impact of talent on organizational performance and has since become a dominant theme in human capital management.

2.4 AI in Talent Management Functions
The integration of AI into HRM has significantly transformed how organizations manage and retain talent. It has emerged as a key enabler across talent management functions, which has increasingly been leveraged to enhance efficiency, improve decision-making, and optimize workforce performance across organizations.

In startup environments, AI tools have been shown to significantly enhance TM effectiveness by improving recruitment efficiency, enabling accurate candidate-job matching, and supporting data-driven HR decision-making. These capabilities allow organizations to streamline key talent processes despite resource constraints, making AI particularly valuable in organizations (Azraa, 2026).

While talent management is generally conceptualized as an integrated process, it is operationalized through a number of different but interrelated functional domains across the employee lifecycle, including recruitment, training and development, performance management, and employee relations (Cappelli & Keller, 2014). Rather than being confined to a single function, AI applications are embedded throughout the employee lifecycle–from candidate selection and onboarding to performance evaluation and predictive analytics–transforming how organizations manage and develop their workforce (Nosaratabadi et al., 2022).

To better understand how AI is applied across these domains, Table 1 synthesizes empirical and review-based evidence on AI-supported applications across major talent management functions, including their reported outcomes and implementation changes.

Table 1

Empirical Evidence of AI-Supported Applications Across Talent Management Functions

Talent Management Function	AI-Enabled Technology/Adoption	Reported Outcomes	Reported Challenges	Key Source(s)
Recruitment & Selection	AI resume screening, candidate matching systems, automated interviews, chatbots	Faster hiring and reduced screening time; improved efficiency and candidate processing; enhanced talent identification	Algorithmic bias; lack of transparency; reduced human judgment; candidate trust concerns	Black & van Esch (2021); Horodyski (2023); Ali and Kallach (2024)
Onboarding	AI-powered onboarding systems, chatbots, workflow automation, AI-driven onboarding platforms	Faster integration; improved onboarding experience; enhanced early performance when onboarding is perceived as fair	Limited personalization; system dependence; fairness and transparency concerns	Belajdžić & Delac Marković (2025); Madanchian (2024)
Learning & Development	Adaptive learning systems, AI-driven personalized learning, skills analytics	Personalized learning pathways; improved engagement; identification of skill gaps; targeted development interventions	Data quality issues; resistance to AI systems; lack of explainability in recommendations	Madanchian (2024); Ali & Kallach (2024)
Performance Management	AI-assisted performance evaluation, predictive analytics, continuous feedback systems	More objective, data-driven evaluations; improved decision-making for promotions and development; reduced subjectivity	Overreliance on algorithms; fairness concerns; employee monitoring and privacy issues	Dima et al. (2024); Bujold et al., (2024); Safshekan et al. (2026)
Retention/ Attrition Management	Predictive analytics, machine learning attrition models, AI-driven engagement monitoring	Early detection of turnover risks; improved workforce planning; targeted retention strategies; reduced turnover	Ethical concerns; data privacy risks; need for interpretability; employee trust issues	Basnet (2024); Nosratabadi et al. (2022)

While table 1 summarizes current empirical evidence, research on AI applications across various TM functions remains uneven, with some areas (e.g. onboarding and retention) still developing.

2.5 Talent Management Effectiveness

Talent Management Effectiveness refers to the extent to which an organization successfully implements TM processes to support organizational performance, workforce capability, and long-term strategic objectives. Within strategic human resource management (SHRM), effective TM systems are associated with improved recruitment outcomes, enhanced employee development, more robust performance management, and the creation of sustainable leadership pipelines (Collings & Mellahi, 2009; Cappelli & Keller, 2014).

From a strategic perspective, TM effectiveness contributes to organizational performance and competitive advantage by aligning human capital with business goals. Organizations with well-integrated TM systems are better positioned to enhance workforce productivity, strengthen employee engagement, and ensure long-term sustainability, as they are able to deploy employees in roles where they can maximize their contribution (Collings & Mellahi, 2009).

Recent literature highlights the growing importance of data-driven and technology-enabled approaches in shaping TM effectiveness. The integration of artificial intelligence (AI) into TM processes enables organizations to enhance recruitment accuracy, optimize workforce planning, and support employee development through personalized learning and predictive analytics (Minbaeva, 2021; Nosratabadi et al., 2022). These capabilities facilitate a shift from intuition-based HR practices toward more objective, evidence-based decision-making.

Empirical studies further suggest that AI-enabled TM systems can improve employee engagement and organizational performance when aligned with strategic objectives. By automating routine tasks and generating actionable insights, AI allows HR professionals to focus on higher-value activities that contribute to more effective talent management (Rožman et al., 2022; Petre et al., 2024).

Rather than viewing TM as a set of isolated HR activities, contemporary research conceptualizes TM effectiveness as a system-level construct encompassing the entire talent lifecycle, including recruitment, onboarding, development, performance management, and succession planning (Cappelli & Keller, 2014). In this study, perceived Talent Management Effectiveness refers to HR professionals' evaluations of how well these processes function cohesively to achieve organizational objectives. Such perceptual measures are commonly used in organizational research when assessing complex, system-level constructs.

2.6 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework, developed by Tornatzky and Fleisher (1990), is one of the most popularly used models for explaining technology adoption in organizations. The framework posits that adaptation and implementation of technological innovations are influenced by three contextual dimensions: technological, organizational, and environmental factors. These dimensions influence how businesses evaluate, adopt and use new technology at the firm level, especially in complex and dynamic environments (Gonzáles et al., 2025; Tornatzky & Fleishcher, 1990).

Technological context refers to the characteristics and availability of technologies relevant to the organization, including advantage, compatibility, cost-effectiveness, and security. Prior studies on AI adoption in HRM suggest that organizations are more likely to adopt AI when it provides clear advantages of existing systems, such as improved efficiency, reduced costs, and enhanced decision-making capabilities. For instance, it has been discovered that cost-effectiveness and relative advantage has had significant influence on the adoption of AI in talent acquisition processes (Pillai & Sivathanu, 2020). However, adoption may be hindered by technological limitations, especially in HR settings where sensitive employee information is involved (Pillai & Sivathanu, 2020).

Organizational context encompasses the internal characteristics of an organization which includes leadership support, resource availability, readiness of the organization, and employee competencies. Among these, top management support and HR readiness are consistently identified as a critical determining factor of AI adoption. Leadership plays a vital role in providing strategic direction, allocating resources, and fostering an innovation-oriented culture that supports technology integration. Similarly, the availability of financial resources, technological competence, and skilled HR professionals determines an organization's ability to effectively implement AI. Empirical research demonstrates that top management support and HR readiness significantly influences the intention to deploy AI in HRM contexts (Fenwick et al., 2024).

Environmental Context refers to the external factors such as competitive pressure, industry dynamics, and support from external stakeholders. Competitive pressure is widely recognized as a key driver of technology adaptations, as organizations are compelled to adopt new technologies to maintain competitiveness within their industry (Pillai & Sivathanu, 2020). In developing countries such as the Philippines, environmental factors also include government initiatives, policy frameworks, and collaboration among industry, academe, and institutions, which influences organizational readiness for AI adoption (Rosales et al., 2020).

While the TOE framework provides a thorough explanation of technology adoption, these elements are not independent of one another. Instead, adoption is determined by the interaction of technological feasibility, organizational capability, and environmental pressure. In emerging economies, where structural and capability constraints are more intense, organizational factors frequently outweigh external forces (González et al., 2025).

In the context of this study, the TOE framework is used to explain how organizational conditions influence AI adoption in talent management. Specifically, how these factors are expected to shape the extent to which AI is adopted within HR processes, which in turn affects talent management effectiveness.

Based on this framework, the following hypotheses are proposed:
H1: Technological context positively influences AI adoption.
H2: Organizational context positively influences AI adoption.
H3: Environmental context positively influences AI adoption.

2.7 Technology-Organization-Environment (TOE) Framework
Recent empirical research supports the integration of TOE and Ability–Motivation–Opportunity (AMO) frameworks in explaining AI adoption and its outcomes. This framework explains how TOE conditions translate into performance outcomes. Evidence from SMEs in emerging economies show that AMO exhibits a strong direct effect and mediating role between TOE factors and AI adoption, highlighting the importance of employee capabilities, motivation, and organizational opportunities in driving effective AI utilization (González et al., 2025).

2.8 AI Adoption and Talent Management Effectiveness
AI technologies are increasingly applied across talent management functions, including recruitment, learning and development, performance management, and retention strategies (Subbaiah et al., 2024). According to Natarajan et al. (2024), AI adoption can enhance TM by streamlining HR processes, enabling data-driven decision-making, and improving overall efficiency.

Empirical studies indicate that AI adoption can enhance talent management effectiveness by improving efficiency, consistency, and decision quality (Latif et al., 2026; Natarajan et al., 2024). However, the magnitude of this effect varies depending on the degree of integration and organizational readiness (Hirtranusi et al., 2026). Notably, AI functions as a performance enhancer in talent management (Mir, 2024).

Thus, the hypothesis below is proposed:

H4: AI adoption positively influences perceived talent management effectiveness.

Beyond direct effects, prior research suggests that the value of technological and organizational readiness is often realized through actual technology utilization rather than mere availability (Malik et al., 2023). This implies that AI adoption may function as a mediating mechanism that translates organizational readiness into improved talent management outcomes. In this context, technological and organizational conditions enable adoption, but improvements in effectiveness occur only when AI is actively integrated into HR processes.

Accordingly, the following mediation hypotheses are proposed:
H5: AI adoption mediates the relationship between technological context and talent management effectiveness.
H6: AI adoption mediates the relationship between organizational context and talent management effectiveness.
H7: AI adoption mediates the relationship between environmental context and talent management effectiveness.

2.9 AI Adoption in the Philippines Context
AI adoption in the Philippines remains in an early stage, characterized by uneven levels of readiness and implementation across industries. While global trends suggest rapid integration of AI technology into business operations, the Philippine environment reflects a more gradual and fragmented adoption pattern, particularly among small and medium-sized enterprises (SMEs).

At the national level, empirical evidence indicates that AI adoption among Philippine firms is still relatively low. Quimba et al. (2024) report that only 14.9% of firms in the Philippines have formally adopted AI technologies, with adoption concentrated in larger organizations and sectors such as information and communications technology (ICT) and business process outsourcing (BPO). This shows that, while AI technologies are accessible, its adoption is limited and inconsistent throughout the business landscape. At the same time, there is increasing evidence of AI integration in HR practices within Metro Manila. AI tools are being used to automate recruitment processes which includes resume screening, candidate sourcing, and improving efficiency and ultimately reducing time-to-hire (Cacatian et al., 2024).

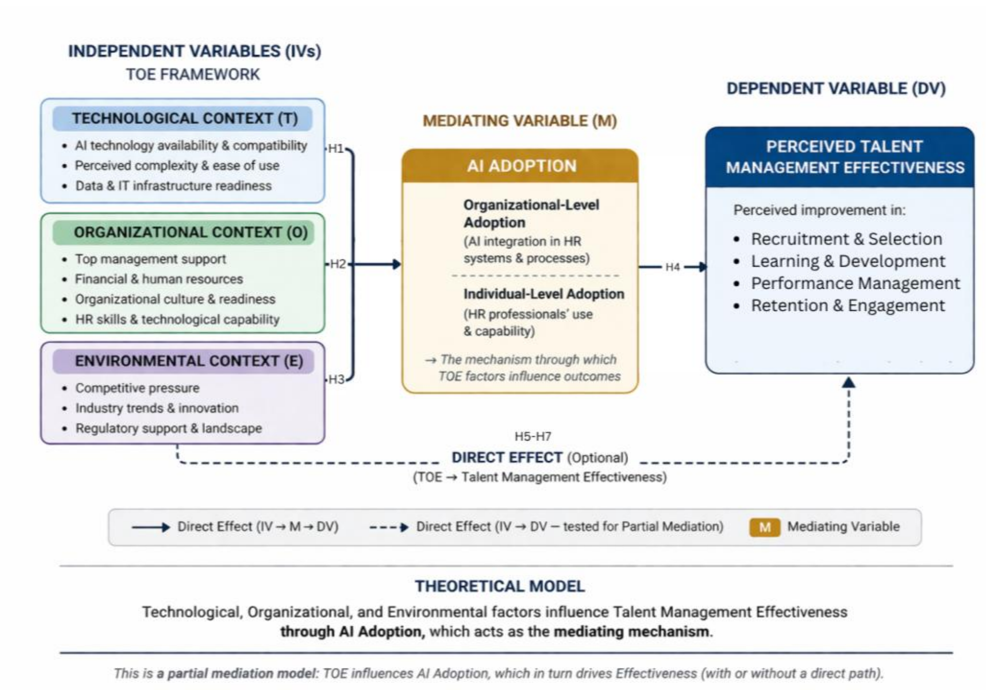
Despite low formal adoption, the Philippines demonstrates strong potential for AI-driven transformation. AI applications are already emerging across sectors, contributing to improvements in productivity, efficiency, and innovation (Rosales et al., 2020). Notably, evidence suggests that employees may already be utilizing AI tools in their work even when organizations have not yet fully integrated these technologies into formal systems. Reports indicate that 83% of the Philippine workforce "bring their own AI" (BYOAI) to tasks even without clear strategies or training from company leadership (Microsoft & LinkedIn, 2024, as cited in Cheng & Danao, 2024). This highlights a gap between technological availability and organizational adoption, reinforcing the importance of internal readiness in driving meaningful adoption (Cheng & Danao, 2024).

Given the uneven and developing nature of AI in the Philippines, these findings imply that access to technology alone is insufficient to drive meaningful outcomes. Instead, organizational readiness and capability determine whether AI is effectively utilized. While AI presents opportunities to improve talent management functions, its value is realized only through adoption and integration. Therefore, positioning AI adoption as a mediating variable allows this study to explain how organizational readiness translates into enhanced talent management effectiveness.

3. Conceptual Framework

Figure 1

Conceptual Framework



The conceptual framework proposes that organizational readiness factors, represented by the Technological, Organizational, and Environmental (TOE) contexts,influence the extent to which organizations engage in AI adoption within talent management processes. AI adoption, in turn, influences perceived talent management effectiveness, reflecting the organization's ability to effectively execute key talent management functions.

In this framework, AI adoption serves as a mediating variable, explaining how organizational conditions translate into improved talent management outcomes.

Specifically, the model assumes that:

- Technological, organizational, and environmental factors directly influence AI adoption;
- AI adoption directly influences Talent Management effectiveness; and AI adoption mediates the relationship between TOE factors and Talent Management effectiveness.

Although AI adoption is theorized as the primary mechanism linking organizational readiness to talent management effectiveness, the model examines direct effects from TOE factors to TM effectiveness. This approach is consistent with HRM literature suggesting that organizational capability, leadership support, and technological readiness can independently improve HR and talent management outcomes even without advanced technologies. Testing both direct and indirect paths allows the model to determine whether AI adoption fully or partially mediates these relationships.

While the TOE framework explains the conditions that drive AI adoption, this study draws on the Ability–Motivation–Opportunity (AMO) framework, employee performance is understood as a function of individuals' abilities, motivation, and opportunities to perform, which are shaped by HR practices (Appelbaum et al., 2000; Jiang et al., 2012). This perspective suggests that AI-enabled talent management systems enhance effectiveness not directly, but through their influence on employees' capability, motivation, and opportunity to contribute.

4. Methodology

4.1 Research Design

This study employed a quantitative, cross-sectional, explanatory research design to examine the relationships among Technological Context, Organizational Context, Environmental Context, AI Adoption, and Perceived Talent Management Effectiveness. A quantitative approach was appropriate given the objective of empirically testing hypothesized relationships among multiple latent constructs through structured survey data, enabling statistical validation of the proposed model.

The cross-sectional design enables data collection at a single point in time, which is suitable for assessing organizational perceptions and conditions. The explanatory component aimed to determine the causal relationships within the proposed model, particularly the mediating role of AI Adoption

4.2 Participants and Sampling

The target population consisted of HR professionals working in organizations located in Metro Manila. Respondents were required to be involved in HR, specifically with talent management functions and to have at least one year of relevant work experience.

A non-probability sampling approach was employed, specifically a combination of purposive and snowball sampling. Purposive sampling was used to ensure that respondents possessed relevant experience in HR and talent management functions aligned with the objectives of the study (Palinkas et al., 2013). Snowball sampling was subsequently applied by requesting initial participants to refer to other qualified HR professionals within their networks, thereby expanding access to a specialized population that is not easily identifiable through formal sampling frames (Goodman, 1961). This approach was appropriate given the absence of a comprehensive registry of HR professionals engaged in talent management roles in Metro Manila. Initial respondents were recruited through professional networks, and subsequent participants were reached through referrals.

A total of 137 valid responses were obtained. This sample size is considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM), which is suitable for studies with relatively small to medium sample sizes. Prior research indicates that PLS-SEM can produce reliable estimates with samples as low as 50 to 100 observations (Ahmed et al., 2024; Jhantasana, 2023).

In addition, the sample size satisfies the commonly used "10-times rule" in PLS-SEM, which suggests that the minimum sample size should be at least ten times the maximum number of structural paths directed at a latent construct (Hair et al., 2022). Given the model structure in this study, the sample size of 137 exceeds this minimum requirement, indicating preliminary adequacy for model estimation in an exploratory context. However, recent research cautions that the 10-times rule is a heuristic that may underestimate required sample sizes, and more rigorous approaches such as statistical power analysis are recommended for more precise estimation (Kock & Hadaya, 2018; Wagner & Grimm, 2023).

This study focused on Metro Manila as the geographic scope due to its concentration of organizations across diverse industries and its role as the primary business and economic hub of the Philippines. This context provides a relevant setting for examining AI adoption in HR, as organizations in metropolitan areas are more likely to have exposure to digital transformation initiatives and access to technological infrastructure. Additionally, the concentration of HR professionals in Metro Manila increases the feasibility of data collection while ensuring variability in organizational characteristics

4.3 Research Instrument

The instrument was designed to measure five major constructs in the study:

1) Technological Context
2) Organizational Context
3) Environmental Context
4) AI Adoption
5) Perceived Talent Management Effectiveness

The full survey instrument is provided in Appendix H. It consists of six sections, including demographic information and statements measuring the study variables. The construct-based items were measured using a four-point Likert scale (1=Strongly Disagree to 4=Strongly Agree), which encouraged respondents to express a clearer position by removing a neutral midpoint. The Technological Context, Organizational

Context, and Environmental Context sections each contained five items. The AI Adoption construct contained six items, while Perceived Talent Management Effectiveness contained five items. The survey items were framed to reflect the organizational use of AI-enabled tools in talent management functions and the respondents' perceptions of the effectiveness of those practices.

4.4 Data Collection Procedure

Data were collected through a structured online questionnaire administered through Google Forms, distributed through professional HR networks, online communities, and relevant social media platforms. Respondents were informed of the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. Only respondents who provided informed consent and met the inclusion criteria were included in the study. Consent was operationalized through a mandatory data privacy agreement at the start of the questionnaire, and eligibility controls were embedded via screening items (e.g., relevant HR experience and involvement in talent management), ensuring that only qualified participants could proceed and complete the survey. Collected responses were screened for completeness and consistency. Data were then cleaned and coded to prepare for statistical analysis

4.5 Data Analysis Technique

Data were analyzed using SmartPLS 4 to test the proposed model. Descriptive statistics were first computed in Jamovi to summarize respondent characteristics and construct levels. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to assess the measurement and structural models.

The measurement model was evaluated using indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity (HTMT). The structural model was assessed via collinearity diagnostics (VIF), path coefficients of determination (R^2), and effect sizes (f^2). Significance of direct and indirect effects, including mediation, was examined using bootstrapping procedures.

4.6 Ethical Considerations

The study adhered to ethical research principles, including voluntary participation, informed consent, confidentiality, and data privacy. Respondents were informed about the purpose of the study and their right to withdraw at any time. No personally identifiable information was collected or disclosed. All data were used solely for academic purposes and handled in accordance with the Data Privacy Act of 2012.

5. Results

The results presented below are compressed to reflect the important aspects of the study. Detailed item-level statistics are provided in Appendix B.

5.1 Respondent Profile

Descriptive statistics were computed to summarize respondent characteristics (see Table 2). The sample (N = 137) was primarily composed of individual contributors (41.6%) and managerial-level roles (28.5%). Most respondents reported 1–3 years of exposure to AI-related tools (69.3%) and were employed in large organizations (78.1%). Representation spanned multiple industries, with higher participation from service-oriented sectors.

Table 2
Frequency Distribution of Respondent Profile Variables (N = 137)

Variable	Category	n	%
Current Role	Entry-Level HR (e.g., HR Staff, HR Associate)	7	5.1
	Executive Search Leader (Director level)	1	0.7
	HR Consultant	1	0.7
	HR/Payroll Specialist	1	0.7
	Individual Contributor (e.g., HR Specialist, HR Analyst)	57	41.6
	Managerial Level (e.g., HR Manager, HR Business Partner)	39	28.5
	Senior Leadership (e.g., Head of HR, HR Director, VP for HR)	13	9.5
	Supervisory Level (e.g., HR Supervisor, Team Lead)	18	13.1
Years of exposure to AI-related tools in work	1–3 years	95	69.3
	4–6 years	15	10.9
	7 years or more	2	1.5
	Less than 1 year	22	16.1
	None	3	2.2
Organization size	Large enterprise (200 or more employees)	107	78.1
	Micro enterprise (1–9 employees)	3	2.2
Industry Sector	Small enterprise (10–99 employees)	12	8.8
	Accommodation and Food Service (hotels, restaurants)	9	6.6
	Administrative and Support Services (BPO, outsourcing, HR services)	38	27.7
	Arts, Entertainment and Recreation (events, gaming, creative industries)	2	1.5
	Construction (infrastructure, contractors)	2	1.5
	Electricity and Utilities (power, energy supply)	4	2.9
Industry Sector	Financial and Insurance Activities (banks, insurance, fintech)	13	9.5
	Healthcare and Social Work (hospitals, clinics)	5	3.6
	Information and Communication (IT, telecom, media, publishing)	18	13.1
	International / Extraterritorial Organizations (UN, embassies)	2	1.5
	Manufacturing (factory production, industrial goods)	11	8
	Mining and Quarrying (mining, oil, gas)	5	3.6
	Not sure	2	1.5
	Other Service Activities (repair, personal services, associations)	1	0.7
	Professional and Technical Services (consulting, legal, accounting, engineering)	13	9.5
	Transportation and Storage (logistics, shipping, delivery)	1	0.7
	Wholesale and Retail Trade (stores, trading companies)	11	8

Table 3
Descriptive Statistics of Constructs

Construct	M	SD
Technological Context	3.09–3.20	0.73–0.80
Organizational Context	3.01–3.47	0.65–0.85
Environmental Context	3.10–3.46	0.59–0.72
AI Adoption (org-level items)	2.71–2.99	0.78–0.88

AI Adoption (individual use)	3.47	0.65
Talent Management Effectiveness	3.07–3.20	0.65–0.74

Note. M = Mean; SD = Standard Deviation. Values represent aggregated construct-level
Statistics.

Table 3 presents the means and standard deviations for the study constructs. Overall, respondents reported moderate-to-high technological, organizational, and environmental readiness. AI adoption at the organizational level was moderate, whereas perceived talent management effectiveness was generally high.

5.3 Measurement Model Assessment

The reflective measurement model demonstrated acceptable reliability and validity. All constructs exceeded recommended thresholds for internal consistency (Cronbach's α and composite reliability > .70) and convergent validity (AVE > .50). Discriminant validity was supported, with all HTMT values below .85.

Table 4

Reliability and Convergent Validity

Construct	α	CR	AVE
Technological Context	.91	.93	.74
Organizational Context	.89	.92	.70
Environmental Context	.84	.89	.61
AI Adoption	.87	.91	.63
Talent Management Effectiveness	.91	.93	.73

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

5.4 Structural Model Assessment

Table 5

Structural Model Quality Indicators

Criterion	Construct or Path	Value
Inner VIF	Environmental Context → AI Adoption	1.465
	Organizational Context → AI Adoption	2.138
	Technological Context → AI Adoption	2.060
	AI Adoption → Talent Management Effectiveness	2.623
	Environmental Context → Talent Management Effectiveness	1.509
	Organizational Context → Talent Management Effectiveness	2.623
	Technological Context → Talent Management Effectiveness	2.354
R^2	AI Adoption	.619
Adjusted R^2	AI Adoption	.610
R^2	Talent Management Effectiveness	.590
Adjusted R^2	Talent Management Effectiveness	.578

Criterion	Construct or Path	Value
f^2	Environmental Context → AI Adoption	.030
	Organizational Context → AI Adoption	.227
	Technological Context → AI Adoption	.142
	AI Adoption → Talent Management Effectiveness	.165
	Environmental Context → Talent Management Effectiveness	.039
	Organizational Context → Talent Management Effectiveness	.054
	Technological Context → Talent Management Effectiveness	.004

The model explained 61.9% of the variance in AI Adoption and 59.0% in Talent Management Effectiveness, indicating moderate explanatory power. Collinearity diagnostics (VIFs = 1.46–2.62) indicated no multicollinearity concerns. Organizational Context showed the strongest effect on AI Adoption (f^2 = .227), followed by Technological Context (f^2 = .142). Environmental Context had a small effect (f^2 = .030). AI Adoption demonstrated a moderate effect on Talent Management Effectiveness (f^2 = .165).

Note. VIF = variance inflation factor. f^2 values of .02, .15, and .35 generally indicate small, medium, and large effects, respectively.

5.5 Hypothesis Testing

Table 6
Direct Effects and Hypothesis Testing

Hypothesis	Path	β	SD	t	p	Decision
H1	Technological Context → AI Adoption	0.334	0.095	3.519	< .001	Supported
H2	Organizational Context → AI Adoption	0.43	0.081	5.317	< .001	Supported
H3	Environmental Context → AI Adoption	0.13	0.069	1.889	0.059	Not supported
H4	AI Adoption → Talent Management Effectiveness	0.421	0.102	4.122	< .001	Supported

Note. β = standardized path coefficient; SD = standard deviation from bootstrapping.

Table 6 summarizes indirect effects. AI Adoption fully mediated the relationship between Technological Context and Talent Management Effectiveness (β = .141, p = .013), supporting H5. Partial mediation was observed for Organizational Context (β = .181, p < .001; direct β = .240, p = .011), supporting H6. No mediation was found for Environmental Context (β = .055, p = .083), and H7 was not supported.

Table 7
Mediation Results: Bootstrapped Specific Indirect Effects and Mediation Testing

Hypothesis	Indirect Path	Indirect Effect (β)	*t*	*p*	Direct Effect (β)	*p*	Mediation Type	Decision

H5	Technological Context → AI Adoption → Talent Management Effectiveness	0.141	2.48	0.013	0.064	0.42	Full mediation	Supported
H6	Organizational Context → AI Adoption → Talent Management Effectiveness	0.181	3.41	< .001	0.24	0.01	Partial mediation	Supported
H7	Environmental Context → AI Adoption → Talent Management Effectiveness	0.055	1.74	0.083	0.156	0.05	No mediation	Not supported

*Note***.** Full mediation is indicated when the indirect effect is significant and the direct effect is not significant. Partial mediation is indicated when both the indirect and direct effects are significant.

5.6 Summary of Findings

Overall, results indicate that internal readiness factors (technological and organizational) significantly drive AI adoption, which in turn enhances perceived talent management effectiveness. Environmental factors did not significantly influence adoption in this sample.

6. Discussion

This study examined the extent to which technological, organizational, and environmental factors influence AI adoption in talent management and whether AI adoption, in turn, enhances perceived talent management effectiveness. The findings provide several important insights into how AI functions within HR contexts, particularly in emerging markets such as the Philippines.

First, the results confirm that technological and organizational contexts are significant predictors of AI adoption, supporting H1 and H2. Among these, organizational context emerged as the strongest driver. This suggests that internal readiness—particularly leadership support, innovation culture, and resource commitment—plays a more decisive role than technological availability alone. While organizations may possess adequate infrastructure, adoption is unlikely to occur without managerial alignment and strategic intent. This finding reinforces prior research emphasizing that AI value in HR is not derived from tools themselves but from how organizations enable and support their use (Cahyani & Musslifah, 2025; Pedrami & Vaezi, 2025).

In contrast, environmental context did not significantly influence AI adoption, leading to the rejection of H3. Although respondents reported strong industry trends and external pressures toward digitalization, these factors did not translate into actual adoption behavior. This suggests that external signals—such as competition or market expectations—may raise awareness but are insufficient to drive implementation in the absence of internal capability. This finding contributes to the literature by highlighting a gap between environmental pressure and organizational action, particularly in service-oriented and developing economy contexts.

Importantly, this finding reinforces the research gap identified in the introduction, that while AI technologies are increasingly available, their adoption and impact relies on internal organizational readiness rather than external environmental forces. This suggests that the gap between technological availability and organizational availability is not only present but also empirically validated in this study. While the research gap is formally positioned in the introduction, its implications become evident in the discussion through observed misalignment between external measures and actual adoption outcomes.

These findings can be interpreted through the AMO framework. AI adoption may enhance talent management effectiveness by improving ability through analytics, skills insights, and learning support; strengthening motivation through feedback and engagement mechanisms; and expanding opportunity through streamlined HR processes and wider access to talent information.

In this sense, AI does not automatically create performance outcomes; it enables the HR conditions through which employees and HR professionals can contribute more effectively.

Second, the study found that AI adoption positively influences talent management effectiveness, supporting H4. Organizations that reported higher levels of AI integration also reported stronger outcomes in recruitment, onboarding, performance management, and overall talent management practices. However, it is important to note that perceived effectiveness was already relatively high even at moderate levels of AI adoption. This suggests that while AI enhances effectiveness, it is not a prerequisite for achieving strong HR outcomes. Rather, AI appears to function as an augmenting capability, strengthening existing systems rather than replacing foundational HR practices.

The findings also suggest that AI adoption in talent management is not a one-size-fits-all solution. Organizations differ in their structure, culture, resource availability, and digital maturity, which influence how AI is implemented and utilized. The strong influence of organizational context observed in this study indicates that AI effectiveness depends on internal alignment, rather than standardized implementation. This implies that organizations must tailor AI adoption strategies to their specific operational needs, workforce capabilities, and cultural context, rather than adopting uniform or generic solutions.

The mediation analysis provides deeper insight into this mechanism. The finding of full mediation for technological context (H5) indicates that infrastructure and system readiness do not directly improve talent management outcomes. Instead, their value is realized only when translated into actual AI use. This reinforces the view that technological capability is an enabler rather than an outcome driver.

For organizational context (H6), partial mediation was observed, indicating that internal readiness contributes to talent management effectiveness both directly and indirectly through AI adoption. This suggests that strong HR leadership, employee capability, and organizational culture can independently improve outcomes even before AI is fully integrated. AI adoption then further amplifies these effects. This dual pathway highlights the central role of organizational factors in both traditional and technology-enabled HR performance.

In contrast, no mediation effect was found for environmental context (H7). This further supports the earlier finding that external pressures alone are insufficient to influence either adoption or effectiveness. Environmental factors appear to operate at a more distal level and require internal translation into organizational capabilities before they can impact outcomes.

An important emerging insight from the descriptive results is the disparity between high individual-level AI use and moderate organizational-level adoption. Respondents reported strong personal use of generative AI tools, yet organizational integration across talent management functions remained limited. This suggests a bottom-up pattern of AI diffusion, where individual experimentation precedes formal institutionalization. This finding aligns with recent literature on generative AI adoption, which highlights the growing role of employees as early adopters in the absence of formal organizational systems (Aguinis et al., 2024; Bujold et al., 2024).

Overall, the findings support the TOE framework but also refine it by demonstrating that not all contextual dimensions contribute equally to adoption and outcomes. Internal organizational readiness—particularly leadership support and capability development—emerges as the most critical factor. AI adoption, in turn, acts as a mechanism that translates readiness into enhanced talent management effectiveness.

More broadly, the study contributes to the ongoing debate on the role of AI in HR by demonstrating that AI is not strictly necessary for effective talent management but serves as a performance-enhancing capability. Organizations with strong HR foundations can achieve effective outcomes even with limited AI adoption, but those that successfully integrate AI may achieve incremental gains in efficiency, consistency, and decision quality.
These findings can be further interpreted through the AMO framework, where AI adoption enhances talent management effectiveness by improving employee ability through data-driven insights, strengthening motivation through feedback and engagement systems, and expanding opportunity by streamlining HR processes.

6.1 Additional Descriptive Insights on AI Adoption Patterns

In addition to construct-level descriptive statistics, the data revealed meaningful patterns in how AI-enabled tools are used across talent management functions and organizational roles. Recruitment and candidate screening emerged as the most AI-supported HR function, with the highest organizational-level adoption score (M1=2.99). This finding indicates that AI adoption in talent management is still in its early stages, concentrated primarily in front-end hiring processes rather than in more complex functions such as onboarding (M2=2.71), learning and development (M3=2.92), or performance management (M4= 2.82). These results align with global trends identifying recruitment as the earliest and most common entry point for AI in HR practice.

Interestingly, the strongest indicator of AI use was not organizational integration but individual-level AI use, particularly generative AI tools such as ChatGPT or Gemini (M6 = 3.47). This suggests that while organizational-level AI adoption remains moderate, HR professionals personally leverage AI tools to support their daily tasks. The difference between personal and organizational adoption may reflect early bottom-up experimentation that precedes formal system-level integration.

Role-based observations further support this interpretation. Because a substantial proportion of respondents were managers, supervisors, and senior leaders (approximately 51% combined), the elevated individual use score may indicate that AI experimentation is more prevalent among those in decision-making roles, who are more exposed to strategic tools and digital experimentation. This pattern reinforces the importance of organizational context—particularly leadership support and innovation culture, which had the highest scores within the Organizational Context construct.

Together, these descriptive insights clarify that AI adoption in Metro Manila organizations is characterized by moderate organizational integration, strong individual experimentation, and concentration in recruitment-related processes.

The pattern of high individual generative AI use alongside moderate organizational integration may be described as shadow AI or informal AI use. In this study, shadow AI refers to HR professionals using tools such as ChatGPT or Gemini for work-related talent management tasks on a personal level, even when the organization has not yet formally embedded AI into HR systems, policies, or governance structure. This is important because it reveals a bottom-up diffusion pattern: employees may already be realizing productivity gains, but organizations may not yet have sufficient controls for governance, privacy, bias, accuracy, accountability, or consistent HR practice. Therefore, shadow AI should be treated as an opportunity for capability-building and a governance risk requiring clearer guidelines, training, and responsible-use protocols.

7. Conclusion

This study investigated how technological, organizational, and environmental contexts influence AI adoption in talent management and whether AI adoption enhances perceived talent management effectiveness. Drawing on the T-O-E framework and a PLS-SEM analysis of HR professionals in Metro Manila, the findings yield three core conclusions.

First, internal readiness is decisive for AI adoption. Technological and, more strongly, organizational contexts significantly predict adoption, whereas environmental pressures do not. This indicates that leadership support, resource commitment, and an innovation-oriented culture are more critical than external trends in driving AI implementation in HR.

Second, AI adoption improves talent management effectiveness but is not a prerequisite for achieving it. Organizations report relatively strong talent management outcomes even at moderate levels of AI adoption, suggesting that AI functions as an augmenting capability–enhancing efficiency, consistency, and decision quality in already capable HR systems.

Third, AI adoption functions as the critical mechanism that converts organizational readiness into measurable talent management outcomes. It fully mediates the effect of technological context and partially mediates the effect of organizational context on talent management effectiveness, while no mediation is observed for environmental context. These results clarify that readiness conditions yield value primarily when converted into actual AI use within HR processes.

Overall, organizations do not need AI to achieve effective talent management; however, those that successfully adopt and integrate AI are better positioned to enhance talent management performance outcomes.

7.1 Theoretical Implications

The study extends the TOE framework by demonstrating unequal contributions technological, organizational, and environmental dimensions in an HR context, while specifying AI adoption as the key mechanism linking readiness to outcomes. By integrating AMO as a complementary HRM lens, the study also explains why AI adoption may improve TM effectiveness: AI strengthens the ability, motivation, and opportunity conditions through which HR systems support performance.

7.2 Practical Implications

For HR practitioners, the results indicate that investments in AI should be coupled with organizational readiness, particularly leadership alignment, capability development, process integration, and governance. Organizations may achieve meaningful gains from AI only when it is embedded into talent management workflows rather than deployed in isolated functions. Practically, this means redesigning HR roles away from manual tracking and data entry toward strategic partnership, employee advocacy, and evidence-based decision support.

For organizational leaders, the results suggest that organizations should prioritize internal capability development over merely responding to external trends. Before investing in expensive AI tools, leaders should assess whether the organization has aligned leadership, usable HR data, clear ownership, employee training, and responsible-use guidelines and governance. This is especially important because the study shows that organizational context is the strongest predictor of AI adoption

Strategic and Cost Implications of AI Adoption

Although adopting AI requires investment from organizations, including in talent management, studies suggest that these costs can be balanced by gains in efficiency, consistency, and better decision-making across HR functions. Costs associated with AI adoption may include software acquisition, employee training, process integration, governance development, and change management. However, AI-enabled systems may also reduce administrative workload, improve recruitment efficiency, support workforce planning, and enhance the consistency of HR decisions.

From a Resource-Based View (RBV) perspective, AI should not be seen simply as a technological tool, but as a strategic organizational capability whose value depends on supporting resources such as leadership support, employee skills, governance, and process integration. This is consistent with the study’s findings, which show that organizations with stronger internal readiness are more likely to benefit from AI adoption than those adopting AI mainly because of external pressure.

Table 8

Illustrative Cost–Benefit Considerations of AI Adoption in Talent Management

Potential Costs of AI Adoption	Potential Organizational Benefits
Software acquisition and licensing	Faster recruitment and candidate screening
Employee training and upskilling	Reduced administrative workload
Process integration and governance	Improved decision-making quality
Change management efforts	Enhanced consistency in HR processes
Data management and compliance requirements	Improved workforce planning and HR analytics

7.3 Limitations

This study is subject to several limitations. The use of non-probability (purposive and snowball) sampling limits statistical generalizability. The Metro Manila focus may also constrain applicability to other regions with different levels of digital maturity.

Measures are self-reported, which may introduce common method bias. In addition, the study was limited to HR professionals involved in HR or talent management functions, regardless of organizational rank or position level. As such, the findings reflect HR practitioners’ perceptions and may not fully represent the perspectives of employees or non-HR stakeholders within organizations.

Although industry-specific studies can yield deeper insights, this study did not limit its sample to a single industry due to the small number of AI-adopting firms within sectors such as fintech in the Philippines. Restricting the sample to one industry would have resulted in insufficient respondents (often only one HR professional per company). Future research may conduct industry-focused or multi-site studies once adoption levels increase.

7.4 Future Research

Future studies may employ probability or multi-site sampling across regions to improve generalizability, examine objective performance outcomes beyond perception-based measures, and investigate transition from individual to organizational AI adoption, particularly in the context of generative AI and agentic AI governance and integration would deepen understanding of emerging AI-driven HR capabilities.

Moreover, future research may incorporate organizational performance indicators and AI-related ROI measures to empirically assess the cost-effectiveness and strategic value of AI-enabled talent management systems. Industries such as ICT, BPO, or Healthcare, where AI adoption is more advanced, may also be considered as future research contexts to enable sector-level comparison.

Additionally, future research may integrate individual-level models such as Technology Acceptance Model (TAM) to explain how perceived usefulness and ease of use influence the adoption of AI tools by HR professionals, and how these individual behaviors scale into organization-wide AI integration.

Beyond operational and performance outcomes, the findings suggest the potential relevance of AI adoption in supporting broader sustainability and ESG (Environmental, Social, and Governance) objectives. While ESG outcomes were not directly measured in this study, the observed improvements in efficiency, consistency, and decision quality indicate that AI may contribute to governance-related outcomes such as transparency and objectivity in HR decision-making. The integration of AI in HRM must also be approached from a human-centered and ethical perspective. While AI enhances operational efficiency, it may also introduce concerns related to autonomy, fairness, and job security if not implemented responsibly. Thus, organizations must ensure transparency, inclusivity, and ethical governance in AI adoption to align with broader ESG and sustainability objectives (Croitoru et al., 2025).

In sum, the findings indicate that while AI can meaningfully enhance talent management effectiveness, its value depends on organizational readiness and actual use, rather than on the mere presence of technology.

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References to the work should follow the 7th APA style and carefully checked for accuracy and consistency. Please ensure that every reference cited in the text is also present in the reference list and vice versa.

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