Int. j. adv. multidisc. res. stud. 2026; 6(3):1377-1382

Received: 22-04-2026
Accepted: 02-06-2026

International Journal of Advanced Multidisciplinary Research and Studies

ISSN: 2583-049X

The Impact of Artificial Intelligence on Workforce Restructuring in Small and Medium-Sized Manufacturing Enterprises in Hanoi

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Abstract
The rapid advancement of Artificial Intelligence (AI) is profoundly transforming production systems and human resource management practices within organizations. The adoption of AI not only contributes to improving labor productivity but also accelerates workforce restructuring by altering skill requirements, employment structures, and workforce utilization patterns. This study aims to examine the impact of AI adoption on workforce restructuring in small and medium-sized manufacturing enterprises (SMEs) in Hanoi, Vietnam.
Drawing upon Human Capital Theory and Skill-Biased Technological Change Theory, the study proposes a research framework comprising four key constructs: AI adoption, reskilling and upskilling, workforce restructuring, and organizational performance. Research data were collected from 350 small and medium-sized manufacturing enterprises in Hanoi using a structured questionnaire survey.
The findings indicate that AI adoption has a significant positive effect on employee training and skill development activities. Furthermore, AI facilitates workforce restructuring by increasing demand for employees with digital competencies, technological expertise, and data-related capabilities. The study provides important empirical evidence for managers and policymakers in formulating human resource development strategies to enhance workforce adaptability in the context of digital transformation and AI implementation.

Keywords: Artificial Intelligence, Workforce Restructuring, Reskilling and Upskilling, Small and Medium-Sized Manufacturing Enterprises, Human Resource Management

1. Introduction

Artificial Intelligence (AI) has emerged as one of the core technologies of the Fourth Industrial Revolution, generating profound transformations in production activities, business management, and labor markets worldwide. Through its capabilities in processing large volumes of data, automating business processes, and supporting managerial decision-making, AI is expected to enhance labor productivity, optimize resource utilization, and foster business model innovation. According to the *Future of Jobs Report 2025* published by the World Economic Forum (WEF), approximately 86% of organizations worldwide are expected to accelerate the adoption of digital technologies and artificial intelligence between 2025 and 2030, leading to substantial changes in employment structures and workforce skill requirements. While AI offers significant benefits in terms of productivity and operational efficiency, it also intensifies workforce transformation pressures, as many routine, manual, and standardized tasks are increasingly being automated. At the same time, demand for workers possessing digital skills, data analytics capabilities, and technological adaptability continues to rise.
In Vietnam, digital transformation has been identified as a key driver of economic growth and national competitiveness enhancement. As the country's political, economic, and technological center, Hanoi is home to more than 400,000 active enterprises, of which small and medium-sized enterprises account for approximately 98% of the total. Although many firms have begun adopting AI-based solutions in management and production processes, the overall level of AI implementation remains relatively limited, particularly among small and medium-sized manufacturing enterprises. In this context, investigating the impact of AI on workforce restructuring is not only academically significant in enriching empirical evidence related to technology and human resource theories but also practically important for formulating workforce development policies, designing skill development strategies, and enhancing organizational adaptability in the rapidly evolving digital economy.

2. Theoretical Background and Research Model

2.1 Human Capital Theory

Human Capital Theory, developed by Becker (1964) [4], is widely regarded as one of the most influential theoretical foundations in human resource management research. According to this theory, human capital comprises the knowledge, skills, competencies, and experiences accumulated by individuals through education, training, and work experience. Becker (1964) [4] argued that investment in human capital generates economic returns comparable to those derived from investments in physical capital, as enhancing employees' knowledge and skills contributes to higher labor productivity, improved operational efficiency, and stronger organizational competitiveness.

In the context of digital transformation, the concept of human capital extends beyond traditional professional expertise to include digital competencies, data literacy, technological adaptability, and lifelong learning capabilities. The rapid advancement of artificial intelligence (AI) has fundamentally altered workforce skill requirements, resulting in the automation of many traditional occupations while simultaneously increasing demand for technology-related, data-driven, and analytical roles. According to the *Future of Jobs Report 2025* published by the World Economic Forum (WEF), approximately 59% of the global workforce will require reskilling or upskilling by 2030 due to the impact of AI and emerging digital technologies. This trend highlights that reskilling and upskilling have become essential for maintaining workforce adaptability and enhancing the value of human capital in modern production environments.

From the perspective of Human Capital Theory, the adoption of AI within organizations not only transforms work processes and job design but also increases the need for investment in employee training and development. Therefore, Human Capital Theory provides a theoretical foundation for explaining the relationship between AI adoption and workforce reskilling and upskilling initiatives.

2.2 Skill-Biased Technological Change Theory

The Skill-Biased Technological Change (SBTC) Theory posits that technological progress tends to increase demand for highly skilled workers while reducing demand for workers engaged in routine and low-skilled tasks (Autor, Katz, & Krueger, 1998) [3]. According to this perspective, technological advancement does not affect all workers equally; instead, it creates disparities in employment opportunities and earnings based on workers' skill levels.

Autor (2015) [2] argued that modern technologies primarily replace programmable and standardized tasks, whereas tasks requiring critical thinking, creativity, and social interaction continue to rely heavily on human capabilities. Extending this perspective, Acemoglu and Restrepo (2019) [1] suggested that automation not only displaces labor through task substitution but also creates new tasks and occupations, thereby stimulating workforce restructuring within organizations.

In contemporary manufacturing environments, AI has been increasingly adopted in warehouse management, quality control, demand forecasting, predictive maintenance, and human resource management. These applications reduce demand for routine and manual jobs while simultaneously increasing the need for employees possessing digital competencies, data analytics skills, and the ability to operate intelligent systems. Consequently, SBTC Theory provides a valuable theoretical lens for understanding workforce restructuring processes resulting from AI adoption in manufacturing enterprises.

2.3 Hypothesis Development and Research Model

2.3.1 AI Adoption and Reskilling/Upskilling Activities

The implementation of AI within organizations often leads to significant changes in production processes, management practices, and workforce skill requirements. To adapt to these technological transformations, organizations need to invest in training and development programs that equip employees with digital skills, data-related competencies, and the ability to work effectively in technology-enabled environments. The *Future of Jobs Report 2025* indicates that organizations worldwide are increasingly investing in reskilling and upskilling initiatives to meet the demands of digital transformation.

Accordingly, the following hypothesis is proposed:

H1: *AI adoption positively influences employee reskilling and upskilling activities.*

2.3.2 Reskilling/Upskilling and Workforce Restructuring

According to Human Capital Theory, enhancing employees' knowledge and skills enables them to adapt to new job requirements and facilitates occupational mobility across different positions. In the context of AI implementation, reskilling and upskilling initiatives help employees transition from routine and repetitive jobs to positions requiring higher levels of knowledge, technological expertise, and analytical capabilities.

Therefore, the following hypothesis is proposed:

H2: *Reskilling and upskilling activities positively influence workforce restructuring.*

2.3.3 AI Adoption and Workforce Restructuring

Previous studies have shown that AI directly affects workforce structures through the automation of production tasks and the creation of new job positions related to data management, digital technologies, and intelligent systems administration (Acemoglu & Restrepo, 2019; Autor, 2015) [1, 2]. These developments contribute to significant changes in both occupational structures and workforce skill compositions within organizations.

Accordingly, the following hypothesis is proposed:

H3: *AI adoption positively influences workforce restructuring.*

2.3.4 The Mediating Role of Reskilling and Upskilling

Human Capital Theory suggests that AI influences workforce structures not only directly but also indirectly by encouraging organizations to invest in employee training and development. When employees acquire new competencies, their ability to adapt to technological changes and transition into emerging occupations is enhanced, thereby facilitating workforce restructuring.

Based on this rationale, the final hypothesis is proposed:

H4: *Reskilling and upskilling play a mediating role in the relationship between AI adoption and workforce restructuring.*

3. Research Methodology

3.1 Research Design and Data Collection

This study adopts a quantitative research approach using a structured questionnaire survey to examine the impact of Artificial Intelligence (AI) adoption on workforce restructuring in small and medium-sized manufacturing

enterprises (SMEs) in Hanoi, Vietnam. The survey method was selected because it is appropriate for measuring perceptions regarding AI adoption, workforce development initiatives, and changes in workforce structure within organizations.

The target respondents consisted of individuals holding managerial positions and possessing substantial knowledge of manufacturing operations and human resource management practices within their organizations. Specifically, the survey targeted chief executive officers (CEOs), human resource managers, production managers, and workshop supervisors. These respondents were considered capable of providing reliable information regarding the extent of AI implementation, workforce training activities, and organizational workforce restructuring processes.

A combination of convenience sampling and purposive sampling techniques was employed to access SMEs operating in the manufacturing sector in Hanoi. According to Hair *et al*. (2022) [8], studies employing Structural Equation Modeling (SEM) should achieve a minimum sample size equivalent to five to ten times the number of observed variables. In the present study, a total of 16 observed variables were included, suggesting a minimum sample size ranging from 160 to 320 observations. To ensure the reliability of the research findings and minimize potential bias arising from invalid responses, 400 questionnaires were distributed. After data screening and the removal of incomplete or invalid responses, 350 valid questionnaires were retained for analysis, yielding a valid response rate of 87.5%.

3.2 Measurement Development

All research constructs were measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The measurement items were adapted from prior studies on digital transformation, AI adoption, and human resource management, with modifications to ensure their suitability for the context of small and medium-sized manufacturing enterprises in Vietnam.

AI Adoption

The AI Adoption construct reflects the extent to which AI technologies are implemented and utilized in organizational production and management activities. The construct consists of five observed items capturing various dimensions of AI utilization, including production management, quality control, human resource management, demand forecasting, and decision-support systems.

Reskilling and Upskilling

This construct measures the degree to which organizations invest in employee capability development initiatives aimed at adapting to emerging technologies. The scale comprises five observed items related to digital skills training, technology-oriented training programs, knowledge updating activities, data utilization capabilities, and employees' adaptability development.

Workforce Restructuring

Workforce restructuring refers to changes in occupational composition, skill composition, and job structures resulting from AI adoption. This construct includes six observed items measuring changes in workforce allocation across departments, increasing demand for technology-skilled employees, the emergence of AI- and data-related job positions, and the gradual reduction of routine and repetitive occupations.

The measurement scales were developed based on the theoretical foundations of Human Capital Theory (Becker, 1964) [4], Skill-Biased Technological Change Theory (Autor, Katz, & Krueger, 1998) [3], and recent studies examining the impact of AI on workforce transformation.

3.3 Data Analysis Techniques

The collected data were analyzed using SPSS 26.0 and AMOS 24.0 software packages. The analytical procedure consisted of the following stages:

Descriptive Statistics

Descriptive statistical analysis was conducted to examine the characteristics of the research sample, including business sector, workforce size, years of operation, and the level of AI adoption within the surveyed enterprises.

Reliability Analysis

The reliability of the measurement scales was assessed using Cronbach's Alpha coefficients. Following the recommendations of Hair *et al*. (2022) [8], a scale was considered reliable when the Cronbach's Alpha coefficient exceeded 0.70 and the Corrected Item–Total Correlation exceeded 0.30.

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis was employed to assess the convergent and discriminant validity of the measurement scales. The criteria adopted included a Kaiser-Meyer-Olkin (KMO) value greater than 0.50, a statistically significant Bartlett's Test of Sphericity ($p < 0.05$), factor loadings above 0.50, and a cumulative variance explained exceeding 50%.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was performed to evaluate the adequacy of the measurement model. The model fit was assessed using several goodness-of-fit indices, including Chi-square/df < 3.0, Goodness-of-Fit Index (GFI) > 0.90, Tucker–Lewis Index (TLI) > 0.90, Comparative Fit Index (CFI) > 0.90, and Root Mean Square Error of Approximation (RMSEA) < 0.08 (Hair *et al*., 2022) [8].

Structural Equation Modeling (SEM)

After establishing the adequacy of the measurement model, Structural Equation Modeling (SEM) was employed to test the proposed hypotheses and examine the relationships among the research constructs. In addition, the Bootstrap procedure with 5,000 resamples was conducted to assess the mediating effect of Reskilling and Upskilling in the relationship between AI Adoption and Workforce Restructuring.

The application of SEM enables the simultaneous examination of both direct and indirect relationships among the research variables, thereby providing robust empirical evidence regarding the impact of AI adoption on workforce restructuring in small and medium-sized manufacturing enterprises in Hanoi.

4. Research Results

4.1 Sample Characteristics

A total of 350 valid questionnaires were collected from small and medium-sized manufacturing enterprises (SMEs) operating in Hanoi. The descriptive statistics indicate that the surveyed firms were distributed across a variety of manufacturing sectors, thereby enhancing the representativeness of the research sample.

Table 1: Sample Characteristics

Industry Sector	Number of Firms	Percentage (%)
Mechanical Engineering and Manufacturing	170	48.6
Electrical and Electronics Manufacturing	75	21.4
Food Processing	64	18.3
Others	41	11.7
Total	**350**	**100.0**

Source: Research findings.

The results indicate that mechanical engineering and manufacturing firms accounted for the largest proportion of the sample (48.6%), followed by electrical and electronics enterprises (21.4%) and food processing firms (18.3%). These sectors have experienced relatively high levels of automation and digital transformation in recent years.

Regarding AI adoption, 109 enterprises (31.2%) reported having implemented at least one AI-based application in their production or management activities. Among these firms, the most common AI applications included demand forecasting (67.9%), computer vision-based quality control (54.1%), intelligent warehouse management (48.6%), and human resource management (35.8%).

4.2 Reliability and Validity Assessment of Measurement Scales

Table 2: Results of Cronbach's Alpha Reliability Analysis

Construct	Number of Items	Cronbach's Alpha
AI Adoption	5	0.891
Reskilling/Upskilling	5	0.874
Workforce Restructuring	6	0.903

Source: Research findings.

The results demonstrate that all constructs achieved Cronbach's Alpha coefficients above the recommended threshold of 0.70, indicating satisfactory internal consistency and reliability. Therefore, all measurement scales were retained for subsequent Exploratory Factor Analysis (EFA).

Table 3: Results of Exploratory Factor Analysis (EFA)

Indicator	Value
KMO	0.901
Bartlett's Test of Sphericity (Sig.)	0.000
Total Variance Explained (%)	68.45
Minimum Factor Loading	0.673

Source: Research findings.

The Kaiser–Meyer–Olkin (KMO) value of 0.901 exceeds the recommended threshold of 0.50, while Bartlett's Test of Sphericity is statistically significant ($p < 0.001$), confirming the suitability of the data for factor analysis. Furthermore, the total variance explained reached 68.45%, exceeding the minimum requirement of 50%, thereby supporting the convergent validity of the measurement scales.

Table 4: Results of Confirmatory Factor Analysis (CFA)

Fit Index	Obtained Value	Recommended Threshold
Chi-square/df	2.146	< 3.0
GFI	0.928	> 0.90
TLI	0.951	> 0.90
CFI	0.959	> 0.90
RMSEA	0.057	< 0.08

Source: Research findings.

The CFA results indicate that the measurement model exhibits a satisfactory fit to the empirical data. In addition, all Composite Reliability (CR) values exceeded 0.70, and all Average Variance Extracted (AVE) values were above 0.50, confirming both convergent validity and discriminant validity of the constructs.

4.3 Structural Equation Modeling (SEM) Results

The SEM analysis revealed that the proposed research model demonstrated an acceptable fit with the survey data. The model fit indices met the criteria recommended by Hair *et al*. (2022) [8], including $\chi^2/df = 2.287$, GFI = 0.921, TLI = 0.947, CFI = 0.953, and RMSEA = 0.061.

Table 5: Results of Hypothesis Testing

Hypothesis	Relationship	Standardized Coefficient (β)	C.R.	p-value	Result
H1	AI Adoption → Reskilling/Upskilling	0.648	8.942	< 0.001	Supported
H2	Reskilling/Upskilling → Workforce Restructuring	0.534	7.618	< 0.001	Supported
H3	AI Adoption → Workforce Restructuring	0.312	4.215	< 0.01	Supported

Source: Research findings.

The results demonstrate that AI adoption exerts a significant positive influence on employee reskilling and upskilling activities ($\beta = 0.648$, $p < 0.001$). This represents the strongest relationship in the proposed model, indicating that AI implementation requires employees to continuously acquire new knowledge and skills to meet evolving job demands.

Furthermore, reskilling and upskilling activities positively affect workforce restructuring ($\beta = 0.534$, $p < 0.001$). This finding suggests that workforce development initiatives play a crucial role in enabling employees to adapt to smart manufacturing environments and digital transformation processes.

The findings also reveal that AI adoption directly influences workforce restructuring ($\beta = 0.312$, $p < 0.01$). Although the magnitude of this direct effect is lower than the indirect effect mediated through reskilling and upskilling activities, the result confirms that AI contributes significantly to changes in occupational structures, skill compositions, and job configurations within organizations.

Table 6: Bootstrap Analysis of the Mediating Effect

Indirect Relationship	Indirect Effect	p-value
AI Adoption → Reskilling/Upskilling → Workforce Restructuring	0.346	< 0.001

Source: Research findings.

The Bootstrap analysis demonstrates that the indirect effect of AI adoption on workforce restructuring through reskilling and upskilling is statistically significant ($\beta = 0.346$, $p < 0.001$). This finding confirms the mediating role of Reskilling/Upskilling in the relationship between AI Adoption and Workforce Restructuring.

4.4 Discussion

The findings indicate that Artificial Intelligence has become a critical driver of workforce restructuring in small and medium-sized manufacturing enterprises in Hanoi. The adoption of AI not only transforms production and management processes but also generates substantial demand for employee reskilling and upskilling initiatives.

This finding is consistent with Human Capital Theory (Becker, 1964) [4], which emphasizes that investments in education, training, and skill development enhance employees' capacity to adapt to technological change. The results are also aligned with the studies of Autor (2015) [2] and Acemoglu and Restrepo (2019) [1], which argue that automation and AI do not merely replace routine jobs but also create new skill requirements and facilitate workforce transitions toward more knowledge-intensive occupations.

Notably, the significant mediating effect of reskilling and upskilling suggests that workforce restructuring does not occur automatically following AI adoption. Rather, it depends substantially on organizations' ability to develop human capital and on employees' readiness to embrace new technologies. This finding provides important practical implications for both business managers and policymakers in designing workforce development programs that align with the requirements of the digital economy and smart manufacturing environments.

5. Conclusion and Managerial Implications

5.1 Conclusion

This study was conducted to examine the impact of Artificial Intelligence (AI) adoption on workforce restructuring in small and medium-sized manufacturing enterprises (SMEs) in Hanoi, Vietnam. Drawing upon Human Capital Theory and Skill-Biased Technological Change Theory, the study developed a theoretical framework comprising three key constructs: AI adoption, employee reskilling and upskilling, and workforce restructuring.

The findings reveal that AI adoption has a positive and statistically significant effect on employee reskilling and upskilling activities. This result reflects the reality that AI implementation is not merely a technological transformation but also entails substantial changes in workforce competency requirements. As organizations increasingly integrate AI into their production and management processes, employees are required to acquire new digital, technological, and analytical skills to effectively perform their jobs.

The results further indicate that reskilling and upskilling serve as important drivers of workforce restructuring by facilitating the transition toward a workforce characterized by higher levels of digital competence, technological expertise, and adaptability to smart manufacturing environments. In addition to its indirect effect through workforce development activities, AI also exerts a direct influence on workforce restructuring by reshaping occupational structures, skill compositions, and job positions within organizations.

A notable finding of this study is the mediating role of reskilling and upskilling in the relationship between AI adoption and workforce restructuring. This finding suggests that the effectiveness of digital transformation depends not only on technological investment but also on organizations' capacity to develop and upgrade their human capital. Consequently, the integration of technological innovation and human capital investment should be regarded as a critical prerequisite for enhancing the competitiveness of SMEs in the context of digital transformation and the emerging digital economy.

5.2 Managerial Implications for Small and Medium-Sized Manufacturing Enterprises

First, manufacturing SMEs should develop AI adoption strategies that are closely aligned with their human resource development strategies. In practice, many organizations prioritize technological investments without adequately preparing their workforce to effectively utilize AI-enabled systems. Therefore, AI implementation should be accompanied by comprehensive assessments of existing employee competencies, identification of skill gaps, and the development of targeted workforce development plans.

Second, organizations should increase investment in reskilling and upskilling programs aimed at strengthening employees' digital capabilities. Training initiatives should focus on data literacy, automated system operation, AI-assisted decision-making, data analytics, and problem-solving skills in digital work environments. Continuous learning opportunities are essential to ensure that employees remain adaptable to rapid technological advancements and changing job requirements.

Third, enterprises should proactively establish workforce restructuring roadmaps that prioritize the development of high-value-added positions. Rather than focusing solely on reducing routine jobs, organizations should emphasize workforce redeployment and talent development for roles related to data management, business analytics, intelligent system supervision, and production process innovation. Such an approach can maximize the complementary relationship between human capabilities and AI technologies while enhancing organizational performance.

5.3 Implications for Educational and Training Institutions

The findings suggest that demand for workers possessing digital competencies and technological expertise will continue to increase in the coming years. Therefore, universities, colleges, and vocational education institutions should review and update their curricula to incorporate greater emphasis on artificial intelligence, data analytics, manufacturing automation, and digital transformation.

In addition to technical knowledge, educational institutions should focus on developing soft skills such as critical thinking, creativity, teamwork, adaptability, and lifelong learning capabilities. Previous international studies have consistently identified these competencies as being less

susceptible to automation and increasingly important in future workplaces characterized by human–AI collaboration. Furthermore, strengthening collaboration between educational institutions and industry partners through internships, demand-driven training programs, and joint curriculum development initiatives can help reduce the gap between graduates' competencies and labor market requirements. Such collaborations are crucial for preparing a workforce capable of thriving in the AI-driven economy.

5.4 Policy Implications for Government and Public Authorities

For local governments and labor management agencies, policies should be developed to support SMEs in their digital transformation and AI adoption efforts. Such policies may include financial assistance for workforce training programs, digital transformation consulting services, and initiatives that foster collaboration between enterprises and educational institutions.

In addition, policymakers should establish labor market intelligence systems capable of forecasting future skill demands and workforce requirements across manufacturing industries. Providing timely and accurate labor market information can assist businesses, educational institutions, and workers in preparing for technological changes associated with AI and digital transformation.

Moreover, policymakers should continue to strengthen national strategies for digital workforce development, lifelong learning, and occupational transition support for workers affected by automation. These measures are essential to ensuring labor market resilience, social inclusion, and sustainable economic development in the digital era.

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