JDI
JOURNAL OF DEVELOPMENT AND INTEGRATION

JOURNAL OF DEVELOPMENT AND INTEGRATION
No. 89 (2026) 71-79 | jdi.uef.edu.vn

The Impact of Automation on Labor Market Transformation and Sustainable Development: Empirical Evidence from Vietnam

Nguyen Thi Hong Mai[1,*], Le Cong Doan[2]
[1]Ho Chi Minh City University of Economics and Finance, Vietnam
[2]Industrial University of Ho Chi Minh City, Vietnam

KEYWORDS

Automation,
Labor Market Transformation,
Skill Upgrading,
Sustainable Development,
Vietnam.

ABSTRACT

This study investigates the impact of automation on labor market transformation and sustainable development in Vietnam using the Skill-Biased Technological Change (SBTC) framework. Based on a survey of 296 employees and analyzed through SEM, findings reveal that automation intensity significantly influences job change, skill upgrading, and job quality. Moreover, job change enhances labor market flexibility and social protection, while skill upgrading strengthens adaptability. Ultimately, job quality, social protection, and flexibility positively affect sustainable development outcomes. The research highlights automation's dual role - both as a driver of productivity and a challenge to equitable, sustainable growth in emerging economies.

1. Introduction

Automation has become an inevitable trend among Vietnamese enterprises in the era of the Fourth Industrial Revolution. It not only enhances productivity and reduces operational costs but also strengthens firms' adaptability in an increasingly volatile business environment, especially in the aftermath of the COVID-19 pandemic. This process is driven by the need to optimize value chains, improve competitiveness, and leverage advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, and Robotic Process Automation (RPA). According to Nguyen (2024), digital transformation currently plays a strategic role in enhancing the efficiency and growth potential of Vietnamese enterprises. In the manufacturing sector, government support, cost awareness, and managerial capability are considered key drivers for AI adoption. While large corporations are at the forefront of technological advancement, small and medium-sized enterprises (SMEs) continue to face barriers related to capital and human resources, thus implementing automation only at a basic level. Overall, automation is reshaping labor structures, production processes, and management systems, thereby creating new opportunities for sustainable development in the digital era.

Alongside its evident advantages in productivity and efficiency, automation is also bringing about fundamental changes in Vietnam's labor market, reflecting a global trend of digital and technological transformation. The integration of AI and automated systems not only alters the nature of work but also redefines skill requirements. According to Tyson and Zysman (2022), automation tends to replace labor in repetitive tasks while increasing demand for digital competencies and adaptive flexibility. Consequently, a clear polarization emerges within the labor market:

*Corresponding author. Email: *mainth@uef.edu.vn*
http://doi.org/10.61602/jdi.2026.89.08
Submitted: 5-Jan-2026; Revised: 15-Feb-2026; Accepted: 23-Mar-2026; Online first: 11-Apr-2026
ISSN (print): 1859-428X, ISSN (online): 2815-6234

high-skilled workers benefit the most, whereas low- and medium-skilled groups face the risk of unemployment or income reduction. Nevertheless, Otoiu et al. (2022) argue that automation can still enhance national competitiveness by lowering production costs, improving supply chain efficiency, and fostering global integration. However, these economic benefits are not evenly distributed, thereby exacerbating income inequality among labor groups. In this context, Vietnam must develop appropriate education and retraining policies to restructure its workforce toward sustainable development.

Notably, labor-intensive industries such as textiles, footwear, and electronic assembly are among the most affected by automation, as machines and AI systems gradually replace manual work. This transformation leads to job displacement, rising social inequality, and an urgent need for workers to acquire new skills. However, current reskilling programs remain limited in strategic vision, methodology, and coordination among the government, enterprises, and vocational institutions. Moreover, automation alters labor relations and places pressure on the social welfare system, particularly in the absence of adequate labor protection policies (Zhang & Feng, 2025). Therefore, improving training quality, promoting lifelong learning, and aligning labor policies with international standards are imperative to ensure both sustainable and equitable development.

Although international economic theories have established a close nexus between automation, structural employment transformation, and sustainable development (Acemoglu & Restrepo, 2018) empirical evidence from emerging economies such as Vietnam remains fragmented and lacks systematic rigor. A notable divergence lies in the analytical focus: while studies conducted in developed economies predominantly emphasize “job displacement,” research in Vietnam presents multidimensional yet inconclusive perspectives. Specifically, Nguyen et al. (2021) argue that digital transformation imposes substantial upskilling pressures while simultaneously generating new opportunities in the service sector and e-commerce. In contrast, Pham et al. (2023) highlight the acute vulnerability of low-skilled workers in assembly manufacturing—the backbone of Vietnam’s economy. Nevertheless, most existing studies remain largely confined to qualitative assessments or scenario-based projections grounded in theoretical assumptions, lacking rigorous quantitative analyses based on micro-level data to measure the actual impact of automation on Sustainable Development Goals (SDGs) indicators.

This deficiency creates a critical “knowledge gap,” particularly given the distinctive characteristics of Vietnam’s labor market, which is marked by delayed technological absorption and a strong reliance on labor-intensive industries. As a result, forecasting models developed in Western contexts cannot be directly transplanted without substantial adaptation. Accordingly, this study is undertaken to: (1) decode structural employment shifts through empirical data analysis; (2) assess the adaptive capacity of the workforce; and (3) determine whether automation functions as a “lever” for social equity or as a catalyst for new forms of inequality. This research constitutes a necessary step toward filling the empirical evidence gap in developing countries and provides a scientific foundation for labor policy formulation in the digital era.

2. Literature review, research method

2.1. Literature review

The increasing level of automation within organizations is profoundly transforming labor structures, the nature of work, and the skill requirements of employees. The integration of robots, artificial intelligence (AI), and robotic process automation (RPA) systems to optimize operational efficiency has led to the substitution of numerous repetitive and manual tasks, thereby heightening the risk of job loss, particularly in labor-intensive industries (Tyson & Zysman, 2022). The fear of being replaced by machines has intensified employees’ perceptions of job insecurity, resulting in higher stress levels and lower work engagement. However, the magnitude of this impact varies across worker groups: those with limited skills or physical capacity are more vulnerable, whereas individuals who demonstrate adaptability and a commitment to continuous learning are less affected.

H1.1: The automation intensity has a significant effect on job-loss risk.

In addition to the risk of job displacement, automation is also reshaping job quality within organizations. The adoption of AI and collaborative robots not only eliminates monotonous tasks but also enables employees to focus on creative and higher-value activities. Several studies have reported that higher levels of automation can be associated with increased job satisfaction, driven by improvements in working conditions, income, and flexibility. Nonetheless, this process may also intensify occupational stress, as the pace of work and technical demands increase, posing risks to employees’ mental well-being. Furthermore, the divide between highly skilled workers who benefit from opportunities for skill upgrading and those with medium or low skills whose career prospects may become more limited (Cuccu & Royuela, 2024) suggests that automation exerts a dual effect on job quality.

H1.2: The level of automation has a significant effect on job quality.

Furthermore, automation is restructuring the skill demands of the labor market and driving a widespread process of skill transformation. As technologies such as AI, robotics, and intelligent systems replace a substantial portion of repetitive tasks, digital literacy, analytical thinking, and adaptability have become increasingly essential. This trend accelerates the phenomenon of skill upgrading, in which the proportion of highly skilled workers increases while the demand for low-skilled labor declines. However, automation may also contribute to skill polarization, leading to the erosion of middle-skill jobs. Hence, workers' ability to transition and upgrade their skills depends not only on the degree of automation but also on organizational policies that support reskilling and upskilling initiatives.

H1.3: The level of automation has a significant effect on skill upgrading.

In the context of increasing automation and digital transformation, the risk of job loss has emerged as a major concern in modern labor markets. The rapid development of robotics and artificial intelligence (AI) has enhanced the potential for machines to replace humans in repetitive and manual tasks, leading to greater employment instability and heightened perceptions of job insecurity. Although labor markets are designed to facilitate occupational mobility and efficient reallocation, a growing fear of job loss may hinder this process as workers become more cautious about changing jobs or investing in new skills. Moreover, traditional employment contracts are losing their stability and lack adequate protection mechanisms, making labor market flexibility increasingly synonymous with instability particularly for middle-aged or low-skilled workers.

H2.1: Job-loss risk has a significant effect on labor market flexibility.

Job-loss risk due to automation not only affects individual career stability but also interacts with labor support policies. When workers perceive a higher likelihood of technological replacement, they tend to experience greater anxiety about income and career stability, thereby increasing their demand for welfare policies, retraining programs, and unemployment insurance. Job insecurity induced by automation heightens individuals' awareness of economic vulnerability, prompting a preference for short-term welfare and social protection policies over long-term investment. Additionally, unemployment or the threat of it can negatively affect mental health, underscoring the crucial role of social service policies in helping displaced workers recover and reintegrate into the labor market.

H2.2: Job-loss risk has a significant effect on labor support policies.

Job-loss risk also serves as a key driver of workers' skill transformation in the digital economy. As AI and robotics increasingly replace repetitive tasks, workers are compelled to adapt to maintain competitiveness in the labor market. Heightened job insecurity motivates individuals to invest in reskilling and upskilling, particularly in digital and STEM-related fields, as a strategy to mitigate the risk of redundancy. Soft skills such as critical thinking, creativity, and interdisciplinary collaboration are becoming increasingly valuable in technology-integrated workplaces. However, fear of job displacement may also generate psychological stress and feelings of helplessness, which can undermine motivation for learning and career development. Therefore, job-loss risk exerts a dual influence on skill transition: it simultaneously encourages the pursuit of lifelong learning while highlighting the need for supportive policies and organizational initiatives that enable workers to adapt effectively and prevent widening skill inequality in the digital economy (Krutova et al., 2021).

H2.3: Job-loss risk has a significant effect on skill upgrading.

Skill upgrading, particularly in digital competence and technological adaptability, plays a crucial role in shaping the flexibility of the labor market. Workers with higher digital literacy are more capable of adjusting to disruptions caused by automation, digitalization, or crises, thereby enhancing productivity, competitiveness, and income levels. In addition, soft skills such as critical thinking, creativity, and problem-solving help individuals remain adaptable in a rapidly changing work environment. However, flexible employment models may hinder continuous learning and upskilling, especially for short-term or contract workers, while relaxed labor regulations only temporarily improve job accessibility. Therefore, linking digital skill development with appropriate support policies is essential for ensuring the sustainability of a flexible labor market.

H3.1: Skill upgrading affects labor market flexibility.

In the context of widespread digitalization and automation, the process of skill transformation has become a key driver that compels governments, organizations, and firms to reshape their labor support policies. The growing need for retraining and digital upskilling highlights the importance of flexible learning environments, unemployment insurance, and accessible career support programs. Organizational and managerial support is essential for successful skill transfer and adaptation to new technologies. Moreover, coordination among governments, enterprises, and educational institutions is fundamental to designing effective and demand-driven retraining programs (Mburu et al., 2021). Consequently, the pressure stemming from skill transformation has guided labor policies toward greater inclusiveness and sustainability.

H3.2: Skill upgrading affects labor support policies.

A flexible labor market serves as a cornerstone for sustainable development, as its adaptability enables economies to maximize human resource utilization amid digital and automation transitions. When workers can switch occupations or move into technology-intensive roles, firms can restructure production, boost productivity, and invest more aggressively in innovation (You et al., 2023). Labor mobility also facilitates the adoption of environmentally friendly technologies, contributing to green growth and emission reduction. Conversely, a rigid labor market slows innovation and hinders the reallocation of resources, thereby obstructing sustainable development goals. Hence, labor market flexibility acts as a critical lever for advancing inclusive and sustainable economic transformation.

H3.3: Labor market flexibility affects sustainable development.

Labor market flexibility plays a central role in promoting sustainable development, as its adaptive capacity enables economies to fully utilize human resources in the context of digitalization and automation. When workers can shift to new occupations or move into technology-intensive positions, firms gain opportunities to restructure production, enhance productivity, and invest more strongly in technological innovation (You et al., 2023). Flexible labor mobility also facilitates the adoption of environmentally friendly technologies in the production sector, contributing to emission reduction and green growth. Conversely, a rigid labor market slows down innovation and hinders sustainability goals by limiting resource allocation and lowering efficiency. Hence, labor market flexibility serves as a key driver for transitioning toward a greener and more sustainable economy.

H4.1: Labor market flexibility affects sustainable development.

Job quality constitutes the foundation of sustainable development, as it reflects not only income and working conditions but also creativity, job security, and opportunities for skill enhancement. When employees work in safe environments, receive stable income, and are encouraged to innovate, they tend to demonstrate higher organizational commitment, thereby improving productivity and contributing positively to sustainable growth (Bonnemain, 2025). Furthermore, automation and technological innovation if appropriately implemented can reduce repetitive tasks, allowing workers to focus on creative and value-adding activities, thus fostering the green transformation of production systems. Therefore, high job quality not only enhances human well-being but also serves as a direct catalyst for balancing economic, social, and environmental sustainability.

H4.2: Job quality affects sustainable development.

Labor Support policies, including unemployment insurance, retraining programs, and assistance for workers affected by automation, are crucial for achieving sustainable development. When coherently designed and coordinated between governments and enterprises, public policy instruments such as financial support, legal frameworks, and awareness initiatives not only protect workers but also encourage green investment, improve industrial productivity, and reduce social inequality. Such policies contribute to resource efficiency, emission reduction, and the diffusion of environmentally friendly technologies, thereby accelerating the green transition and sustainable growth. Overall, the effectiveness of these policies depends on their contextual relevance and adaptability to global dynamics (Basheer et al., 2022).

H4.3: Labor support policies affect sustainable development.

2.2. Research method

2.2.1. Theoretical background and Model

According to the Skill-Biased Technological Change (SBTC) theory, new technologies and automation reshape the structure of labor demand by favoring high-skilled workers, while exposing medium- and low-skilled workers to heightened risks of job displacement and deteriorating job quality. To operationalize this theoretical framework in empirical research, the study constructs its research concepts based on well-established and academically validated measurement scales. The core mechanisms of SBTC are captured through Automation Intensity (adapted from Tyson & Zysman, 2022). Job Displacement Risk (derived from Frey & Osborne, 2017), and Skill Upgrading (based on Wang et al., 2021).

Furthermore, Labor Market Flexibility (adapted from You et al., 2023) and Labor Support Policies (sourced from Basheer et al., 2022; Zhang & Feng, 2025) represent the necessary institutional responses to mitigate the adverse impacts of technological change. Finally, the key outcome variables of this transformation process—Job Quality and Sustainable Development—are measured using validated scales developed by Bonnemain (2025), Cuccu and Royuela (2024), and Basheer et al. (2022). This integrated system of variables comprehensively captures the causal chain articulated by SBTC theory, ensuring both generalizability and strong explanatory power for the Structural Equation Modeling (SEM) framework, without the need to add or omit any theoretical components. Accordingly, the proposed research framework is established as follows:

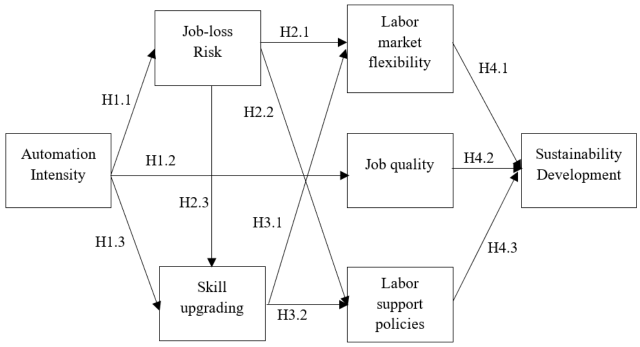

Figure 1. Research model

2.2.2. Data collection and analysis

The data collection process was conducted using a purposive convenience sampling approach, targeting industry groups with high levels of technological exposure. Of the 350 questionnaires distributed between November 7 and 10, 2025, the study obtained 296 valid responses (an 84.5% response rate) after excluding those that failed to meet consistency requirements. The cleaned dataset was processed using SPSS to assess reliability through Cronbach's Alpha and to conduct exploratory factor analysis (EFA). Subsequently, the observed variables were analyzed in AMOS to perform confirmatory factor analysis (CFA) and structural equation modeling (SEM).

The deliberate focus on IT staff, consultants, online lecturers, and customer service personnel is justified by their direct exposure to the wave of robotic process automation (RPA) and artificial intelligence (AI). According to SBTC theory, knowledge- and communication - intensive service occupations are undergoing substantial structural changes in skill requirements; therefore, responses from these groups provide the most contextually grounded empirical evidence of labor market transformation in Vietnam's digital era.

3. Results and discussion

3.1. Results

Table 1. Cronbach's Alpha

No	Scale	Alpha	Conclusion
1	Automation Intensity (AI)	0.891	The scale is reliable
2	Job-loss risk (JR)	0.903	The scale is reliable
3	Skill upgrading (SU)	0.935	The scale is reliable
4	Job Quality (JQ)	0.897	The scale is reliable
5	Labor Market Flexibility (LMF)	0.853	The scale is reliable
6	Labor support policies (LSP)	0.870	The scale is reliable
7	Sustainability Development (SD)	0.914	The scale is reliable

The Cronbach's Alpha reliability test indicated that all constructs in the model achieved satisfactory reliability, with Alpha coefficients ranging from 0.853 to 0.935, all exceeding the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). Specifically, the Automation Intensity (AI) scale achieved $\alpha = 0.891$; Job-loss Risk (JR) $\alpha = 0.903$; Skill Upgrading (SU) $\alpha = 0.935$; Job Quality (JQ) $\alpha = 0.897$; Labor Market Flexibility (LMF) $\alpha = 0.853$; Labor Support Policies (SP) $\alpha = 0.870$; and Sustainable Development (SD) $\alpha = 0.914$. These results demonstrate high internal consistency among the observed variables within each construct and indicate that the items effectively capture the intended concepts. Therefore, the measurement scales employed in this study are considered reliable and suitable for subsequent analyses, including exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM).

Table 2. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.916
Bartlett's Test of Sphericity	Approx. Chi-Square	7841.846
	df	630
	Sig.	.000

The Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.916, exceeding the minimum threshold of 0.5 and indicating the suitability of the data for exploratory factor analysis (EFA). In addition, Bartlett's Test of Sphericity was statistically significant (χ^2 significance = 0.000 < 0.05), confirming that the observed variables are sufficiently correlated to justify factor extraction.

In the Total Variance Explained table, seven factors with eigenvalues greater than 1 were retained in the exploratory factor analysis (EFA) model. The cumulative variance explained by these factors was 72.465%, exceeding the recommended threshold of 50%, indicating that the EFA model is appropriate. Considering the total variance as 100%, the seven extracted factors accounted for 72.465% of the variance in the dataset comprising 36 observed variables included in the EFA.

The results of the confirmatory factor analysis (CFA) indicate that the model demonstrates a good fit with the data. Specifically, CMIN/df = 1.784, which is below the recommended threshold of 3, suggesting a good fit. The Comparative Fit Index (CFI) = 0.941 exceeds 0.9, indicating a high level of fit. The Standardized Root Mean Square Residual (SRMR) is equal to 0.0561 < 0.08, so the model meets the suitability requirement. Additionally, the Tucker-Lewis Index (TLI) = 0.935 reflects a satisfactory improvement in model fit. The Root Mean Square Error of Approximation (RMSEA)

Table 3. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	11.333	31.480	31.480	11.333	31.480	31.480	4.877
2	4.865	13.514	44.993	4.865	13.514	44.993	8.261
3	2.453	6.813	51.807	2.453	6.813	51.807	6.792
4	2.194	6.094	57.901	2.194	6.094	57.901	6.694
5	1.967	5.464	63.364	1.967	5.464	63.364	7.051
6	1.808	5.024	68.388	1.808	5.024	68.388	6.560
7	1.468	4.077	72.465	1.468	4.077	72.465	5.283
8	.720	1.999	74.464				
9	.648	1.800	76.264				
10	.609	1.690	77.954				
11	.597	1.658	79.613				
12	.506	1.407	81.019				
13	.505	1.404	82.423				
14	.490	1.362	83.785				
15	.477	1.324	85.110				
16	.437	1.213	86.322				
17	.410	1.140	87.462				
18	.401	1.113	88.576				
19	.393	1.090	89.666				
20	.365	1.014	90.680				
21	.354	.984	91.665				
22	.327	.907	92.572				
23	.304	.845	93.417				
24	.270	.749	94.166				
25	.240	.668	94.834				
26	.228	.632	95.466				
27	.219	.607	96.074				
28	.204	.568	96.641				
29	.193	.537	97.178				
30	.185	.514	97.693				
31	.178	.493	98.186				
32	.154	.427	98.613				
33	.148	.412	99.024				
34	.135	.374	99.398				
35	.117	.326	99.724				
36	.099	.276	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

= 0.052 is below 0.06, indicating a high degree of fit, and PCLOSE = 0.304 exceeds 0.05, confirming that the model is both acceptable and reliable.

The unstandardized regression coefficients indicate that all relationships in the SEM model are statistically significant, with p-values less than 0.05, suggesting that all proposed hypotheses are supported.

The standardized regression coefficients indicate that job quality exerts the strongest effect on sustainable development (β = 0.566), followed by labor support

Table 4. Pattern Matrix[a]

	Component						
	1	2	3	4	5	6	7
SU1	.929						
SU5	.921						
SU3	.905						
SU2	.856						
SU4	.805						
SD3		.920					
SD6		.887					
SD4		.796					
SD5		.795					
SD2		.767					
SD1		.725					
JQ5			.893				
JQ3			.854				
JQ1			.817				
JQ2			.783				
JQ4			.770				
AI5				.980			
AI4				.827			
AI2				.824			
AI3				.789			
AI1				.776			
JR3					.873		
JR5					.866		
JR1					.859		
JR4					.770		
JR2					.749		
LSP1						.958	
LSP3						.922	
LSP2						.743	
LSP4						.670	
LSP5						.636	
LMF2							.909
LMF4							.839
LMF3							.789
LMF1							.744
LMF5							.635

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

policies (β = 0.300), while labor market flexibility has the smallest effect (β = 0.155).

Regarding indirect effects, job change has a greater impact on labor support policies (β = 0.495) than on labor market flexibility (β = 0.360). Conversely, skill upgrading affects labor market flexibility (β = 0.280) more strongly than demand for labor support policies (β = 0.123). Considering the two indirect factors, job-loss risk demonstrates a stronger influence on the direct outcome variables (labor market flexibility, job quality, and labor support policies) compared to skill upgrading.

Finally, the independent variable automation intensity has a stronger impact on job-loss risk (β

Table 5. Unstandardised Regression Coefficients

			Estimate	S.E.	C.R.	P
JOB-LOSS RISK	<---	AUTOMATION INTENSITY	.488	.061	7.970	***
SKILL UPGRADING	<---	AUTOMATION INTENSITY	.177	.082	2.156	.031
SKILL UPGRADING	<---	JOB-LOSS RISK	.210	.081	2.600	.009
LABOR MARKET FLEXIBILITY	<---	JOB-LOSS RISK	.341	.058	5.918	***
LABOR SUPPORT POLICIES	<---	JOB-LOSS RISK	.495	.063	7.834	***
LABOR MARKET FLEXIBILITY	<---	SKILL UPGRADING	.232	.049	4.778	***
LABOR SUPPORT POLICIES	<---	SKILL UPGRADING	.107	.051	2.118	.034
JOB QUALITY	<---	AUTOMATION INTENSITY	.445	.064	6.962	***
SUSTAINABILITY DEVELOPMENT	<---	LABOR MARKET FLEXIBILITY	.130	.042	3.094	.002
SUSTAINABILITY DEVELOPMENT	<---	JOB QUALITY	.437	.041	10.672	***
SUSTAINABILITY DEVELOPMENT	<---	LABOR SUPPORT POLICIES	.239	.041	5.772	***

Table 6. Standardized Regression Coefficients

		Relation	Estimate
JOB-LOSS RISK	<---	AUTOMATION INTENSITY	.478
SKILL UPGRADING	<---	AUTOMATION INTENSITY	.151
SKILL UPGRADING	<---	JOB-LOSS RISK	.183
LABOR MARKET FLEXIBILITY	<---	JOB-LOSS RISK	.360
LABOR SUPPORT POLICIES	<---	JOB-LOSS RISK	.495
LABOR MARKET FLEXIBILITY	<---	SKILL UPGRADING	.280
LABOR SUPPORT POLICIES	<---	SKILL UPGRADING	.123
JOB QUALITY	<---	AUTOMATION INTENSITY	.423
SUSTAINABILITY DEVELOPMENT	<---	LABOR MARKET FLEXIBILITY	.155
SUSTAINABILITY DEVELOPMENT	<---	JOB QUALITY	.566
SUSTAINABILITY DEVELOPMENT	<---	LABOR SUPPORT POLICIES	.300

= 0.478) and job quality (β = 0.423) than on skill upgrading (β = 0.151). Moreover, job-loss risk also affects the need for skill upgrading (β = 0.183). These results suggest that automation increases job quality but simultaneously raises the risk of job loss and occupational changes for certain labor segments, compelling workers to upgrade their skills to survive in a more flexible labor market, even when supported by social protection policies.

3.2. Discussion

This study provides an important empirical contribution to the theoretical discourse on the impact of technology on labor in developing economies. The findings strongly support the Skill-Biased Technological Change (SBTC) hypothesis, demonstrating that automation is not merely a process of mechanical substitution but rather a profound restructuring of job quality and skill composition. In contrast to studies conducted in developed countries—such as that of Daron Acemoglu and Pascual Restrepo (2018)—which emphasize job displacement effects, evidence from Vietnam indicates that the impact of automation on sustainable development is most strongly mediated by Job Quality. This suggests that in the Vietnamese context, satisfaction and creativity unlocked by technological adoption exert a greater influence than pressures arising from labor market flexibility. These findings are consistent with the observations of Pham et al. (2023) regarding the sensitivity of Vietnam's labor market, yet they extend the literature by demonstrating that labor support policies function as an essential "filter," transforming job displacement risks into drivers of sustainable development.

4. Conclusion

This study empirically examined how automation reshapes Vietnam's labor market and contributes to sustainable development through the lens of the Skill-Biased Technological Change (SBTC) framework. The findings confirm that automation intensity significantly affects job-loss risk, skill upgrading, and job quality, revealing both opportunities and challenges for emerging economies. While automation enhances productivity and job quality, it simultaneously raises displacement risks, necessitating continuous skill transformation and policy adaptation. The results further demonstrate that job-loss risk and skill upgrading jointly influence labor market flexibility and labor support policies, which, in turn, contribute positively to sustainable development. Among all factors, job quality exerts the strongest influence on sustainability, highlighting the importance of human-centered automation that values creativity, security, and well-being.

From a policy perspective, the study underscores the need for governments and enterprises to establish integrated strategies that promote lifelong learning, digital literacy, and inclusive labor protection systems. Encouraging collaboration between industries, educational institutions, and policymakers will be crucial in reducing inequality and enhancing adaptive capacity. Future research could extend this framework by incorporating cross-industry or longitudinal comparisons, examining psychological responses to automation, or exploring the interaction between automation and green innovation. Overall, this study contributes to the growing discourse on how developing economies like Vietnam can harness automation not merely as a technological revolution but as a catalyst for inclusive and sustainable growth.

REFERENCES

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542. DOI: https://doi.org/10.1257/aer.20160696

Basheer, M., Nechifor, V., Calzadilla, A., Ringler, C., Hulme, D., & Harou, J. (2022). Balancing national economic policy outcomes for sustainable development. *Nature Communications*, 13. DOI: https://doi.org/10.1038/s41467-022-32415-9

Bonnemain, A. (2025). Acting on the quality of work to increase its sustainability: An occupational psychology approach. *International Labour Review*, 164(1), 1-17. DOI: https://doi.org/10.16995/ilr.18836

Cuccu, L., & Royuela, V. (2024). Just reallocated? Robots displacement, and job quality. *British Journal of Industrial Relations*, 62(4), 705-731. DOI: https://doi.org/10.1111/bjir.12805

Krutova, O., Koistinen, P., Turja, T., Melin, H., & Särkikoski, T. (2021). Two sides, but not of the same coin: digitalization, productivity and unemployment. *International Journal of Productivity and Performance Management*, 71(8), 3507-3533. DOI: https://doi.org/10.1108/IJPPM-05-2020-0233

Mburu, F., Kamau, A., & Macharia, S. (2021). Assessment of relationship between management policies and transfer of skills. *International Journal of Research in Business and Social Science (2147- 4478)*, 10(6), 355-368. DOI: https://doi.org/10.20525/ijrbs.v10i6.1324

Nguyen, T. H. (2024). *Digital Transformation in Vietnam - Trends and Solutions in the Coming Time*. DOI: https://doi.org/10.62225/2583049x.2024.4.3.2801

Nguyen, T. T. H., & Doan, T. T. T. (2021). Digital transformation and its impact on the labor market: A case study of Vietnam's service sector. *Journal of Asian Finance, Economics and Business*, 8(3), 1015–1025. DOI: https://doi.org/10.13106/jafeb.2021.vol8.no3.1015

Otoiu, A., Titan, E., Paraschiv, D., Dinu, V., & Manea, D. (2022). Analysing Labour-Based Estimates of Automation and Their Implications. *A Comparative Approach from an Economic Competitiveness Perspective. Journal of Competitiveness*, 14(3), 133–152. DOI: https://doi.org/10.7441/joc.2022.03.08

Pham, H. C., Nguyen, H. T., & Vu, K. D. (2023). Automation and the risk of job displacement in Vietnam's manufacturing sector: A firm-level analysis. *Economies*, 11(2), 54. DOI: https://doi.org/10.3390/economies11020054

Piroșcă, G. I., Șerban-Oprescu, G. L., Badea, L., Stanef-Puică, M.-R., & Valdebenito, C. R. (2021). Digitalization and Labor Market—A Perspective within the Framework of Pandemic Crisis. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(7), 2843–2857. DOI: https://doi.org/10.3390/JTAER16070156

Tyson, L. D., & Zysman, J. (2022). Automation, AI & Work. *Daedalus*, 151(2), 256–271. DOI: https://doi.org/10.1162/daed_a_01914

Wang, J., Hu, Y., & Zhang, Z. (2021). Skill-biased technological change and labor market polarization in China. *Economic Modelling*, 100, 105507. DOI: https://doi.org/10.1016/j.econmod.2021.105507

You, C., Qiu, H., Pi, Z., & Yu, M. (2023). Sustainable Enterprise Development in the Manufacturing Sector: Flexible Employment and Innovation in China. *Sustainability*, 15(10), 8180. DOI: https://doi.org/10.3390/su15108180

Zhang, Z., & Feng, Q. (2025). How Does Automation Reshape the Labor Market: Evidence From China. *Review of Development Economics*, 30(1), 458-469. DOI: https://doi.org/10.1111/rode.13263