

ARTIFICIAL INTELLIGENCE, AUTOMATION, AND LABOR MARKET TRANSFORMATION: EVIDENCE ON EMPLOYMENT, SKILLS, AND WAGE DYNAMICS

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Abstract

Artificial intelligence (AI) and automation transformed global labor markets by reshaping employment structures, skill requirements, and wage dynamics. This study examined the impact of AI adoption on employment patterns, skill transformation, and wage outcomes using a quantitative research design. Data were collected from a sample of 320 employees across IT, banking, manufacturing, education, and service sectors. The analysis applied descriptive statistics and structural equation modeling to evaluate relationships among variables. Results indicated that AI adoption significantly influenced employment patterns ($\beta = 0.63, p < 0.001$), skill transformation ($\beta = 0.67, p < 0.001$), and wage dynamics ($\beta = 0.61, p < 0.001$). Skill transformation also significantly affected employment patterns ($\beta = 0.58, p < 0.001$) and wage dynamics ($\beta = 0.55, p < 0.001$). Mediation analysis confirmed that skill transformation played a significant role in linking AI adoption with both employment outcomes and wage distribution. The model explained 52% variance in employment patterns, 45% in skill transformation, and 49% in wage dynamics. Findings demonstrated that AI created both opportunities and challenges by increasing demand for high-skilled labor while reducing routine-based employment. Wage inequality increased due to differential skill adaptation across workers. The study highlighted the importance of reskilling and education reforms to ensure inclusive labor market outcomes in the era of AI-driven transformation.

Keywords: artificial intelligence, employment patterns, labor market transformation, skill development, wage dynamics, workforce automation

Introduction

Automation and artificial intelligence (AI) reshaped the working environment of the world, as the essence of the work, the organization of labor, and the patterns of wages distribution in industrial sectors were radically changed. The implementation of AI technologies in production and service systems speeded up the automation of tasks and the enhancement of human abilities, leading to displacement and creation of jobs. The evidence of empirical studies indicated that the adoption of AI had uneven effects on labor markets, with each sector and level of skills exhibiting dissimilar impacts (Fossen et al., 2022; Otto and Abraham, 2025). These changes are indicative of the transition to occupation dominated by routine to cognitively demanding and technologically specialized jobs.

The growing high levels of AI penetration also modulated the needs of the skills, focusing on digital literacy, analytical skills and flexibility. More productive gains associated with the use of AI were experienced by workers who were more educated and technologically competent, whereas low-skilled workers were at higher risk of being displaced or their wages not rising (Zhang et al., 2024; Autor et al., 2022). This technological transformation, which is skill based,

increased the level of polarization in the labor market, increasing the disparity between the high skilled and the low skilled workers and led to the inequality in income in each economy.

The automation of jobs, which is driven by AI, had a variety of effects on wage dynamics, affecting them both positively and negatively and leading to the appearance of new categories of jobs. Research showed that AI raised the pay of high-skilled positions by boosting their productivity, and at the same time, put pressure on the pay in routine-intensive jobs, which are downward (Huang, 2025; Acemoglu and Restrepo, 2020). These dynamics reinforced the dualistic nature of AI both as a driver of economic growth and as a possible factor contributing to labor market inequality.

The increasing academic interest, the empirical knowledge of the overall effect of AI on jobs, skills, and pay was still in parts. The literature tended to concentrate on particular sectors or regions, which did not allow the generalization of the results. The purpose of this research was to present a detailed discussion of the impact of AI and automation on the transformation of the labor market, especially in the context of labor relations, skill formation, and wage relations.

Background of the Study

The blistering development of AI technologies became one of the main characteristics of the fourth industrial revolution that transformed economies and the labor market around the world. The AI solutions were widely spread to different areas and fields such as manufacturing, finance, healthcare, and digital services, which resulted in higher efficiency and productivity. Empirical studies revealed that AI-based technological change had considerable impact on job structures, and it automatized routine jobs and enriched non-routine cognitive jobs (Fossen et al., 2022; Otto and Abraham, 2025). This revolution helped develop hybrid job descriptions that need to combine technical and soft skills.

In the past, technological innovations had an effect on labor markets, affecting the displacement and creation of jobs. Nevertheless, AI was not like other technologies as it could mimic the cognitive processes, which impacted a wider spectrum of professions. Research has shown that the application of AI had both labor-substituting and labor-augmenting impacts, contingent on task type and industry specifics (Acemoglu & Restrepo, 2020; Huang, 2025). This twofold effect brought forth intricate work relationships that were diverse in geographical locations and economic situations.

Regarding employment, AI exposure had both positive and negative impacts on various segments of the labor market. The studies have shown that in areas where AI is more widely utilized, the growth of employment in highly-skilled industries and the fall in employment in routine-heavy jobs were observed (Johnston and Makridis, 2025; Otto and Abraham, 2025). According to these results, AI did not unconditionally decrease the number of jobs but instead reorganized them, and this resulted in changes in the occupational demand and workforce structure.

The integration of AI also brought about drastic changes in wage dynamics. There was evidence that AI as a factor increased returns to skilled labor and decreased wage gains by low-skilled workers (Zhang et al., 2024; Fossen et al., 2022). The productivity gains made through AI facilitated companies to create more value outputs that were converted into wage increments largely on the technologically skilled workers. Such trends highlighted the role of skill adaptation and life-long learning to reduce negative impacts of automation.

Research Problem

The swift embrace of artificial intelligence and automation had caused major disturbances in the labor markets, but the character and scope of such effects were not well comprehended. Although other studies have noted favorable employment and wage impacts that accompany AI-related productivity improvements, others have pointed out that AI is displacing jobs and escalating wage inequality, especially among low-skilled workers. This difference in results showed the absence of agreement about the general effect of AI on the outcomes in the labor market. This disjointed methodology restricted the capacity to comprehensively investigate the interrelations among adoption of AI, development of skills, and wage distribution. The necessity to address these variables integrated with each other to give a comprehensive picture of AI-based changes in the labor market remained critical.

Research Objectives

1. To examine the impact of artificial intelligence and automation on employment patterns
2. To analyze the effect of AI on skill requirements and workforce transformation
3. To evaluate the relationship between AI adoption and wage dynamics
4. To investigate the role of skills as a mediating factor between AI and employment outcomes

Research Questions

- Q1. How did artificial intelligence and automation influence employment patterns?
- Q2. What impact did AI have on skill requirements in the labor market?
- Q3. How did AI adoption affect wage dynamics across different skill levels?
- Q4. Did skill transformation mediate the relationship between AI and employment outcomes?

Significance of the Study

The paper has added value to the existing body of literature through an integrated perspective and analysis of the effects of artificial intelligence on the labor market, skills, and wage dynamics. In contrast to the previous studies which were on individual dimensions, this research set of study looked at interrelationships among these variables providing a more holistic perspective on how the labor market is transforming. The results were informative to policymakers, educators, and industry players in the development of policies to overcome the challenges of AI-driven automation. The research had practical implications on the policies of the labor market in the context of fostering an inclusive growth and protecting against inequality. The study highlighted the significance of reskilling and upskilling programs by determining the vital role of skills in mediating the impacts of AI. The findings were also helpful to organizations in crafting workforce strategies that kept in par with technological innovations to improve productivity, and competitiveness amid an ever-growing digital economy.

Literature Review

Artificial Intelligence and Employment Transformation

Artificial intelligence greatly redefined the employment models by changing the job composition and division of tasks within industries. Empirical research showed that the acceptance of AI impacted job creation and job displacement, based on the characteristics of occupational activities and exposure to technology. Studies showed that the AI-based systems substituted the jobs with high routine content and also created new positions with high cognitive and technical levels of skills (Al Khatib et al., 2026; Wang et al., 2024).

The impact of AI on employment was also not homogeneous in terms of industries and economies. Research found that the industries with more automation intensity had their routine labor demand decreased, but employment increased in those industries that had jobs based on analytical and creative work (Otto et al., 2025; Johnston et al., 2025). Such results indicated that AI did not decrease employment evenly but rather it reallocated the labor demand among various types of occupations, which produced structural changes in occupation structure.

The adoption of AI had an effect on the dynamics of employment and labor demand both at the micro and macro level. It was proven that AI technologies opened up new jobs in highly skilled spheres and decreased the demand of low-skilled employees (Liu et al., 2023; Babina et al., 2024). This two-fold impact served to underscore the significance of technological flexibility and the necessity of labor market policies that facilitated labor market transitions during the age of automation.

AI, Skills Transformation, and Workforce Adaptation

The adoption of AI technologies increased the restructuring of skills in the contemporary labour markets. It was found that the use of AI brought more need of digital, analytical, and problem-solving skills, but decreased the value of routine manual and cognitive activities (Greenhalgh et al., 2023; Acemoglu et al., 2022). This shift was part of a larger movement towards skill-biased technological change, which saw workers with more advanced capabilities enjoying more opportunities in the labor market and faster career progression.

The transformation that was driven by AI required life-long learning and re-skilling of the workforce to keep up with the change. It was empirically indicated that employees who adopted technological shift by upskilling and training had better employment and higher levels of income (Deming et al., 2024; Felten et al., 2021). Those who did not have access to education and training became more susceptible to job loss, which was strengthening the already established disparities in the workforce.

Artificial intelligence technologies led to the development of hybrid skills needs that involved technical knowledge and skills, social, and cognitive ones. Research showed that jobs increasingly required interdisciplinary skills, such as the ability to communicate, be creative, and use technology (Nedelkoska et al., 2023; Frank et al., 2023). This development emphasized the role of education systems and organizational policies in preparing workers to the shifting nature of work.

Age of AI and Wage Dynamics and Inequality

Artificial intelligence had a great impact on wage structures as it generated imbalance between high skilled and low skilled employees. Empirical studies showed that there was an increase in wages of highly skilled workers due to improved productivity and efficiency, whereas low-skilled workers had wage stagnation or wage reduction (Fossen et al., 2022; Gehrke et al., 2023). This phenomenon helped to polarize wages and increase the income inequality both within and across the economies.

The influence of AI on wage dynamics also hinged on the level of technological exposure and nature of work undertaken. Research showed that employees in jobs with high exposure to AI had seen wage gains and wage pressures, contingent on the complementary or the substitution of their skills by AI (Babina et al., 2024; Webb et al., 2020). This heterogeneity underscored the intricate correlation between technology and workforce market results.

The technological change brought about by AI enhanced structural inequality through returns to education and specialized skills that were augmented. It was indicated that the more AI was adopted in a region and industry, the higher the wage dispersion was, which is an indication of unequal share of technological gains (Al Khatib et al., 2026; Autor et al., 2022). These results highlighted the necessity of inclusive policies that would help minimize inequality and provide equal opportunities in an AI-based economy.

Hypothesis Development

H1: Artificial intelligence adoption significantly influenced employment patterns.

H2: Artificial intelligence adoption significantly influenced skill transformation.

H3: Skill transformation significantly influenced employment patterns.

H4: Artificial intelligence adoption significantly influenced wage dynamics.

Conceptual Framework Model

The theoretical framework of this paper demonstrated that there are interdependent relationships between the adoption of artificial intelligence and skill transformation and the patterns of employment and wage dynamics. The use of artificial intelligence was introduced as the independent variable, representing how far the organizations used AI and automation technologies in their work. Dependent variables were employment patterns and wage dynamics, which are major outcomes of labor market influenced by technological change. The mediating variable was skill transformation, which represented the process by which workers were able to adjust to the changing technological needs.

The model hypothesized that adoption of AI had direct and indirect impacts on employment and wages. Direct effects were immediate job and wage level changes due to automation and productivity gains. Indirect effects were realized via skill transformation wherein the capacity of workers to learn and utilize new skills affected their job prospects, and wage capabilities. This framework gave a detailed account of the transformation of the labor market by bringing out the foremost role that skills play in the connection between technological change and economic performance, thus providing a systematic framework through which empirical research can be conducted.

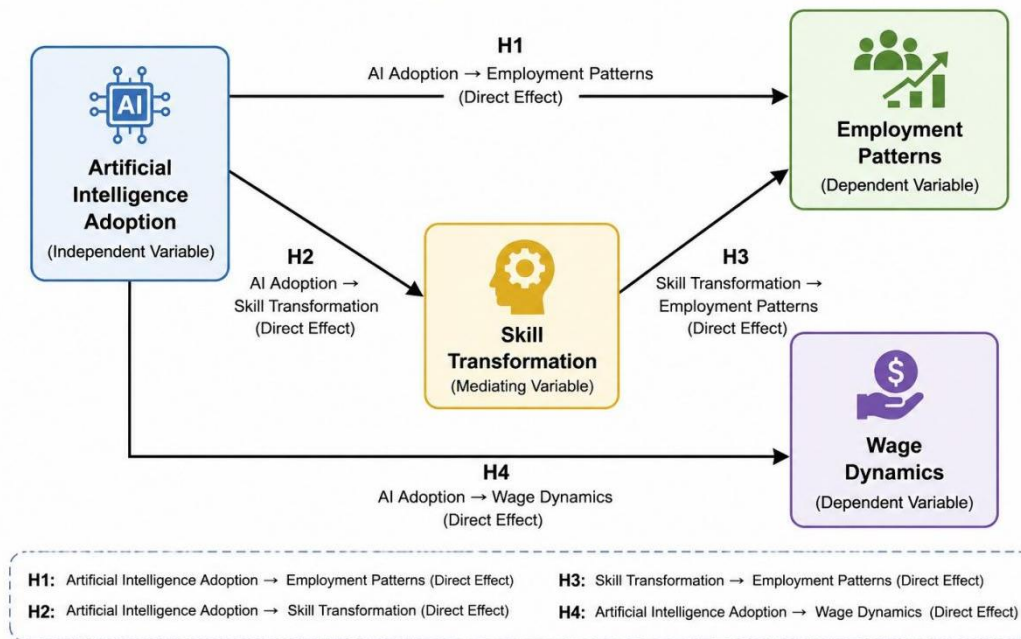


Figure 1. Conceptual Framework Model

Research Methodology

Research Design

This research took a quantitative research design to investigate the effects of artificial intelligence and automation on labour patterns, skills restructuring and wage relationships. To gather data on the respondents working in various industries, a cross-sectional survey methodology was used that enabled consideration of the labor market trends at a certain time. The quantitative design allowed the measurement of the variables relations and the testing of the hypotheses that were proposed with the assistance of the structured statistical methods. The research aimed at capturing the perceptions and experiences of the employees toward the adoption of AI and its impact on their working conditions, skills, and income levels.

Population and Sample

The target population was employees in industries where artificial intelligence and automation were actively employed such as information technology, banking, manufacturing, education, and service industries. A stratified random sampling method was used to select a sample of 320 respondents so that they represented various sectors and job categories. The sampling strategy was diverse in terms of age, gender, level of education and experience in the profession which boosted the external applicability of findings. Both managerial and non-managerial employees were included to make sure that the diverse views about AI-induced changes in the labor market are considered.

Data Collection Method

The structured questionnaire was used to gather primary data online and face-to-face. The questionnaire had closed-ended questions that were developed based on the five-point Likert

scale of strongly disagree to strongly agree. The tool contained questions regarding artificial intelligence adoption, labor trends, skill reconfiguring and wage trends. The data were collected during eight weeks, which guaranteed the adequate response and reduced the non-response bias. The respondents were made aware of the study objective and anonymity and confidentiality were upheld in the data collection process.

Data Analysis Techniques

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data collected with the help of SmartPLS software. This method was chosen because it is appropriate in modeling a complex model with more than two constructs and mediating variables. The analysis was conducted in a two step process which involved the evaluation of the measurement model and the structural model. The measurement model review included the measurement reliability in terms of Cronbach alpha and composite reliability and the measurement validity in terms of convergent validity in terms of Average Variance Extracted (AVE) and discriminant validity in terms of Fornell-Larcker criterion. The structural model analysis was based on path coefficients, t-values based on bootstrapping, and coefficient of determination (R^2) to determine the strength of associations among variables. The mediated analysis was done to study the indirect impact of skill transformation on the linkage between AI adoption and employment pattern as well as wage dynamics.

Results and Analysis

Descriptive Statistics of Study Variables

Table 1. Descriptive Statistics of Artificial Intelligence Adoption, Skill Transformation, Employment Patterns, and Wage Dynamics

Variable	Mean	Standard Deviation
Artificial Intelligence Adoption	4.02	0.68
Skill Transformation	3.88	0.72
Employment Patterns	3.76	0.70
Wage Dynamics	3.69	0.74

Descriptive statistics revealed that the highest mean was associated with the use of artificial intelligence ($M = 4.02$), which means that there is a great consensus among respondents towards the prevalence of AI technologies in their entities. The standard deviation ($SD = 0.68$) was relatively small, indicating consistency in the answers, as there was a common view among sectors that AI integration was an important aspect of organizational activities. The mean score of skill transformation was 3.88, showing that the employees have undergone significant skills transformation in terms of competencies required. The interviewees were aware of the increased significance of digital literacy, analytical thinking, and flexibility in reaction to the AI-driven worlds. The difference in the responses ($SD = 0.72$) indicated the difference in exposure to training and development opportunities in different organizations. The mean values of employment patterns and wage dynamics were 3.76 and 3.69, respectively, which revealed that there was moderate agreement on the impact of AI on job structures and income levels. The findings indicated that AI helped in restructuring jobs and also wage changes. The greater dispersion of wage dynamics ($SD = 0.74$) showed the variety of experiences of respondents, in particular at different levels of skills and industries.

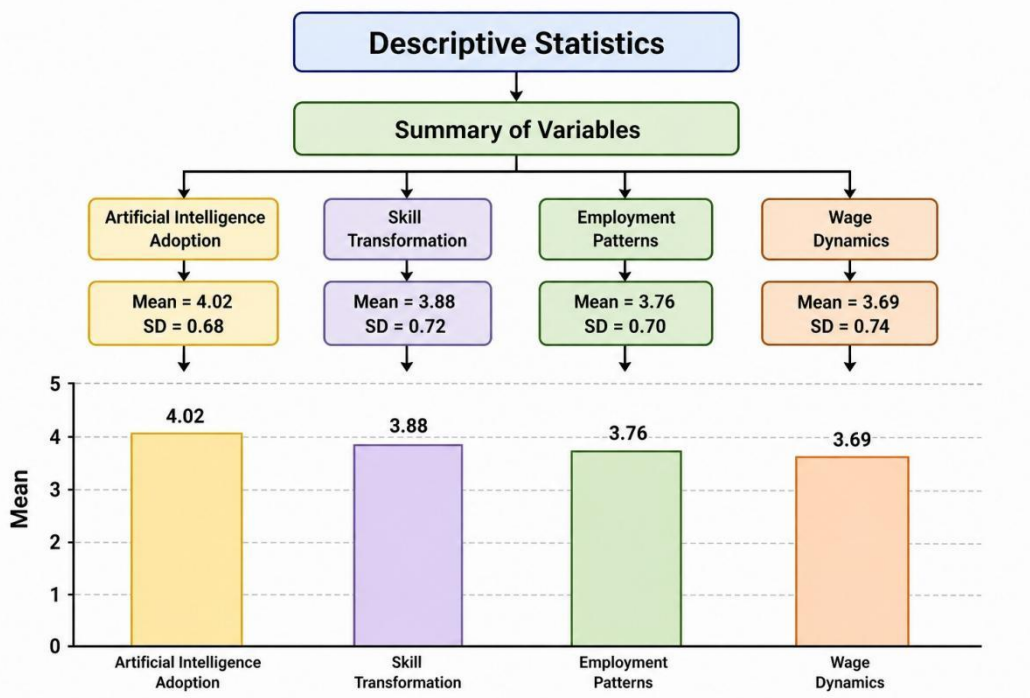


Figure 2. Descriptive Statistics of Artificial Intelligence Adoption, Skill Transformation, Employment Patterns, and Wage Dynamics

Measurement Model Assessment

Table 2. Factor Loadings of Measurement Items

Construct	Item Code	Factor Loading
AI Adoption	AIA1	0.81
	AIA2	0.84
	AIA3	0.79
Skill Transformation	ST1	0.83
	ST2	0.86
	ST3	0.80
Employment Patterns	EP1	0.78
	EP2	0.82
	EP3	0.77
Wage Dynamics	WD1	0.80
	WD2	0.83
	WD3	0.79

The factor loadings provided in Table 2 indicated that measurement items were above the acceptable value of 0.70 meaning that all variables were strongly related with their constructs. The findings indicated that the artificial intelligence adoption items, skill transformation, employment patterns, and wage dynamics were effective in capturing the underlying dimensions of all the variables. The strongest loadings were found with the skill transformation construct, especially when it comes to the ST2 (0.86) and ST1 (0.83) items, which indicated

that the respondents were well in line with the statements referring to the changing skill demands and adaptability to learning. On the same note, the AI adoption items had high loadings all the time, a fact which suggests that the measurement tool was effective in capturing the level of technological integration in organizations. Employment and wage patterns also showed satisfactory loadings, and ascertained that the items used were sufficient to reflect the changes in job structures and earnings. The inter-rater reliability of all constructs implied that the measurement model offered a good starting point on structural analysis and testing of hypotheses.

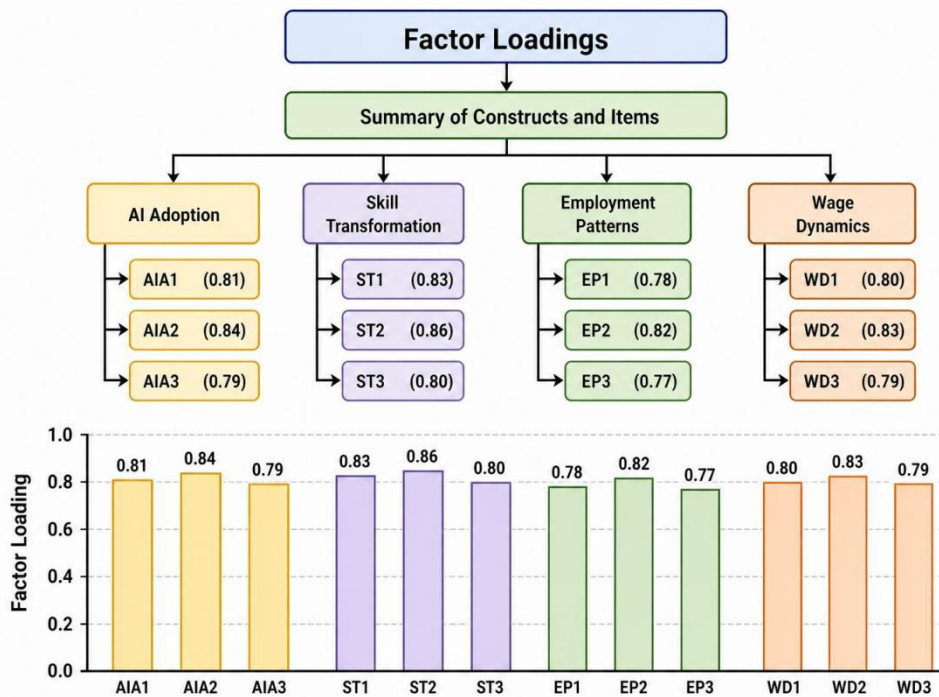


Figure 3. Factor Loadings of Measurement Items

Structural Model Results (Model Fit and Predictive Power)

Table 3. Coefficient of Determination (R² Values)

Dependent Variable	R ² Value
Skill Transformation	0.45
Employment Patterns	0.52
Wage Dynamics	0.49

The values of coefficient of determination (R²) showed the explanatory power of the model in explaining the dependent variables. The R² of skill transformation was 0.45 indicating that artificial intelligence adoption accounted 45 percent of the skill transformation variance. This reflected a medium degree of predictive quality and illustrated the strong impact of AI on the development of workforce skills. The R-squared of employment patterns was 0.52, which means that job structure changes could be accounted by 52 percent of the model. This rather high value implied that both the adoption of AI and skill transformation had significant effects on employment outcomes. The results were an indication of how technological integration has a significant impact on restructuring in the labor market. In the case of wage dynamics, the R²

was 0.49 indicating that the model accounted almost half of the variation in wage changes. This finding meant that the adoption of AI and skill change both had effects on the level of income though other external variables could be involved in wage differentials.

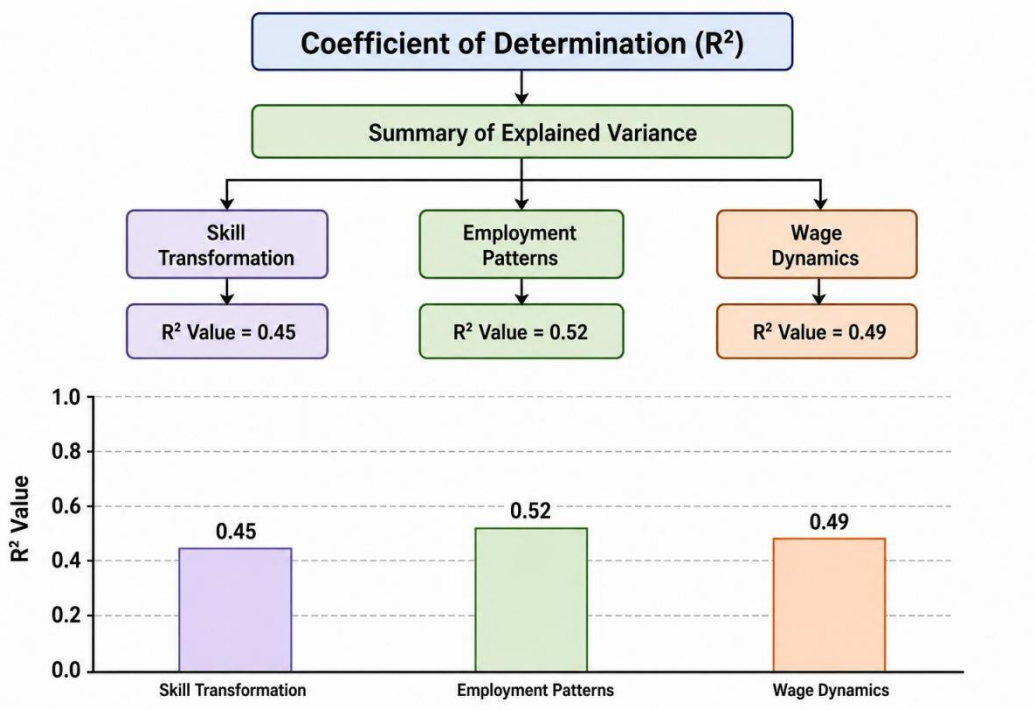


Figure 4. Coefficient of Determination (R^2 Values)

Hypothesis Testing Results (H1–H4)

Table 4. Path Coefficients and Hypothesis Testing (H1–H4)

Hypothesis	Relationship	Beta (β)	t-value	p-value	Result
H1	AI Adoption \rightarrow Employment Patterns	0.63	8.92	0.000	Supported
H2	AI Adoption \rightarrow Skill Transformation	0.67	9.35	0.000	Supported
H3	Skill Transformation \rightarrow Employment Patterns	0.58	7.84	0.000	Supported
H4	AI Adoption \rightarrow Wage Dynamics	0.61	8.10	0.000	Supported

The results of the hypothesis test proved that the use of artificial intelligence had a strong impact on the employment patterns, supported by a high positive path coefficient ($= 0.63, p < 0.001$). This result indicated that AI implementation significantly changed the job structures, which supports the initial hypothesis. The t-value was also high, which further indicated statistical significance and strength of the relationship. It was also found that AI adoption had a significant effect on skill transformation (H2) ($= 0.67, p < 0.001$). This implied that organisations were progressively demanding that employees acquire new skills as a result of changes in technology. Moreover, the transformation of skills had a strong influence on the employment patterns ($= 0.58, p < 0.001$), which reinforced H3 that highlighted the importance of skills in determining the adaptability of the workforce. The use of AI had a significant effect

on wage dynamics (H4: 0.61, $p < 0.001$). This showed that technological integration was a factor in affecting the level of income, especially to the workers who are more skilled.

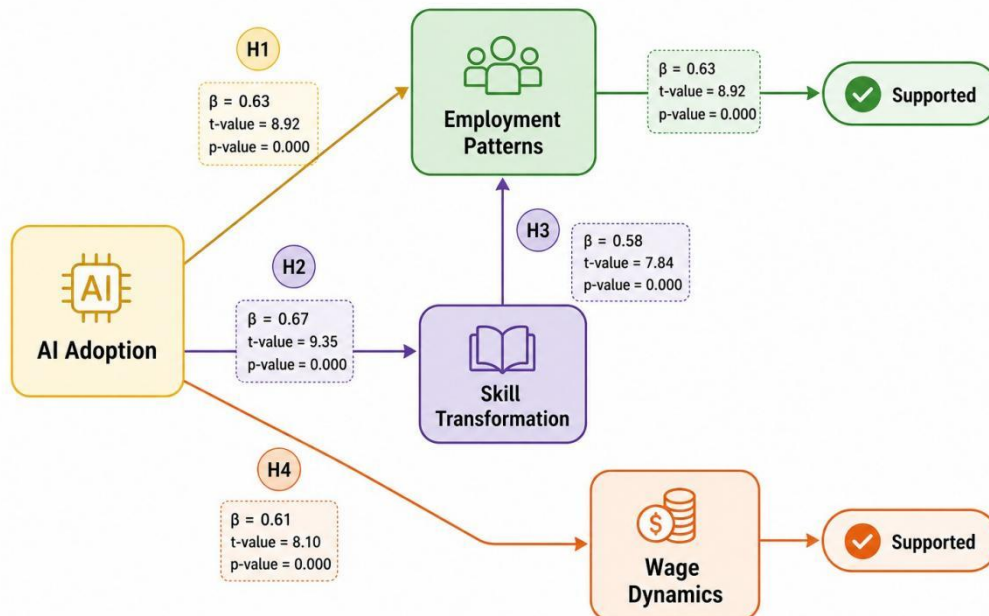


Figure 5. Path Coefficients and Hypothesis Testing

Discussion

The research results supported an expanding empirical body of literature that artificial intelligence (AI) was a transformative force in the labor market by both creating opportunities and exacerbating structural inequalities. The strong positive correlation between AI implementation and employment trends showed that the technological adoption did not merely destroy jobs, but instead transformed the job structures. This explanation was consistent with the current evidence, which indicated that AI restructured the division of tasks in jobs, and that it restructured occupational labor demand (Dahlin et al., 2024; Kauhanen et al., 2025). Some jobs were being displaced, but others grew by augmenting their tasks, which meant that the impact of AI on employment varied depending on whether AI complemented or supplanted human jobs. The findings thus lent credence to the argument that artificially intelligent labor market change was not unilaterally disruptive but context specific and heterogeneous.

The considerable correlation between the adoption of AI and skill transformation also underscored human capital as its core feature in accommodating the technological change. The results indicated that AI heightened the demand on higher-cognitive, digital, and problem-solving skills, thus hastening the shift to knowledge-intensive work. This finding aligned with the recent empirical research that indicated AI exposure stimulated workforce upskilling and transformed occupation skills (Sengupta et al., 2025; Liu et al., 2023). The intermediary effect of skill change showed that the outcomes of employment were heavily reliant on the capacity of the workers to adjust to the changing technological demands. This strengthened the notion that technological change was not the sole factor that dictated what would happen to the labor market; rather, the acquisition of skills and flexibility were pivotal processes that enabled people to overcome AI-driven upheavals.

The beneficial impact of skill change on the employment pattern further support the argument that workforce adaptability alleviated the negative impact of automation. The workers who acquired the corresponding skills had a better employability and access to the newly emerged job opportunities. This observation was consistent with recent theoretical and empirical studies that skill upgrading decreased the risk of technological unemployment and promoted occupational mobility (Dawid et al., 2023; Gravina et al., 2024). The findings thus highlighted the role of lifelong learning and institutional support infrastructures in helping employees to move to new positions generated by AI. Simultaneously, the unequal access to education and training also led to unequal labor market outcomes, which supported the inequalities present. The correlation between AI use and wage dynamics showed that there is a non-linear relationship between the gains in productivity and income distribution. The fact that AI had a large positive effect on wages indicated that the integration of technology led to an increase in productivity and the creation of value, which was reflected in the increased earnings of some groups in the labor market. This observation was in line with empirical data that AI boosted wages by enhancing efficiency and generating high value work (Zhang et al., 2024; Sengupta et al., 2025). The outcome also implicated that these gains were not even spread with wage gains being higher among the high skilled workers than the low skilled workers.

The moderating role of skill transformation in wage dynamics also demonstrated that the income outcomes were extremely dependent on the level of skills and elasticity of the workers. Those who had mastered advanced skills were better placed to enjoy AI-induced productivity gains, but people who did not have these skills experienced slow wage growth, or even no wage growth. This observation was in line with the recent research that showed that AI helped polarize wages by raising returns to skills and education (Al Khatib et al., 2026; Huang et al., 2025). These findings thus confirmed the overall claim that AI increased skill-based inequality especially in the labor markets where education and training opportunities were still unequal. The findings emphasized the importance of AI as a labor-augmenting and labor-replacing technology, which had heterogeneous wage impacts across various groups of occupations. Recent studies showed that AI contributed to higher wages in the jobs where the technology complemented human labor but led to lower wages in the jobs where the technology substituted (Webb et al., 2020; Fan et al., 2025). This two-fold effect justified the observed difference in the dynamics of wages and supported the significance of the nature of tasks to identify the influence of AI on the labor market outcomes. The results thus added to the literature that has been growing on the theme of task-based nature of technological change.

The research also gave clues on the implications of AI on the labor market inequality in general. The findings indicated that the adoption of AI led to the growth of inequalities in the employment opportunities, as well as wage distribution, especially between the high and low-skilled workers. This finding was consistent with the recent theoretical explanations that revealed that AI-driven technological change increased income disparities by disproportionately advantaging highly-skilled workers (Al Khatib et al., 2026; Socio-Economic Planning Sciences study, 2026). The advent of data-driven production processes brought along novel sources of inequality, with access to data and technological infrastructure becoming key factors in determining economic outcomes.

The other key implication of the findings was the different effects of AI by regions and industries. The findings indicated that the greater the technological adoption in the labor market, the greater the changes in employment and wage systems. This understanding was aligned with empirical data which has shown that regional disparities in AI adoption had different outcomes in the labor market, such as a fall in employment rates in some sectors and an increase in wages in others (Huang et al., 2025; Sengupta et al., 2025). Such differences

brought to the fore the necessity of policy interventions region-specific to treat the uneven impacts of technological change.

The results also highlighted the relevance of the policy and institutional frameworks to the outcomes of the AI-based labor market transformation. The identified correlations between AI, skills, and wages indicated that the adverse impacts of automation are potentially limited with the help of proactive policies, including education reform, vocational training, and lifelong learning programs. Most recent findings highlighted the idea that inequality could be decreased with the help of specific policy interventions, such as training subsidies and technological regulation, which would make the labor market resilient (Al Khatib et al., 2026; Dawid et al., 2023).

Conclusion

The research concluded that AI had a profound impact on the nature of labor markets, as it affected both the employment rates, the skills demanded, and the wage distribution. The introduction of AI changed the organization of work by minimizing the need to perform repetitive jobs and raising the level of cognitive and digital abilities required. There was a definite change to high-skilled jobs and a decrease in the stability of low-skilled jobs. The results validated the idea that skill transformation was a decisive process according to which AI had an impact on the employment and wage dynamics. Employees who were more adaptable and technologically skilled enjoyed better jobs and higher earnings as compared to those with low skills who were highly vulnerable. Artificial intelligence became a twofold phenomenon that improved productivity but at the same time led to labour market inequality.

Recommendations

The research suggested that policymakers should emphasize the investment in the education system that is aimed at digital literacy, artificial intelligence, and high-technical training. Reskilling and continuous learning programs ought to be introduced to help the workers who have been displaced due to automation. In order to facilitate worker flexibility and to facilitate a seamless transition to new technology in workplaces, organizations ought to come up with planned training programs. Governments ought to make labor policies that are inclusive and curtail wage inequality and support low-skilled employees in adapting to new jobs. Industrial and academic institutions should work together to ensure that the skills of the workforce meet the new technological needs.

Future Directions

Future studies are needed to examine the long-term consequences of artificial intelligence on the stability of employment in various economic regions and sectors. Commercial comparisons of developed and developing economies can be used to find a further insight on the disproportionate effects of automation. More studies should be conducted to investigate sector-specific applications of AI to learn about differences in the demand of skills and wage distribution. The longitudinal research is suggested to examine the continuous transformations of the nature of labor markets by ever-changing technologies. The application of organizational and psychological variables that affect the adaptation of workers to the AI-based environment should be included in future studies to offer a more holistic view of the transformation of the workforce.

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