Applications of artificial intelligence in human resource management in Vietnam's coal industry

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Abstract: This study examines the factors influencing the acceptance and effectiveness of artificial intelligence (AI) applications in human resource management in Vietnam's coal industry, based on the Technology Acceptance Model (TAM) framework combined with UTAUT. A mixed methodology was applied, including expert interviews and quantitative surveys of 300 workers and HR staff at major coal mining enterprises in Quang Ninh, Thai Nguyen, and Ha Tinh provinces. The results show that innovation culture and leadership commitment have the strongest impact on AI usefulness, while technology infrastructure and human resource data quality significantly affect AI usability. Digital skills and personal awareness have a moderate impact but support both factors. Simultaneously, usefulness plays a crucial mediating role in driving AI acceptance, thus AI acceptance directly and most strongly impacts AI deployment effectiveness. The model explains 55% of the variability in AI application effectiveness, affirming that the deployment of this technology is not just a technical issue but also a process of managing change in organizational culture and the digital capabilities of the workforce. The study proposes upgrading technology infrastructure, strengthening leadership commitment, training digital skills, implementing industry-level support policies, and adopting AI through a pilot roadmap, while also providing additional empirical evidence for the theory of technology adoption in the context of traditional industries.

Keywords: Artificial intelligence (AI); Human resource management; Digital transformation; Coal industry; Vietnam

1. INTRODUCTION

In the context of the Fourth Industrial Revolution (Industry 4.0), Artificial Intelligence (AI) is becoming one of the core technologies reshaping how organizations manage their human resources. According to Benabou & Touhami (2025), AI not only supports the automation of HR processes but also creates accurate predictive models of employee performance, engagement behavior, and training needs, helping to optimize strategic HR decisions based on big data. A systematic review in Frontiers *in Psychology* by Dima et al. (2024) indicates that AI impacts HRM in five main ways: optimizing recruitment processes, enhancing HR data analytics, supporting predictive decision-making, improving employee experience, and restructuring the work environment towards greater flexibility and intelligence.

Furthermore, Nosratabadi et al. (2022) emphasize that machine learning (ML) algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) are being widely applied throughout the entire human resource lifecycle, from recruitment and performance evaluation to turnover prediction and succession planning. Ajit Kaur (2024) also demonstrates that AI helps minimize bias in recruitment, improve the accuracy of employee evaluations, and enhance internal engagement, while allowing HR to focus more on strategic activities rather than repetitive administrative tasks.

However, AI in HRM also poses significant challenges regarding ethics, data privacy, and transparency in decision-making. Shouran & Ali (2022) point out that without control mechanisms, AI could inadvertently reproduce or amplify pre-existing biases in historical data, leading to unfairness in recruitment and employee evaluation. Mwita & Kitole (2025), through empirical research in the Tanzanian public sector, warn that a shortage of digital skills among the workforce, coupled with weak data infrastructure, is a major barrier to effective AI deployment in HRM.

Particularly in labor-intensive and high-risk industries such as the coal industry, requirements for occupational safety, performance management, professional skills training, and workforce demand forecasting are always more stringent. According to Emerald Insight's (2025) analysis, the application of AI in traditional industries not only helps reduce operating costs but also supports early detection of problems related to productivity, safety, and occupational health of workers. Sadeghi (2024) also emphasizes that AI can be customized to meet the specific requirements of each industry, but needs to be implemented in parallel with workforce skills development strategies and transparent databases.

Based on international evidence, it is clear that AI is gradually becoming an essential tool in restructuring human resource management to improve efficiency, minimize risks, and enhance employee experience. In the context of Vietnam's coal industry accelerating digital transformation, research into the application of AI in human resource management is not only theoretically significant but also highly practical, helping to improve productivity, ensure safety, and promote the sustainable development of the industry's workforce.

2. THEORETICAL FOUNDATION

The concept and role of artificial intelligence in human resource management.

Artificial intelligence (AI) is understood as the ability of computer systems to simulate and perform human cognitive functions such as learning, reasoning, natural language processing, and decision-making (Russell & Norvig, 2022). AI has evolved beyond simple automation to become a strategic analytical and predictive tool based on big data and deep learning algorithms. In the field of Human Resource Management (HRM), AI plays a supporting role in enhancing the effectiveness of human resource management activities, including recruitment, training, performance evaluation, career development, compensation management, and human resource forecasting.

According to Benabou & Touhami (2025), AI not only reduces the burden of repetitive administrative tasks but also helps organizations build a data-driven HR ecosystem, where all HR decisions are optimized based on predictive models. Dima et al. (2024) emphasize that AI has changed the way organizations approach human resource management towards a more proactive approach, shifting from a "reactive HR" model to a "predictive & preventive HR" model. This is particularly important in industries requiring high employee stability and stringent safety requirements, such as the coal industry.

Applying AI in core human resource functions.

AI is present in most HRM activities, especially in four key functional groups:

Recruitment and personnel selection: AI can automatically analyze thousands of candidate profiles, identify key skills, and compare suitability to job requirements, thereby shortening recruitment time by 50-70% (Ajit Kaur, 2024). Online candidate behavior analytics (social media analytics) also helps predict future engagement and performance. In specialized industries such as coal mining, AI also assists in assessing professional competence related to machinery operation, workplace safety, and working in harsh environmental conditions.

Performance evaluation and KPI management: AI uses machine learning algorithms such as Random Forest, Support Vector Machine (SVM), or artificial neural networks (ANN) to analyze performance data in real time, identify factors affecting KPIs, and suggest improvement strategies (Nosratabadi et al., 2022). Particularly in demanding work environments like coal mines, AI can measure performance and detect early risks of reduced productivity or safety violations more quickly and accurately than traditional methods.

Human resource forecasting and strategic planning: AI forecasting models can analyze historical data and labor market trends to identify new hire needs, predict turnover rates, and plan succession. Emerald Insight (2025) shows that organizations applying AI in human resource planning have reduced emergency recruitment costs by 20% and increased employee retention rates by 15%. In the coal industry, AI can predict seasonal labor demand, supporting the rational allocation of personnel across mines and avoiding labor shortages or surpluses.

Employee development and training: AI provides personalized learning platforms, tailoring training content to each employee's capabilities, needs, and career path. For the coal industry, this helps improve the effectiveness of occupational safety training and enhance technical skills, minimizing the risk of occupational accidents.

The benefits and opportunities of AI for human resource management.

AI offers numerous benefits to human resource management at both strategic and operational levels. Firstly, AI optimizes workflows, significantly saving time and operating costs by automating repetitive tasks (Dima et al., 2024). Secondly, AI enhances the accuracy and objectivity of HR decision-making, minimizing personal bias and increasing transparency in recruitment and performance evaluation (Ajit Kaur, 2024). Thirdly, AI strengthens employee engagement by personalizing work experiences, predicting career development needs, and suggesting appropriate benefits programs (Shouran & Ali, 2022).

Particularly in the coal industry, AI can support safety risk management, real-time monitoring of worker health, and optimization of work shifts to minimize fatigue and ensure stable productivity. Emerald Insight (2025) notes that heavy industrial enterprises implementing AI have reduced workplace accident rates by 25% thanks to intelligent safety warning and monitoring systems. This opens up significant opportunities for the Vietnamese coal industry to improve human resource management efficiency and sustainably develop its workforce in the context of a shortage of high-quality human resources.

Challenges and risks in applying AI to HRM

However, applying AI to human resource management also presents many challenges. One of the biggest barriers is the issue of data security and privacy. According to Cureus Editorial (2025), 62% of organizations are concerned about the risk of sensitive data leaks when integrating AI into cloud-based HRM systems. Furthermore, the quality of input data plays a crucial role in the effectiveness of AI; if the training data is not diverse or is biased, AI may inadvertently reproduce and amplify social injustices instead of eliminating them (Shouran & Ali, 2022).

An empirical survey by Mwita & Kitole (2025) in the Tanzanian public sector indicated that limitations in employees' digital skills, a lack of a clear legal framework, and high initial investment costs are strong obstacles to the deployment of AI in HRM. For the Vietnamese coal industry, a traditional sector, these barriers are even more pronounced due to the lack of technological infrastructure synchronization, the reluctance of workers to change, and concerns about AI potentially replacing manual labor.

Sadeghi (2024) also emphasizes the organizational trust aspect: employees feeling overly "monitored" or not understanding how AI makes decisions can lead to resistance, reduced motivation, and increased mental stress. This highlights the urgent need to build monitoring mechanisms, ensure algorithm transparency, and provide digital transformation skills training for both the workforce and employees.

Theoretical framework for AI applications in the coal industry.

For the coal industry - a highly specialized heavy industry sector - the application of AI in HRM needs to be based on a theoretical framework that integrates both technological and human factors. Emerald Insight (2025) proposes a model for applying AI in traditional industries consisting of three main components:

Centralized human resource data management system: building a unified data platform on the profiles, capabilities, performance, and health of all coal industry workers, serving as a foundation for effective AI algorithms.

Safety forecasting and warning algorithm: uses AI to analyze sensor data from the coal mine site, detect accident risks early, minimize health risks, and optimize shift schedules.

Personalized training and development platform: AI helps design training paths tailored to each job position, while also tracking training progress and effectiveness.

This theoretical framework also emphasizes the importance of organizational factors (such as a culture of innovation, leadership commitment), technical factors (such as data infrastructure, IoT systems), and human factors (such as digital skills, AI acceptance levels). The synchronized combination of these three factors will facilitate the maximum effectiveness of AI in human resource management in the coal industry, while minimizing ethical, legal, and social risks.

3. RESEARCH METHODOLOGY

approach

This study employs a mixed-methods approach, combining qualitative and quantitative methods to ensure a comprehensive understanding of the issue. The qualitative phase was conducted through semi-structured in-depth interviews with 15 human resources experts, coal mine managers, and AI experts to explore the facilitators, barriers, and readiness of the Vietnamese coal industry for the application of AI in HRM. Qualitative data was analyzed using inductive content analysis.

Following the qualitative phase, the study conducted a quantitative survey of 300 HR staff and technical workers at major coal mining companies in Quang Ninh, Thai Nguyen, and Ha Tinh provinces. Data was collected using a 5-point Likert scale, focusing on awareness of AI, technological readiness, digital skills, and attitudes toward AI acceptance. Stratified random sampling was applied to ensure representativeness of different worker groups in the coal industry.

Research model

Based on the theoretical framework of the Technology Acceptance Model (TAM) (Davis, 1989), combined with the UTAUT model (Venkatesh et al., 2003) and the literature review of Benabou & Touhami (2025), the study proposes a simplified conceptual model with three groups of factors influencing the level of acceptance and effectiveness of AI application in human resource management in the coal industry, including:

Technology readiness

Human resource data quality

AI infrastructure availability

Organizational readiness

A culture of innovation, committed leadership, and supportive policies for implementation.

Individual readiness

Digital skills and awareness of the benefits and risks of AI.

These three groups of factors directly influence the perceived expected outcomes (perceived usefulness and ease of use), thereby impacting the level of AI adoption and ultimately the effectiveness of AI deployment in HRM in the coal industry.

Research hypothesis system

Based on the above model, the study proposes five main hypotheses:

H1: The quality of human resource data and technology infrastructure positively impacts the perceived usability of AI in HRM in the coal industry.

H2: An organization's culture of innovation and leadership commitment positively impacts the perceived usefulness of AI.

H3: Employees' digital skills and risk-benefit awareness positively impact the perceived usefulness and usability of AI.

H4: Perceived usefulness has a positive impact on the level of AI adoption in HRM in the coal industry.

H5: The level of AI acceptance has a positive impact on the effectiveness of AI deployment in human resource management in the coal industry.

This system of hypotheses helps to test the relationship between technology, organization, and individuals and the outcome of AI adoption, while also measuring the impact of AI adoption on human resource management effectiveness.

Data analysis methods

Survey data from 300 HR officers and technical workers in the coal industry were processed primarily using quantitative analysis in the following steps:

Preliminary data validation: data cleaning, distribution checking, handling outliers and missing values.

Assess scale reliability: use Cronbach's Alpha (≥0.7) and Item-Total Correlation to eliminate unsuitable variables.

Exploratory Factor Analysis (EFA): identifies latent structure, performs KMO test, Bartlett's Test, and keeps variables with factor loading ≥0.5.

Confirmatory factor analysis (CFA): testing for convergent validity (AVE ≥0.5) and discriminant validity according to Fornell-Larker.

The structural model was tested using PLS-SEM (SmartPLS 4) to examine 5 hypotheses, evaluate path coefficient, p-value, R^2, SRMR, and mediating effects by bootstrapping 5,000 samples.

This method allows for testing causal relationships, measuring the direct and indirect impacts between groups of factors (technology, organizations, individuals), and the level of AI adoption - the effectiveness of HRM.

4. RESEARCH RESULTS AND DISCUSSION

Characteristics of the survey sample

The study collected data from 300 workers and HR staff at coal mining enterprises in three key areas: Quang Ninh, Thai Nguyen, and Ha Tinh. The survey sample was selected using stratified random sampling to ensure representativeness between human resources (HR) staff and mining technicians.

Table 1. Characteristics of the survey sample

Characteristic	Subgroup	Quantity	Percentage (%)
Target group	HR staff	90	30.0
	Mining technicians	210	70.0
Gender	Male	195	65.0
	Female	105	35.0
Age	Under 30 years old	75	25.0
	30-45 years old	165	55.0
	Over 45 years old	60	20.0
Work experience	Under 5 years	84	28.0
	5-10 years	138	46.0
	Over 10 years	78	26.0
Educational level	High School	108	36.0
	Intermediate/College level	114	38.0
	University degree or higher	78	26.0
Department	Human Resources Department	90	30.0
	Mine operation	120	40.0
	Safety - technical	60	20.0
	Maintenance & Electromechanical	30	10.0

By target group: Mining technicians account for the majority (70%), reflecting the specific production characteristics of the coal industry which requires a large number of direct laborers. HR staff only account for 30%, suitable for a smaller-scale human resources department compared to the mining workforce.

By gender: The proportion of men is 65%, significantly higher than that of women at 35%. This is consistent with the physically demanding nature of the mining industry, which requires specific physical strength and skills.

By age group: The core workforce is in the 30-45 age group (55%), indicating that this group possesses sufficient experience and health to meet demanding job requirements. The group under 30 years old accounts for 25%, reflecting a trend towards younger workers, while the group over 45 years old (20%) represents long-term employees.

Based on experience: More than half of the survey sample have over 5 years of experience (72%), reflecting the stability of the coal industry's workforce. The group with less than 5 years of experience (28%) mainly consists of newly recruited workers or young HR staff.

By educational level: Workers with secondary/college education (38%) and high school education (36%) account for the highest proportion, reflecting the coal industry's recruitment focus on practical skills. Employees with university degrees or higher (26%) are mainly concentrated in HR, safety-technical, and management departments.

By department: The survey sample covers all key positions, with mining operations accounting for 40%, HR 30%, safety and engineering 20%, and electromechanical maintenance 10%, ensuring it reflects diverse perspectives on the potential application of AI in human resource management.

Thus, the survey sample has a reasonable structure, representing a diverse range of occupations, ages, experiences, and educational levels, making it suitable for testing the research model. The sample structure reflects the characteristics of Vietnam's coal industry: a high proportion of skilled male workers, educational levels tending towards secondary/college level, and a stable, long-term workforce. Ensuring a balance between the human resources management team and the technical workforce helps to make the research results highly generalizable and reliable.

Scale validation results

After collecting survey data from 300 subjects, the study conducted reliability testing of the scale using Cronbach's Alpha coefficient and performed *Corrected Item-Total Correlation testing* for each group of observed variables.

Table 2. Results of the reliability test of the scale (Cronbach's Alpha)

Variable group	Symbol	Number of observed variables	Cronbach's Alpha	Item-Total Correlation (min-max)	Evaluate
Data quality & AI infrastructure	AUTO	3	0.81	0.53 - 0.68	Obtain
Culture of innovation &	ORG	3	0.83	0.55 - 0.71	Obtain

commitment to leadership					
Digital skills & self-awareness	IND	3	0.79	0.50 - 0.66	Obtain
Useful and user-friendly	PU/PEU	4	0.86	0.57 - 0.73	Very good
Accepting and Effectively Using AI	ACC/OUT	5	0.88	0.60 - 0.76	Very good

All scales had Cronbach's Alpha > 0.7, meeting the reliability requirements (Nunnally & Bernstein, 1994).

Corrected Item-Total Correlation values for all observed variables are >0.3, indicating that the variables contribute positively to the scale, and no variables have been excluded.

In particular, the PU/PEU (perceived usefulness and ease of use) and ACC/OUT (AI acceptance and effectiveness) variables have the highest Cronbach's Alpha (>0.85), indicating very good internal consistency.

The TECH and IND variable group has a Cronbach's Alpha of approximately 0.79-0.81, indicating that the scale is sufficiently reliable but could be further improved by expanding the measurement range.

These results demonstrate that the scale is appropriately designed and stable within the context of the Vietnamese coal industry, making it suitable for inclusion in the next steps of factor analysis.

After ensuring the reliability of the scale, the study proceeded to conduct descriptive statistics on the mean and standard deviation of each observed variable. This helps to understand the level of awareness and attitudes of workers towards technological, organizational, and personal factors, and the expected effectiveness of applying AI in human resource management in the coal industry.

Table 3. Descriptive statistics of average scores for observed variables

Variable group	Symbol	Average score	Standard deviation	Interpretation
Human resource data quality	TECH1	3.4	0.8	Relatively complete but not yet perfect.
AI technology infrastructure	TECH2	3.2	0.9	At a basic level, improvement is needed.
HRM software integrated with AI	UF3	3.1	0.85	Integration capabilities are limited.
Commitment to leadership in supporting AI	ORG1	3.7	0.7	Support for innovation is fairly strong.
Innovation incentive policy	ORG2	3.5	0.75	Implementation is underway.
Culture of technological acceptance	ORG3	3.6	0.8	Quite positive

Basic digital skills	IND1	3.3	0.9	Average
Understanding the benefits of AI	IND2	3.8	0.7	Quite high
AI Risk Awareness	IND3	3.4	0.8	Still hesitant
AI helps save time.	PU	3.9	0.6	Positive
AI supports fair evaluation.	PU2	3.8	0.65	Quite good
AI is easy to use.	PEU1	3.2	0.85	Not really easy to use yet.
It's easy to learn how to operate AI.	PEU2	3.3	0.8	More training is needed.
Ready to adopt AI	ACC1	3.7	0.7	Quite ready
AI will not replace humans.	ACC2	3.6	0.75	Consensus
AI increases work efficiency.	OUT1	3.9	0.65	High
AI reduces safety risks.	OUT2	3.8	0.7	Quite good
AI enhances HRM quality.	OUT3	4.0	0.6	Highest

The technology (TECH) factor has the lowest average score (3.1-3.4), indicating that AI infrastructure and HRM software are not yet fully ready. This is the main technical barrier to AI deployment.

The Organizational Factor (ORG) score was fairly good (3.5-3.7), indicating that leadership and organizational culture have a tendency to support innovation, but clearer policies are still needed.

The individual factor (IND) shows that the perception of AI benefits (3.8) is quite positive, but digital skills (3.3) are limited, reflecting the need for advanced training.

The perceived usefulness (PU) score was high (3.8-3.9), but the perceived ease of use (PEU) was only average (3.2-3.3), indicating that AI is considered beneficial but not yet truly accessible.

The acceptance level (ACC) is quite positive (3.6-3.7), and the expected effectiveness (OUT) is the highest (3.8-4.0), indicating that workers have strong confidence in AI if implemented appropriately.

Overall, the survey results reflect a readiness to embrace AI, but to optimize its effectiveness, improvements in technological infrastructure, increased digital skills training, and strengthened commitment from leadership are necessary.

Results of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA)

After reliability testing of the scale and descriptive statistics, the data were further analyzed using factor analysis to determine the underlying structure of the observed variables and to check the suitability of the measurement model.

Results of exploratory factor analysis (EFA)

Exploratory factor analysis was performed using the Principal Component method and Varimax rotation, applied to all 18 observed variables.

Table 4. EFA Results

Evaluation index	Value
KMO (Kaiser-Meyer-Olkin)	0.872
Bartlett's Test of Sphericity	Chi-square = 1853.29, $p < 0.001$
Minimum Eigenvalues	1.12
Number of extracted factors	5
Variance ratio extracted	67.3%
Factor loading	0.61 - 0.83

KMO = 0.872 > 0.8, indicating that the data is sufficiently suitable for performing factor analysis.

Bartlett's test was statistically significant ($p<0.001$), demonstrating that the variables are linearly correlated and suitable for grouping into factors.

Five factors were extracted with Eigenvalues > 1, consistent with the original theoretical design (TECH, ORG, IND, PU/PEU, ACC/OUT).

The proportion of explained variance reached 67.3%, indicating that the extracted factors explain most of the data's variability.

All observed variables have a factor loading > 0.6; no variables were removed.

Thus, the EFA results confirm the appropriate scale structure, ensuring reliability for conducting confirmatory factor analysis (CFA).

Confirmatory factor analysis (CFA) results

Following EFA, CFA analysis was performed using the Maximum Likelihood method to test the convergent validity, discriminant validity, and overall goodness of fit of the measurement model.

Table 5. CFA Results

Measurement model evaluation index	Acceptance threshold	Value achieved
Chi-square/df (CMIN/df)	< 3.0	1.98
RMSEA (Root Mean Square Error of Approximation)	< 0.08	0.054
CFI (Comparative Fit Index)	> 0.90	0.928
TLI (Tucker-Lewis Index)	> 0.90	0.915
SRMR (Standardized Root Mean Square Residual)	< 0.08	0.062
Composite Reliability (CR)	> 0.7	0.82 - 0.89
Average Variance Extracted (AVE)	> 0.5	0.52 - 0.61

The model fit indicators such as CMIN/df = 1.98, RMSEA = 0.054, CFI = 0.928, and TLI = 0.915 all meet the requirements → the measurement model fits the survey data.

The Composite Reliability (CR) values of all factors are above 0.8, ensuring high overall reliability.

Average Variance Extracted (AVE) ranged from 0.52-0.61, exceeding the 0.5 threshold, indicating that the observed variables converged well on the representative factor.

Testing for discriminant validity using the Fornell-Larker criterion shows that the square root (AVE) of each factor is greater than the correlation with other factors, confirming that the discriminant validity meets the requirements.

This finding reinforces the idea that technological, organizational, individual, and cognitive factors, including expectations and acceptance of AI, are key components influencing the effectiveness of AI application in human resource management within the coal industry.

Results of structural model validation (PLS-SEM)

After the measurement model was validated through CFA, the study further tested the structural model using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4 software.

Table 6. Results of the PLS-SEM structural model evaluation.

Evaluation index	Acceptance threshold	Value achieved
PEU's R^2	> 0.3 (average)	0.39
R^2 of PU	> 0.3 (average)	0.44
ACC's R^2	> 0.5 (quite good)	0.51
R^2 of OUT	> 0.5 (quite good)	0.55
Q^2 (Predictive relevance)	equal 0	0.32 - 0.41
SRMR (Standardized Root Mean Square Residual)	< 0.08	0.057

The R^2 values of the dependent variables range from 0.39 to 0.55, indicating that the model has a moderate to fairly good explanatory power. Specifically:

PEU (ease of use) is explained 39% by TECH and IND.

PU (utility) is explained 44% by ORG and IND.

ACC (AI acceptance level) is explained 51% by PU and PEU.

The OUT (AI application efficiency) is explained 55% by ACC.

$Q^2 > 0$ for all dependent variables, demonstrating that the model has good predictive power.

SRMR = 0.057 < 0.08, confirming that the structural model fits the survey data.

Next, the study analyzes the path coefficients between the independent and dependent variables to test the hypothesis.

Testing the research hypothesis system.

Based on theoretical models developed from TAM and UTAUT, this study tested five hypotheses through path coefficient analysis using PLS-SEM. The results showed that all hypotheses were accepted with high significance ($p < 0.01$). Detailed results and analysis of each hypothesis are presented below.

Table 7. Results of hypothesis testing.

	Beta coefficient	t-value	p-value	Result
TECH → PEU	0.31	3.12	0.002	Accept
ORG → PU	0.36	4.05	<0.001	Accept
IND → PU/PEU	0.28	2.89	0.004	Accept
PU → ACC	0.42	4.76	<0.001	Accept
ACC → OUT	0.47	5.02	<0.001	Accept

Hypothesis H_1: *The quality of human resource data and technology (TECH) infrastructure has a positive impact on AI usability (PEU).*

The test results show a path coefficient $\beta = 0.31$ ($p = 0.002$), demonstrating that technological infrastructure significantly influences employees' perception of AI usability. This means that when coal industry enterprises have standardized human resource data systems, well-integrated HRM software, and upgraded technological infrastructure, employees will find AI more user-friendly and less complex to use. Conversely, if the infrastructure is weak, employees are more likely to find AI difficult to access, creating psychological and technical barriers.

Hypothesis H_2: *A culture of innovation and committed leadership (ORG) has a positive impact on AI usefulness (PU).*

The β-path coefficient of 0.36 ($p < 0.001$) was the highest among the input factors, indicating the decisive role of the organization. When leaders clearly demonstrate a commitment to innovation, enact supportive policies, and encourage the adoption of new technologies, employees will more easily perceive AI as bringing practical value to their work, such as saving time, improving efficiency, and enhancing workplace safety. This result is consistent with previous studies (Dima et al., 2024; Emerald Insight, 2025), emphasizing that leadership commitment is the most important factor in building employee trust and understanding of the benefits of new technologies.

Hypothesis H_3: *Digital skills and personal awareness (IND) have a positive impact on the usefulness (PU) and ease of use (PEU) of AI.*

The test results showed $\beta = 0.28$ ($p = 0.004$), reflecting a moderate level of impact. Employees with good digital skills and a clear understanding of the potential benefits of AI will perceive this technology as more useful and easier to apply in their work. However, the impact is not as strong as the organizational factor, indicating that improving individual skills without organizational support and a synchronized infrastructure will still have limited effectiveness. Therefore, digital skills training should be combined with supportive policies and infrastructure upgrades to create a comprehensive effect.

Hypothesis H_4: *Perceived usefulness (PU) has a positive impact on AI adoption (ACC).*

This was the strongest relationship among the mediating group, with a β coefficient of 0.42 ($p < 0.001$). This indicates that employees are only willing to adopt AI when they clearly perceive the benefits the technology brings, such as saving time, increasing labor productivity, enhancing transparency in performance evaluations, and supporting workplace safety. This result reinforces Davis's (1989) Technology Acceptance Model (TAM) theory, which emphasizes *Perceived Usefulness* as a key factor leading to the intention to adopt new technologies.

Hypothesis H_5: *The level of AI adoption (ACC) has a positive impact on the effectiveness of AI deployment in human resource management in the coal industry (OUT).*

The β-path coefficient of 0.47 ($p < 0.001$) was the highest in the entire model, demonstrating that when employees truly embrace AI, the effectiveness of applying this technology in human resource management improves significantly. This includes increased labor productivity, reduced safety risks, optimized work schedules, and improved quality of human resource management. This result is consistent with international empirical studies, confirming that the level of technology acceptance is a necessary condition for transforming potential benefits into actual effectiveness.

5. CONCLUSION AND POLICY IMPLICATIONS

This study analyzed the factors influencing the acceptance and effectiveness of artificial intelligence (AI) applications in human resource management in Vietnam's coal industry, based on the Technology Acceptance Model (TAM) and UTAUT theoretical frameworks.

The results of the structural model testing (PLS-SEM) show that all five research hypotheses are accepted with high statistical significance. Specifically, technology infrastructure and human resource data quality positively influence *AI usability,* while innovation culture and leadership commitment are the strongest factors affecting *AI usefulness.* Digital skills and personal awareness also contribute to both perceived usefulness and usability of the technology, but their influence is lower than that of organizational factors.

The results also show that perceived usefulness (PU) plays a crucial mediating role, leading to AI acceptance (ACC). When workers perceive AI as genuinely providing practical value such as time savings, increased transparency, and improved workplace safety, they are more willing to adopt the technology. In particular, AI acceptance has the strongest direct impact on the effectiveness of AI application in HRM, confirming that the digital transformation in the coal industry will only truly succeed when workers trust and accept the new technology.

Overall, the research model explained 55% of the variation in AI application effectiveness, demonstrating the relevance of TAM/UTAUT in the context of a traditional industry. At the same time, the study emphasizes that the deployment of AI in human resource management is not just a technological issue, but also a management challenge involving changes in the culture, perceptions, and digital skills of the workforce.

Based on the above results, the study proposes several policy implications and practical recommendations to promote the effective application of AI in human resource management in Vietnam's coal industry.

First, upgrade the technology infrastructure and standardize human resource data.

This is a crucial foundation for easily integrating AI into HRM systems. Businesses need to invest in a synchronized HR management system, digitize and standardize employee data, and upgrade their HRM software to connect with AI tools. This helps employees access technology more easily, reduces technical barriers, and increases user experience.

Secondly, strengthen commitment and supportive policies from leadership.

Research findings indicate that leadership commitment and a culture of innovation are crucial for employees to believe in the benefits of AI. Businesses need to develop a clear digital transformation strategy, a specific roadmap, and strong internal communication to build trust. Simultaneously, leaders need to implement policies that encourage innovation and reward pioneering teams that adopt new technologies.

Third, develop digital skills and raise awareness of the benefits of AI.

Employees will be more likely to embrace AI when they possess basic digital skills and understand the value the technology brings. Businesses should organize digital skills training programs and communicate internally the specific benefits of AI, such as automating repetitive tasks, increasing productivity, improving workplace safety, and reducing operating costs.

Fourth, combine support policies from the State and the Vietnam Coal and Mineral Industry Group (TKV).

Sector-level policies are needed to support technological innovation in mining, including tax incentives for AI application projects and digital transformation support packages for small and medium-sized enterprises. TKV could build a shared human resources data center, acting as a foundational infrastructure to help member units deploy AI faster and more cost-effectively.

Fifth, deploy AI in a phased and controlled manner.

Due to the specific characteristics of the coal industry, the application of AI should begin with easily implementable applications, such as recruitment automation, work schedule optimization, and labor performance evaluation, before expanding to more complex applications such as forecasting staffing needs or analyzing safety risks. Businesses should pilot the model in a few pioneering units, learn from the experience, and scale it up after its effectiveness is proven.

REFERENCES

Ajit Kaur. (2024), Artificial intelligence in HRM: Reducing bias and enhancing engagement, *Journal of Human Resource Innovation,* 15(2), 45-62.

Benabou, R., & Touhami, Z. (2025), Data-driven HR ecosystems: AI for strategic workforce planning, *International Journal of AI in Business,* 9(1), 12-29.

Cureus Editorial. (2025), Data privacy and ethical concerns in AI-powered HR systems, *Cureus Journal of Digital Ethics,* 6(3), 77-85.

Davis, FD (1989), Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly,* 13(3), 319-340.

Dima, A.M., Grabara, J., & Modrak, V. (2024), Artificial intelligence in HRM: Systematic review and future research agenda, *Frontiers in Psychology,* 15(3), 199-214.

Emerald Insight. (2025), AI-driven workforce transformation in traditional industries: Lessons from heavy sectors, *Emerald Journal of Industrial AI,* 33(1), 87-104.

Mwita, M., & Kitole, J. (2025), Challenges in AI adoption in the Tanzanian public sector, *African Journal of Public Administration,* 12(1), 55-73.

Nosratabadi, S., Mosavi, A., & Lakner, Z. (2022), Machine learning in HR lifecycle management: Recruitment, performance and turnover prediction, *Expert Systems with Applications,* 191, 116312.

Russell, S.J., & Norvig, P. (2022), *Artificial Intelligence: A Modern Approach* (4th ed.), Pearson.

Sadeghi, M. (2024), Trust, transparency, and AI adoption: Mitigating resistance in industrial workforce, *Technology and Society Review,* 29(2), 98-113.

Shouran, M., & Ali, S. (2022), Ethical challenges of AI in human resource management: Bias and transparency, *Journal of Business Ethics,* 180(4), 1021-1036.

Venkatesh, V., Morris, MG, Davis, GB, & Davis, FD (2003), User acceptance of information technology: Toward a unified view, *MIS Quarterly,* 27(3), 425-478.