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AI Adoption Determinants and Its Impacts on HRM Effectiveness within MES in Tanzania

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Abstract

This study intends to explore the determinants of AI adoption and its impact on HRM effectiveness in Tanzanian medium enterprises (MEs). With a focus on providing insights for HR professionals and decision-makers, data from 185 respondents comprising HR professionals, IT professionals, and CEOs who have already adopted AI was analyzed using PLS-SEM, where factors of Relative advantage, Complexity, Compatibility, Security/Privacy, Top management, Organisation readiness, Competitive pressure, External support and Government support were tested to the adoption of AI. Results highlight relative advantage, compatibility, and competitive pressure as key drivers of AI adoption in Tanzania's context, subsequently enhancing HR systems' effectiveness. The study bridges the existing gaps and offers recommendations for AI integration into HRM practices. Implications for managers and solution providers were discussed to facilitate a better understanding of the determinants influencing the adoption process within Tanzanian MEs. The study underlies the theoretical understanding of AI adoption by utilizing the TOE model and incorporating technological, organizational, and environmental factors. This study recommends future exploration of additional factors and including a larger sample to enhance the universality of the results.

Keywords

AI Adoption, Human Resource Management, TOE Model, HRM Effectiveness, Medium Enterprises, Tanzania

1. Introduction

The evolution of HRM roles has shifted from traditional administrative functions to strategic activities such as manpower planning and performance management (Fenwick et al., 2024). AI has revolutionized HR practices, enabling more advanced and efficient processes (Basnet, 2024). AI adoption in HR departments has the ability to meaningfully impact business outcomes and employee management, leading to a new era of data-driven and strategic HR practices (Dhamija & Bag, 2020). By 2022, the Global Business Forum expects that AI would displace 75 million employment opportunities, yet generate 133 million new employment opportunities (Satell, 2019). (Hossin et al., 2021) suggested that AI-driven HR strategies can significantly enhance employee productivity, recruitment, training, and retention, ultimately contributing to a transition. In Tanzania, medium enterprises perform as an important part in the economy, accounting for approximately 90% of all registered businesses and employing over 70% of the workforce (International Finance Corporation, 2022). A recent research by the World Economic Forum (WEF) anticipates that AI might contribute up to 2.9% of Tanzania's GDP by 2030 (World Economic Forum, 2020).

This research is expected to improve researchers' experience and knowledge in writing scientific papers and understanding AI adaptation in HR within medium enterprises, specifically through the exclusive use of the TOE model. This provides a valuable methodological framework for studying technological adoptions in specific contexts, particularly in developing economies like Tanzania. Also, the findings can aid the Tanzanian community by guiding companies and governments in making informed decisions, fostering responsible AI integration, boosting local business efficiency, and promoting economic growth and job opportunities. Additionally, HR managers will gain insights into improving HRM procedures through AI adoption, optimizing HR practices, and enhancing organizational performance through better talent acquisition, streamlined operations, and informed decision-making.

There are some literature review which relates to the adoption of technology that needs to be developed that includes, a study by (Kshetri, 2020) with the heading "*Evolving uses of artificial intelligence in human resource management in emerging economies in the global South: some preliminary evidence*", the study of (Goswami et al., 2023) "*Exploring the antecedents of AI adoption for effective HRM practices in the Indian pharmaceutical sector*", the study of (Qahtani & Alsmairat, 2023) "*Assisting artificial intelligence adoption drivers in human resources management*" and the study of (Singh & Pandey, 2024) "*Artificial intelligence adoption in extended HR ecosystems: enablers and barriers. An abductive case research*". All these studies are more based in HRM as a whole without looking the side of medium enterprises in developing country which might help the decision makers and other researchers to know the level of adoption of technologies in this area.

The research problem addressed in this study focuses on determining the factors considered by Tanzanian medium enterprises to the adoption of AI within HRM and if the management perceives the effectiveness of the adoption in HR activities. The study aims to fill the research gap by analyzing the interplay of technological readiness, organizational dynamics, and external environmental influences during the adoption. Additionally, the study aims to conclude with specific factors and recommendations to enhance HRM processes through the effective use of AI technologies.

2. Literature Review and Hypothesis Development

2.1. Theoretical Background

The study includes an examination of technology adoption models such as the Technology Acceptance Model (TAM) which emphasizes the significance of perceived ease of use and perceived usefulness in determining an individual's attitude and intention to use a particular technology, the Theory of Reasoned Action (TRA) by (Ajzen & Fishbein, 1980) focuses on the initial acceptance of new products, considering the role of individual attitudes and subjective norms in predicting behavioral intentions, The Technology Organization Environment Model (TOE) by (Tornatzky & Fleischer, 1990) underscores the influence of technological, organizational, and environmental factors on technology adoption within organizations. The Innovation Diffusion Theory (IDT) is also highlighted, emphasizing the spread of new ideas, products, or technologies within a social system and identifying different adopter categories and factors influencing the rate of adoption by (Rogers, 1985). By considering Tanzanian context of the level of technology adopted and other researchers such as AI within HRM (Kaur et al., 2021) adaptation of BA (Horani et al., 2023), adoption of technology (Kumar et al., 2022), adoption of mobile banking in SMEs (Mujahed et al., 2021), big data adoption. (Agarwal, 2022) described TOE as a "generic" theory applicable to analyzing elements impacting AI adoption in HRM, emphasizing its relevance in assessing how technology take place in fulfilling HR responsibilities.

2.2. Research Model

This study proposes a framework rooted in the TOE model to explore determinants to AI adoption in HRM within MEs since it's more based on dimensions within Organization, Technology and Environmental factors. The findings of this research study provide useful perspectives into the determinants of AI adoption and its impact on HRM effectiveness in medium-sized enterprises in Tanzania. The supported hypotheses highlight the benefits of relative advantage, compatibility, competitive pressure in the adoption of AI and it shows the valuable impact of adopting and implementing AI in stimulating HRM effectiveness (as shown in **Figure 1**).

Relative Advantage and Artificial Intelligence.

It refers towards the acknowledged superiority of a technology in comparison to other current company innovations, as well as the expected advantages, such as operation (Kurup & Gupta, 2022). Adopting new technologies might fail due to perceived complexity and difficulty (Almaiah et al., 2022). (Boonsiritomachai et al., 2016) indicates that technological adoption begins with relative advantage and companies that see technologies as superior to their current procedures and processes are more likely to implement it effectively. Hence,

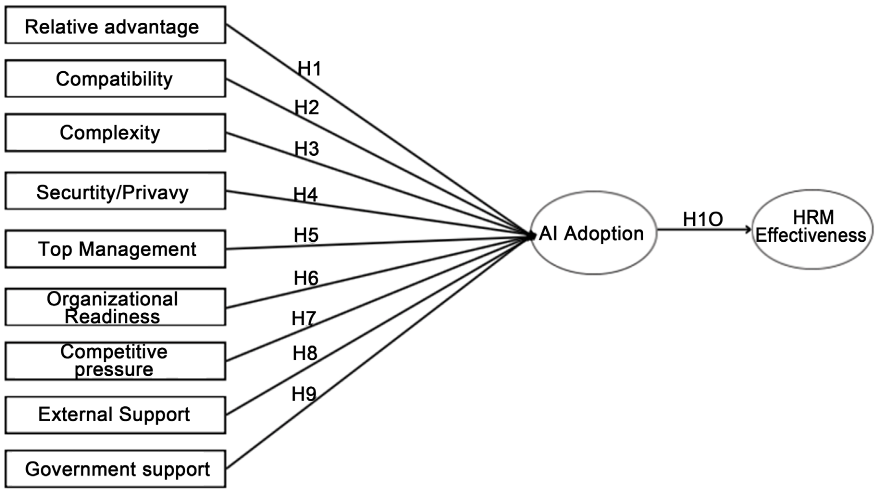

Figure 1. Research model frame work.

H1. Organization factor of Relative advantage influence the adoption of AI.

Compatibility and Artificial Intelligence.

It is a degree of consistency with the firm's present state which may be measured based on the firm's innovation adoption. Compatibility is a key factor in driving technology adoption and influencing AI decision-making and organizations may improve their procedures and policies to promote favorable compatibility and AI adoption (Chong & Lim, 2022). Compatibility increases the option AI advancement and adoption (Neumann et al., 2022). Factors related to compatibility include technical compatibility and commitment (Jöhnk et al., 2021). Aligning AI technologies with technological systems can help organizations leverage new technology and reduce uncertainty in the HR function regarding its adoption (Gangwar, 2018). Hence,

H2. Organization factor of Compatibility influence the adoption of AI.

Complexity and Artificial Intelligence.

Complexity discusses the degree of difficulties, challenges and risks that HRM face in adopting and implementing AI technologies (Jöhnk et al., 2021). Successful AI adoption requires coordinated activities and simplicity of technological functions across the organization towards AI implementation (Xu et al., 2023). The flexibility of utilizing a system is connected to its applicability or accessibility, as a result, the ease in which technology can be implemented and used will encourage the company to adopt it. Complexity in technology adoption may be measured by job completion time, process integration, data processing efficiency, system functionality, and interface design. Factors such as the use of technology and automation in HRM might impact the outcome (Almaiah et al., 2022). Hence,

H3. Organization factor of Complexity influence the adoption of AI.

Security and Privacy and Artificial Intelligence.

The perceived risk of using technology for work and data transmission (Jöhnk et al., 2021). Technology adoption relies heavily on security and privacy considerations. Yabanci (2019) indicates that adopting technology raises concerns regarding security and privacy, particularly with regard to the potential risks to confidentiality, trustworthiness, and accessibility in human-computer interaction. These reflect the level in where AI is considered to be not safe for conducting work and exchange (Kaur et al., 2021). Hence,

H4. Organization factor of Security/Privacy directly influence the adoption of AI.

Top Management and Artificial Intelligence.

This is very vital for the effective implementation of AI in HRM. It is critical in implementing any significant change to an organization (Lutfi et al., 2022). Support from top management is evident in the way they assess and frame the importance of technological innovation in creating value for businesses. In order to handle change-related obstacles and any opposition to the implementation of new technologies, this support guarantees the commitment of resources and fosters a constructive environment. The implementation of technologies in HRM requires the backing of upper management. Hence,

H5. Technology factor of Top management support directly influence the adoption of AI.

Organization Readiness and Artificial Intelligence.

This includes processes, structures, and resources that encourage the use of technology, including automation and AI (Alam et al., 2016). In an organization, HR professional's should conduct an assessment of how ready they think the organization is in terms of the level of knowledge, loyalty, resource allocation and successful implementation of adopting a technology (Chong & Lim, 2022). To be efficiently deployed in enterprises, AI in HRM requires effective infrastructure, the necessary HRM knowledge, and financial allocation of resources (Pillai & Sivathanu, 2020). Organizational technological preparation is thought to influence technology implementation. In order for businesses to use AI to enhance their HRM process, they must retrain and restructure their staff. Hence,

H6. Technology factor of Organization Readiness directly influence the adoption of AI.

Competitive Pressure and Artificial Intelligence.

It discusses the perceived pressure a company feels from its competitors (Almaiah et al., 2022). Businesses must assess, derive lessons from past experiences, and come up with creative solutions to challenging issues in the global economy (Shet et al., 2021). More efficient and economical use of resources can lead to better human resource management (Bhatiasevi & Naglis, 2018). Market competition pushes firms to implement human resource technologies (Alam et al., 2016). When several firms adopt different AI systems in their HRM activities, they gain a strategic advantage over their competitors. This creates pressure and compels the corporation to adopt the technical upgrade (Nguyen et al., 2022). Hence,

H7. Environmental factors of Competitive pressure directly influence the adoption of AI.

External Support and Artificial Intelligence.

Third parties provide guidance for business enterprises in adopting technology solutions including consulting, training and technical assistance in overcoming problems related to the adoption of new technology (Horani et al., 2023). Since AI is termed as a relatively new product, the positive involvement of AI suppliers throughout the introduction process is an important element affecting its acceptance (Malik et al., 2021). For soft adoption, the supplier is expected to offer everything needed throughout every stage, including training and post-implementation assistance (Singh & Pandey, 2024). Depending on the organization's unique demands, the HRM function may need a supplier to create and implement customized AI solutions. Hence,

H8. Environmental factors of external support directly influence the adoption of AI.

Government Support and Artificial Intelligence.

Government rules and regulations, such as motivations, technical requirements, and legislation, may alternatively promote or restrict technology adoption (Horani et al., 2023). Government restrictions may encourage or prevent firms from implementing technology breakthroughs (Dincbas et al., 2021). Financial assistance, necessary tools, and tax incentives can all help to encourage adoption (Chong & Olese, 2017). Hence,

H9. Environmental factors of Government support directly influence the adoption of AI.

Artificial Intelligence and HRM effectiveness.

The implementation of AI presents the field of HRM with a number of advantages and prospects (Agarwal, 2022). AI can increase satisfaction with work and retention rates, quicken hiring, enhance onboarding for staff, and offer individualized opportunities for professional growth (Meister, 2023). Through the analysis of several variables including job happiness, work-life balance, and career advancement, AI can also assist HR managers in creating strategies that will effectively draw in and keep top applicants (Visier, 2013). AI can give HR directors insight into the knowledge and abilities that will be in high demand, enabling them to plan ahead for their hiring needs (Visier, 2013). However, HR professionals must be conscious about some of the weaknesses of using AI in HR, such as AI bias during the hiring process, which can lead to major consequences (Heinze, 2023).

H10. The Artificial intelligence adoption has a significant impact on effective HRM in the medium enterprises in Tanzania.

3. Methodology

3.1. Research Variables Measurements

To create a questionnaire aligned with hypotheses, the study referred to relevant questionnaire from different literatures, which is presented in **Table 1** including name of the variables, item of measurement from questionnaire, and corresponding references.

Table 1. Research variable measurement.

Variables	Items	Source
Relative Advantage (RA)	RA 1. AI adoption in HRM improves the quality of work	(Wael Al-Khatib, 2023)
	RA 2. AI adoption in HRM makes work more efficient	
	RA 3. Adoption of AI in HRM helps in lowering costs	(Lutfi et al., 2022)
	RA 4. AI Adoption attracts and expands new HRM services to employees	
Compatibility (CB)	CB 1. AI adoption in HRM is consistent with our organization's practices	(Lutfi et al., 2022)
	CB 2. AI adoption in HRM fits with our organizational culture	
	CB 3. It easy to incorporate AI into our HRM practices	
Complexity (CO)	CO 1 Learning to use AI tools in HRM is difficult for our employees	(Lutfi et al., 2022)
	CO 2. AI tools in HRM and technologies are high to maintain	
	CO 3. AI tools in HRM is difficult to operate	
Security/Privacy (SP)	SP 1 AI adoption in HRM create concerns regarding data security and privacy	(Lutfi et al., 2022)
	SP 2. Implementing AI in HRM creates vulnerability in access control of the organization's information assets	
	SP 3. Implementation of AI in HRM create risks through excessive dependency on external vendors (AI tools developers)	
	SP 4. Implementation of AI in HRM complicate the process of adhering to corporate policies in protecting individual privacy and data security	
Top Management (TM)	TM 1. Our Top management promotes the use of AI in our HR department	(Lutfi et al., 2022)
	TM 2. Our top management creates support for AI adoption within the organization	
	TM 3. Our top management promotes AI adaption as a strategic priority in our HR department	
	TM 4. Our top management is interested in the news about AI adoption specifically in HRM	
Organization Readiness (OR)	OR 1. Lacking financial resources has prevented our organization from fully adopting AI in HRM	(Lutfi et al., 2022)
	OR 2. Lacking needed IT infrastructures has prevented our organization from adopting AI	
	OR 3. Lacking skilled resources/labor prevent our organization fully exploit AI	
Competitive Pressure (CP)	CP 1. Our choice to adopt AI in HRM would be strongly influenced by what competitors in the industry are doing	(Lutfi et al., 2022)
	CP 2. Our organization is under pressure from competitors to adopt AI in HRM	
	CP 3. Our organization would adopt AI in response to what competitors are doing	
External Support (ES)	ES 1. Community agencies/vendors/AI tools developers can provide required training for AI adoption in our HR department	
	ES 2. Community agencies/vendors/AI tools developers can provide Effective technical support for AI adoption in our HR department	(Maroufkhani et al., 2022)

Continued

	ES 3. Community agencies/vendors/AI tools developers actively market AI adoption in our HR department	
Government Support (GS)	GS 1. The government policies encourage us to adopt new information technology especially in HRM GS 2. The government provides incentives for adopting AI such as offering technical support, training and funding for AI technologies GS 3. There are some laws and regulations to deal with the security and privacy concerns over the AI technologies	(Lutfi et al., 2022) (Maroufkhani et al., 2022)
AI adoption	AI 2. Our organization has already adopted AI in HR department AI 3. AI adoption encourages the integration of HR practices with other functions	(Wael Al-Khatib, 2023) (Agarwal, 2022)
Effective HRM	EHRM 1. AI enhances the operational efficiency of HR functions EHRM 2. AI improves the candidate experiences during recruitment, onboarding and offboarding EHRM 3.AI improves overall employee experience in the company	(Agarwal, 2022)

Source: Author's analysis.

3.2. Research Method

A structured questionnaire survey in English was utilized to examine the hypothesized connection indicated in the model as **Figure 1** indicates. It intends to evaluate the determinants of AI adoption in HRM within Tanzanian MEs and its impacts on effective HRM. The total number of respondents of this study is based on (Hair et al., 2013) calculation, which is 5 - 10 times the number of questionnaire items. The number of items included in this research questionnaire was 37 items, this study chose the multiplication of 5, so the required population is 37 items × 5 = 185 respondents includes both HR Profesionals IT profesionals and CEO from different sectors. The questionnaire incorporated a Likert scale, specifically utilizing a 5 point scale (1 "strongly disagree" to 5 "strongly agree") (Goswami et al., 2023). For the accuracy of data collection, the study collects 200 total number of respondents, in where after the deletion of incomplete questionnaires only remain with 185 respondents. To assess the response rate, the study, calculated the percentage of people who completed and returned the questionnaire out of the total number of people contacted which is the number of completed questionnaires (185)/Number of contacted people (200) × 100 where the total response rate was 92.5% which is efficient according to (Fowler Jr., 2009).

3.3. Unit of Analysis, Population and Sampling Technique

This study is based on the individual who belongs to a group specifically, human resource professionals, IT professionals and CEOs from medium enterprises. According to (Sekaran & Bougie, 2016), the unit of analysis can be at the individual, dyad, and group levels. The present study comprises a diverse population of the HR, IT managers and CEOs. The sample in this study was taken from different sectors in the category of medium enterprises which are categorized by considering the number of employees starting from 50 - 99 (Ministry of Industry and Trade, 2003). The sample is part of the total population selected for research, and the researcher can draw/generalize conclusions about the entire population, so the sample must represent the population (Tabachnick et al., 2013). It must be considered that there are two aspects determined in the sample: the number of samples (sampling size) and the sampling technique. The number of samples in this study is based on (Hair et al., 2013) calculation, which is 5 - 10 times the number of questionnaire items. Number of items in this study questionnaire was 37 items. The technique of sampling for the present study applied purposive and convenience sampling rather than probability sampling (Cooper & Schindler, 2014), Purposive sampling aims to discover information-rich scenarios that can give the most useful information for achieving the study's goals which divides the population into strata depending on important factors such as experience, (Campbell et al., 2020).

3.4. Data Analysis Technique

In the hypothesis testing phase of research, inferential statistical analysis plays a crucial role (Sekaran & Roger, 2016). In the context of this study, inferential analysis is conducted using Structural Equation Modeling (SEM)-PLS with the assistance of SmartPLS 4 software. Evaluating PLS-SEM involves assessing the outer model, inner model, and hypothesis testing, as outlined by (Maroufkhani et al., 2022).

For the outer model, reflective model evaluation includes criteria such as indicator reliability, discriminant validity, and internal consistency. Indicator reliability is assessed with outer loadings ideally between 0.4 and 0.7. Indicators within this range may be considered for removal if their deletion improves composite reliability or average variance extracted (AVE) above the threshold, though their contribution to content validity must also be considered (Hair et al., 2014). Discriminant validity ensures that indicators of a construct are not highly correlated with those of other constructs. This is evaluated through cross-loading tests and the Fornell-Larcker criterion, where indicators should load higher on their respective latent variable than on others, and each construct's AVE should ideally exceed its correlations with other latent variables (Agarwal, 2022). Internal consistency is tested using composite reliability and Cronbach's alpha, with a preferred composite reliability limit of 0.6 (Hair et al., 2019). Composite reliability does not assume equal weighting for each indicator, whereas Cronbach's alpha does (Hair et al., 2014; Hair et al., 2011). These criteria ensure the robustness and validity of the PLS-SEM analysis in hypothesis testing within HRM research contexts.

In the inner model analysis, the focus is on the accuracy of the structural model. Multicollinearity is assessed using the Variance Inflation Factor (VIF) with a low Tolerance value (below 0.10) or a high VIF value (above 10) indicating problematic multicollinearity. The coefficient of determination (R^2) measures the extent to which an exogenous construct explains an endogenous construct, with higher R^2 values indicating a stronger model. Path coefficient values range from −1 to +1, indicating the strength and direction of relationships between constructs, with values closer to +1 denoting strong positive relationships and values closer to −1 indicating strong negative relationships (Maroufkhani et al., 2022). These metrics, along with additional criteria, are essential for evaluating the overall structural integrity and explanatory capacity of the model, ensuring its reliability and validity in HRM research.

4. Results

4.1. Demographic Results

The 200 responses were received from different sectors including Manufacturing, food processing, Mining, Agriculture, Education, Financial, Entertainment, Hospitality, Health, Law aid, ICT and Turism sector. After the elimination of incomplete and invalid questionnaires, only 185 responses were finalized for data analysis. **Table 2** shows the demographic results.

Table 2. Demographic results.

Gender	Female	Male	
	54	131	
Age			
20 - 30	111		
31- 40	50		
41 - 60	24		
Education		**Job tittle**	
Certificate	9	HR professionals	104
Diploma	28	IT professionals	54
Bachelor	94	CEO	27
Masters	49		
Ph.D.	5		

Source: Author's analysis.

4.2. Measurement Model

In the evaluation of the results derived from the PLS SEM, the initial phase includes investigating of the measurement model as suggested by (Hair et al., 2014). It involves a thorough examination of the indicator reliability (Hair et al., 2013). The reliability of an item is confirmed by factor loadings that exceed 0.5, which also implies that the construct explains 50% of the variance (Hair et al., 2014). In the context of this study, all item loadings are above the threshold, thereby, confirm item reliability (**Table 3**).

Table 3. Factor loading for variables.

Variables	Items	Factor Loading
Relative Advantage (RA)	RA 1. AI adoption in HRM improves the quality of work RA 2. AI adoption in HRM makes work more efficient	0.839
	RA 3. Adoption of AI in HRM helps in lowering costs	0.773
	RA 4. AI Adoption attracts and expands new HRM services to employees	0.866
Compatibility (CB)	CB 1. AI adoption in HRM is consistent with our organization's practices	0.874
	CB 2. AI adoption in HRM fits with our organizational culture	0.861
	CB 3. It easy to incorporate AI into our HRM practices.	0.847
Complexity (CO)	CO 1 Learning to use AI tools in HRM is difficult for our employees	0.864
	CO 2. AI tools in HRM and technologies are high to maintain	0.877
	CO 3. AI tools in HRM is difficult to operate	0.855
Security/Privacy (SP)	SP 1 AI adoption in HRM create concerns regarding data security and privacy	0.83
	SP 2. Implementing AI in HRM creates vulnerability in access control of the organization's information assets	0.866
	SP 3. Implementation of AI in HRM create risks through excessive dependency on external vendors (AI tools developers)	0.811
	SP 4. Implementation of AI in HRM complicate the process of adhering to corporate policies in protecting individual privacy and data security	0.825
Top Management (TM)	TM 1. Our Top management promotes the use of AI in our HR department	0.916
	TM 2. Our top management creates support for AI adoption within the organization	0.91
	TM 3. Our top management promotes AI adaption as a strategic priority in our HR department	0.902
	TM 4. Our top management is interested in the news about AI adoption specifically in HRM	0.903
Organization Readiness (OR)	OR 1. Lacking financial resources has prevented our organization from fully adopting AI in HRM	0.863
	OR 2. Lacking needed IT infrastructures has prevented our organization from adopting AI	0.892
	OR 3. Lacking skilled resources/labor prevent our organization fully exploit AI	0.924
Competitive Pressure (CP)	CP 1. Our choice to adopt AI in HRM would be strongly influenced by what competitors in the industry are doing	0.852
	CP 2. Our organization is under pressure from competitors to adopt AI in HRM	0.833
	CP 3. Our organization would adopt AI in response to what competitors are doing	0.911
External Support (ES)	ES 1. Community agencies/vendors/AI tools developers can provide required training for AI adoption in our HR department	0.874
	ES 2. Community agencies/vendors/AI tools developers can provide Effective technical support for AI adoption in our HR department	0.923
	ES 3. Community agencies/vendors/AI tools developers actively market AI adoption in our HR department	0.835

Continued

Government Support (GS)	GS 1. The government policies encourage us to adopt new information technology especially in HRM	0.812
	GS 2. The government provides incentives for adopting AI such as offering technical support, training and funding for AI technologies	0.856
	GS 3. There are some laws and regulations to deal with the security and privacy concerns over the AI technologies	0.831
AI adoption	AI 2. Our organization has already adopted AI in HR department	0.908
	AI 3. AI adoption encourages the integration of HR practices with other functions	0.916
Effective HRM	EHRM 1. AI enhances the operational efficiency of HR functions	0.876
	EHRM 2. AI improves the candidate experiences during recruitment, onboarding and offboarding	0.9
	EHRM 3. AI improves overall employee experience in the company	0.856

Source: Author's analysis.

4.3. Discriminant Validity

Positioning The discriminant validity assessment aims to determine whether the indicators of a construct exhibit low correlation with indicators from other constructs (Hair et al., 2019). This evaluation was conducted using two methods namely Heterotrait–Monotrait (HTMT) criterion and Fornell-Larcker criterion. HTMT is a comparison of the mean of the heterotrait-heteromethod correlations to the geometric mean of the monotrait-heteromethod and monotrait-monomethod correlations, In terms of acceptance criteria, an HTMT value of less than 0.85 is generally considered to indicate adequate discriminant validity (Agarwal, 2022) as **Table 4**.

Table 4. Discriminant validity test (HTMT).

	AI	CB	CO	CP	EHRM	ES	GS	OR	RA	SP	TM
AI											
CB	0.728										
CO	0.420	0.673									
CP	0.613	0.671	0.604								
EHRM	0.645	0.740	0.504	0.647							
ES	0.545	0.597	0.597	0.770	0.647						
GS	0.567	0.685	0.679	0.730	0.754	0.658					
OR	0.381	0.558	0.710	0.716	0.561	0.613	0.672				
RA	0.823	0.879	0.537	0.694	0.691	0.617	0.644	0.500			
SP	0.456	0.634	0.773	0.628	0.643	0.608	0.646	0.733	0.618		
TM	0.51	0.688	0.557	0.726	0.685	0.618	0.744	0.571	0.657	0.683	

Source: Author's analysis.

The subsequent discriminant validity valuation employs the Fornell-Larcker measure, which involves comparing the Average Variance Extracted (AVE) values with the relationship between constructs. This comparison is depicted in **Table 5**. According to the Fornell-Larcker criterion, each latent variable's AVE value should exceed the correlations with other latent variables, ensuring discriminant validity.

Table 5. Discriminant validity results with Forner Larcker.

	AI	CB	CO	CP	EHRM	ES	GS	OR	RA	SP	TM
AI	0.912										
CB	0.595	0.861									
CO	0.350	0.567	0.866								
CP	0.512	0.562	0.500	0.866							
EHRM	0.534	0.624	0.428	0.551	0.877						
ES	0.456	0.507	0.503	0.647	0.550	0.878					
GS	0.450	0.552	0.553	0.582	0.620	0.698	0.833				
OR	0.325	0.478	0.605	0.611	0.491	0.528	0.551	0.893			
RA	0.693	0.748	0.463	0.591	0.594	0.532	0.537	0.436	0.836		
SP	0.385	0.536	0.651	0.525	0.561	0.518	0.539	0.627	0.541	0.833	
TM	0.441	0.604	0.496	0.705	0.614	0.550	0.634	0.514	0.590	0.618	0.908

Source: Author's analysis.

4.4. Construct Reliability

Positioning the following step in the assessment of internal consistency reliability is the calculation of composite reliability, with the acceptance threshold set between 0.6 and 0.7. The current study exhibits Composite Reliability (CR) values that range from 0.949 to 0.872, thereby indicating a high degree of reliability as suggested by (Hair et al., 2011). Furthermore, Cronbach's alpha, another measure of composite reliability, is employed to measure the internal consistency of the constructs utilized. The acceptable level for Cronbach's alpha is set at 0.7 (Hair et al., 2019). As per **Table 3**, all constructs have higher Cronbach's alphas that exceed the 0.7 level, thereby implying that these measures possess high reliability and are suitable for measuring each of the stated constructs.

Additionally, the following step in the evaluation of the measurement model is the assessment of the convergent reliability of each construct measure (Hair et al., 2019). The convergent validity can be assessed using the Average Variance Extracted (AVE) value, which indicates a high correlation between the items and the factor, and confirms their belonging to the construct. The minimum acceptable level for AVE is set at 0.5 (Hair et al., 2011; Agarwal, 2022). As per **Table 6**, all constructs formed in this study have high AVE values that exceed 0.5, thereby indicating that the construct elucidates at least 50% of the variance of its items.

Table 6. Construct reliability.

Variables	Cronbach's alpha	Composite Reliability	Average variance extracted (AVE)
Technological factors			
Relative Advantage (RA)	0.857	0.902	0.698
Compatibility (CB)	0.825	0.895	0.741
Complexity (CO)	0.835	0.900	0.749
Security/Privacy (SP)	0.855	0.901	0.694
Organizational factors			
Top Management (TM)	0.929	0.949	0.824
Organization Readiness (OR)	0.875	0.922	0.798
Environmental factors			
Competitive Pressure (CP)	0.835	0.900	0.750
External Support (ES)	0.852	0.910	0.771
Government Support (GS)	0.780	0.872	0.694
Dependent variables			
Artificial Intelligence (AI)	0.798	0.908	0.832
Effective Human Resource Management	0.851	0.909	0.770

Source: Author's analysis.

4.5. Structural Model

After confirming the adequacy of the measurement model, the study evaluates the structural model which encompasses several key metrics, including the coefficient of determination (R square), and their statistical significance, as outlined by (Hair et al., 2019). The outcomes of these assessments are detailed in Table 7 and Table 8. The model demonstrates no collinearity, as evidenced by Variance Inflation Factor (VIF) values under 3 (Agarwal, 2022). The model also displays a respectable predictive capability, with an R-square value nearing 0.5, which is perceived moderately high by (Hair et al., 2011).

Table 7. Coloniality Statistics (VIF).

	AI	CB	CO	CP	EHRM	ES	GS	OR	RA	SP	TM
AI					1.000						
CB	2.785										
CO	2.219										
CP	2.868										
EHRM											
ES	2.433										
GS	2.568										

Continued

OR	2.228
RA	2.681
SP	2.489
TM	2.783

Source: Author's analysis.

Table 8. R square.

	R-square
AI	0.516
EHRM	0.585

Source: Author's analysis.

4.6. Hypothesis Testing

Table 9 shows hypothesis testing results of this study based on the t values and p values that was obtained after the calculation.

Table 9. Hypothesis testing.

Hypothesis	t values	*p* values	Decisions
H1 Relative Advantage -> AI	5.043	0.000***	Supported
H2 Compatibility -> AI	2.122	0.034**	Supported
H3 Complexity -> AI	0.463	0.643	Rejected
H4 Security/Privacy -> AI	0.071	0.944	Rejected
H5 Top Management -> AI	1.087	0.277	Rejected
H6 Organization Readiness -> AI	0.945	0.345	Rejected
H7 Competitive Pressure -> AI	1.678	0.093*	Supported
H8 External Support -> AI	0.471	0.638	Rejected
H9 Government Support -> AI	0.629	0.529	Rejected
H10 Artificial Intelligence -> EHRM	8.156	0.000***	Supported

Source: Author's analysis. Note: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$ (two tailed test).

5. Discussion

The study utilized the TOE model to examine the determinants of AI adoption in HRM. The hypothesis test results indicate that several factors significantly influence the adoption of AI in HRM in MEs in Tanzania. First hypothesis (H1) suggested that the organization factor of Relative advantage influences the adoption of AI which indicates a significant influence. This aligns with the conclusions of (Sharma et al., 2024); (Almaiah et al., 2022) and (Na et al., 2022) who argued The relative advantage is a strong determinant of technological adoption, So it generally implies that Tanzanian enterprises that perceive a relative advantage in using AI are more likely to adopt it.

The second hypothesis (H2) proposed that the organization factor of Compatibility influences the adoption of AI, suggesting that the compatibility of AI with existing systems and processes is a key determinant of its adoption. This is consistent with the work of (Tuffaha & Perello-Marin, 2022) and (Park & Kim, 2019) who found that compatibility is a substantial factor in the implementations of innovations and technologies in different fields. Therefore, AI technologies that align with the existing operations of Tanzanian enterprises are more likely to be adopted.

The seventh hypothesis (H7) posited that environmental factors of Competitive pressure directly influence the adoption of AI, indicating that competitive pressures can drive AI adoption. This finding supports the work of (Alam et al., 2016) and (Yoon Kin Tong & Sivanand, 2005) who found that competitive pressure is a significant driver of technology adoption. It suggests that Tanzanian enterprises facing significant competitive pressure may turn to AI to obtain a competitive advantage.

Tenth hypothesis (H10) proposed that the adoption of AI has substantial influences on effective HRM in medium enterprises in Tanzania, indicating a significant positive impact of AI adoption on HRM effectiveness. This supports the work of (Goswami et al., 2023); (Wamba-Taguimdje et al., 2020) and (Anderson & Johnson, 2017) who found that AI can significantly enhance HRM effectiveness by automating routine tasks and enabling strategic decision-making. (Agarwal, 2022) found that AI may improve HRM effectiveness by automating regular processes and allowing data-driven decision-making. So, this suggests that Tanzanian enterprises that adopt AI can improve their HRM effectiveness which may stimulate productivity.

However, not all hypotheses were supported. Hypotheses H3, H4, H5, H6, H8, and H9 were not supported, indicating that factors Complexity, Security/Privacy, Top management support, Organization Readiness, external support, and Government support may not directly impact the adoption of AI. Reasons for the rejection of technological factor of Organizational readiness in the Tanzanian context may consider factors such as limited access to advanced technology infrastructure, lack of technical expertise, and inadequate resources for implementing AI systems (Strusani & Houngbonon, 2019). For the rejection of organizational factor of Security/Privacy could be attributed to various factors, including concerns about data privacy and security, lack of awareness about AI-related security measures, and limited resources for implementing robust security measures within a company (Holl et al., 2024). Additionally the rejection of external support factors might be caused by the restricted accessibility to affordable financing (Croucher et al., 2013) which can hinder the adoption of AI, as it requires significant investment and resources. Furthermore, the lack of a developed entrepreneurial ecosystem in Tanzania, as highlighted by (Jeje, 2022), can also limit the availability of external support and resources for MSEs to adopt AI.

6. Conclusion

In conclusion, the findings of this research study provide useful perspectives into the determinants of AI adoption and its impact on HRM effectiveness in medium-sized enterprises in Tanzania. The supported hypotheses highlight the benefits of relative advantage, compatibility, competitive pressure in the adoption of AI and it shows the valuable impact of adopting and implementing AI in stimulating HRM effectiveness. Since the research was conducted specifically in the context of MEs in Tanzania, the findings may not be applicable and generalizable to different circumstances or organization sizes. This study recommends future exploring of additional factors and including a larger sample to enhance the universality of results. Additionally, some factors are more important in adopting AI in HRM; however, they were rejected by this study. These include internal factors which are Top management support and organizational readiness which is very key in new technologies and organisational culture to the adoption acceptance (Chong & Lim, 2022). Also it is more important for HR managers to be cautious, acknowledge and implement ethical practices when adopting AI in HRM processes (Rodgers et al., 2023) because of the complexity in adopting and implementing new technologies (Almaiah et al., 2022).

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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