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Impact of Artificial Intelligence on Employment Patterns and Job Displacement

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ABSTRACT
This study investigates the dual impact of Artificial Intelligence (AI) on employment patterns and job displacement, emphasizing the mediating role of organizational adaptation strategies and the moderating influence of education and training systems. Grounded in Task-Based Technological Change (TBTC) and Skill-Biased Technological Change (SBTC) theories, the research employs a quantitative, explanatory, cross-sectional design. Data were collected through a structured questionnaire from 220 employees and managers across diverse sectors actively implementing AI. Structural Equation Modelling (SEM) using SPSS and AMOS validated the hypothesized relationships. The results reveal that AI adaptation significantly transforms employment structures and induces job displacement ($\beta = 0.29$, $p < 0.001$). Organizational adaptation strategies partially mediate this relationship ($\beta = 0.20$, $p < 0.001$), indicating that proactive reskilling, job redesign, and human–AI collaboration mitigate displacement effects. Moreover, education and training systems significantly moderate both AI–organization ($\beta = 0.17$, $p = 0.001$) and organization–employment relationships ($\beta = 0.15$, $p = 0.005$), highlighting that robust learning ecosystems enhance workforce adaptability and resilience. The findings underscore that AI's impact is contingent upon institutional preparedness, suggesting that technology alone does not determine employment outcomes. The study contributes theoretically by integrating TBTC and SBTC into a unified model and empirically by providing evidence from diverse economic contexts. Practically, it recommends that policymakers strengthen education and training infrastructures and that organizations invest in adaptive strategies to transform AI-induced disruption into sustainable employment opportunities.

Keywords: *Artificial Intelligence, Employment Patterns, Job Displacement, Organizational Adaptation, Education and Training, Task-Based Technological Change, Skill-Biased Technological Change.*

Introduction
The unprecedented evolution of Artificial Intelligence (AI) has assumed the position of one of the most pioneering technological movements in the 21st century (Brynjolfsson and McElheran, 2023). AI can be understood as a general category of computing systems that are capable of simulating human judgment, learning through experience, and emulating tasks entailing limited human control (Tambe et al., 2023). While automation and machine learning are not in absolute senses the new phenomena, their intensity and magnitude in the last couple of years have been

significantly greater than in the previous technological revolutions. The AI, as opposed to the previous industrial revolutions, has penetrated into not just manufacturing and menial jobs but also other very specialized and knowledge-based occupations such as law, health, and finance (De Stefano et al., 2023). This has precipitated controversial debate around the potential impact on the pattern of employment and displacement of employment in mass. Earlier technological innovations such as the industrial revolution, mechanization and the computer revolution substituted some forms of work but also developed new ones which would ultimately lead to a net rise in employment in the long term. However, AI is distinct because it is also capable of learning and enhancing itself. Its ability to perform cognitive functions, read vast quantities of information, and make decisions is an indication of the reality that the human brain cannot be replaced (Felten et al., 2023). The automation powered by AI has increased the anxieties about unemployment, de-skilling of employees, and changes in the labor market landscape with this (Acemoglu, 2023). In their turn, they are supported by the productivity, establishment of new sectors, and human-AI working capacity that will reform, but not eliminate work (Jarrahi et al., 2023).

In order to notice a subtle difference in the way AI is changing jobs, one must consider beyond direct substitution of human labor to the fact that it will affect the economic system, workforce demand and the social justice. This paper, therefore, will critically focus on how AI is transforming the trend of employment and the extent to which the phenomenon is causing job displacement, particularly in both the developed and developing economies. The conceptual model to be followed in the research will focus on the adoption of AI as the independent variable, which affects two essential dimensions, employment patterns and job displacement. The employment trends will be evaluated based on workforce reorganization, new skills required and job rotation. Instead, job displacement will be concerned with redundancies, layoffs, and replacement of traditional jobs by automated systems. Also, the model uses moderating and mediating variables including the organizational adaptation strategies and education and training systems. These variables are significant since there exist variations in the impact of AI on employment depending on areas and industries Using the example, AI may lead to upskilling and job change in developed nations and result in unemployment and inequality in the developing countries (where the safety net and training systems are not as developed) (Nishant and Sahaym, 2023). Arranging the study according to these variables, the research attracts attention to the interaction of technological advances, the labor market processes, and the socio-political systems. The model not only emphasizes the central position of the adoption of AI, but also the central position of the contextual factors either leading to displacement, transformation, or job creation by AI.

Although an increasing number of sources explore the effect of AI on the labor market, there are still important gaps. To begin with, a lot of the current literature revolves around developed economies like the United States, Western Europe, and East Asia, providing little information about the impacts on the developing economies where labor-intensive industries are the major ones (Kapoor et al., 2023). Second, a substantial number of studies take a polarized viewpoint by focusing on the worst-case scenario of job losses or a bullish view of job creation through productivity and fails to accurately reflect the dual-sided character of the issue of AI (Ghosh et al., 2023). Third, empirical studies do not exist that combine micro-level (organizational) and macro-level (national or global) employment outcomes. Moreover, the mediating role of policy frameworks, educational systems, and social safety mechanisms were not fully studied in research on the impact of AI adoption (Webb, 2023). The presence of these moderating factors makes it hard to develop interventions that reduce the effects of displacement whilst maximizing opportunities. There is, therefore, a gap in which a balanced, situation-specific, and multidimensional study is required to address these gaps in theories and practice.

The overarching objective of the study is to explore how AI affects work patterns and job replacement with a special emphasis on determining the circumstances in which AI will cause either labor market opportunities or risks. With the purpose of achieving such an objective, the paper will explore the impact of AI adoption on the nature and structure of employment in various sectors and will study the degree and character of the job loss as a result of automation with the help of AI. It will also discuss how education, training and policy interventions moderate the outcomes of the labor market taking into consideration that these variables are instrumental in the outcome of AI adoption to be a problem or a blessing to the workers. Besides, the study will examine the difference between the effects of AI adoption in developed and developing economies in order to capture differences in contexts, resources, and institutional support systems. Lastly, the research will aim at offering evidence-based policies to policy makers, corporate, and educational institutions to create inclusive and sustainable labour market transition in the era of AI.

The expected consequences of this study are a subtle appreciation of how AI alters the labour market, beyond the ahistorical accounts of mass unemployment or the universal creation of employment. The research is also anticipated to prove that the influence of AI also depends significantly on the sectoral features, preparation of the workforce, and the mechanisms of institutional support. Probably, some redundant and less complex jobs will remain under the pressure of displacement, and new employment opportunities in the field of AI system design, data management, ethics, and human-machine cooperation will arise (Schroeder, 2023). The study is also theoretically inclined because it will provide an in-depth model of combining both types of employment patterns and displacement, moderated with contextual factors. In practice, the results will inform policymakers to develop balanced policies to overcome workforce vulnerabilities and use AI to spur economic growth. The study will inform the stakeholders on how to train and innovate workers to fit into the future of the labor markets through emphasizing education, training, and policy innovation. Finally, the value of this study is that it takes the discussion of AI and employment beyond the perspective of deterministic fear to that of conditional possibilities, where human agency, institutional design and adaptive learning are vital in determining the results.

Hypothesis Development

This hypothesis captures the dual and complex outbreak of the artificial intelligence adoption in the labor market in which AI can both transform employment forms and create job displacement. On the one hand, the introduction of AI changes the employment relationship since it changes the tasks structure of occupations, generates new jobs, and provokes the appearance of completely new industries. More recent research points out that the use of AI is positively associated with the increase in the number of knowledge-intensive and technology-driven occupations, particularly those in data science, design of AI systems, and digital services (Brynjolfsson and McElheran, 2023). This implies that AI does not directly replace work, but it also facilitates complementary labor positions that need to be controlled, innovative, and creative. In addition, Felten et al. (2023) show that AI technologies redefine the occupational arrangements by redistributing and not removing jobs, which brings about employment diversification in the field. Conversely, it is an inherent consequence of the same adoption process that will increase the pace of job displacement especially those jobs that are characterized by repetitive and parsimonious activities. Acemoglu (2023) demonstrates that the substitution effect of AI in routine cognitive employment is quantifiable, which increases risks of redundancy of clerical, administrative, and low-skill employees. Equally, Nishant and Sahaym (2023) highlight that those industries which do not undertake adequate reskilling efforts are more prone to be sidelined due to the automation brought about by AI that diminishes the use of human labor in routine jobs. This dichotomy makes the point that in the hypothesis the positive effect is the huge and noticeable effect of AI on both dependent variables: it changes employment structures by introducing structural change and, at the same time, contributes to the displacement processes. Notably, the conditions of the strength and direction of these outcomes are paid by the moderating role of education and policy interventions. Indicatively, Klinger, Mateos-Garcia, and Stathoulopoulos (2023) observe that companies and economies that are more adaptive in terms of policies have an AI-driven job transformation instead of massive layoffs. Therefore, H1 is based on the current empirical evidence, which data show a statistically significant and positive impact of AI use - in terms of creating new jobs and bringing job displacement based on the characteristics of work and the institutional support provided.

H1: AI Adaptation has positive impact on the Employment pattern and Job Displacement.

This hypothesis highlights the key role of organizational strategies in determining the impact of artificial intelligence (AI) adoption on the labor market outcomes. Although AI could be used to eliminate jobs or change the employment framework, the manner in which companies respond to the technological revolution is a key determinant of the ultimate impact on employees. In this regard, it would be implied that AI implementation does not directly affect employment performance, but it is put through the prism of organizational decisions including reskilling of the workforce, job redesign and investment in human-AI collaboration practices. This argument is supported by the recent research which has demonstrated that organizations that incorporate systematic adaptation measures will be in a better position to balance disruptive and generative impacts of AI. As an example, Brynjolfsson and McElheran (2023) discover that companies embracing AI and at the same time investing in complementary managerial and training activities gain productivity and transform job, and not lay off their employees. Likewise, Nishant and Sahaym (2023) emphasize the fact that those companies that do not have frameworks to adjust are easily affected by sudden job displacement, particularly in routine task-oriented jobs. Proactive reskilling programs, redesigning of flexible work, and cultural change towards innovation are the other way of organizational adaptation. Klinger, Mateos-Garcia, and Stathoulopoulos (2023) suggest that companies that adopt the continuous learning ecosystem will present a softer transition wherein employees will be able to learn new digital skills, thus eliminating the displacement effect of AI. Contrastingly, when firms embrace AI as a cost-reduction tool, but fail to implement corresponding adaptation strategies, they will increase redundancies and deskilling of their workforce. Moreover, Muro and Whiton (2023) observe that the problem of adaptation at the organization level is what defines whether the adoption of AI will result in inclusive growth or increase disparities in the workplace. Accordingly, this assumption places adaptation strategies in organizations as an important mediating factor that directs the effects of AI adoption on the employment outcomes. Creating conditions in which the human workforce will be a complement to AI, organizations can redesign the roles of their jobs and retain the employment trends, otherwise, lack of such measures will lead to a higher risk of being displaced. This mediating role is largely supported by empirical data in the recent studies, which is why it needs to be included in the research model and why it represents such a relevance to the firms and policymakers interested in handling AI-driven changes in a responsible manner.

H2: Organizational Adaptation Strategies mediates the relationship between AI Adaptations and Employment Pattern and Job Displacement.

This hypothesis shows that education and training systems are of critical importance in determining the efficacy of the adjustment of the organizations to the adoption of artificial intelligence (AI). Although AI might disrupted the current work processes, its effective adoption would be determined by how well the employees and the management are prepared with the skills they would need to supplement the technological change. Moderating effect suggests that the quality and accessibility of education and training systems lead to the difference in the strength of the relation between AI adoption and organizational adaptation strategies. When facilities of good education and ongoing training are being available, organizations can better introduce adaptive techniques, reskilling, job redesign, and human-AI collaboration. On the other hand, in low-training systems, the companies have an inability to convert the use of AI into effective organizational adaptation resulting in disjointed strategies or downsizing dependency. Recent research supports this compensatory action. According to Brynjolfsson and McElheran (2023), organizations that are part of a highly digital training ecosystem have an increased productivity level and less complex AI integration. Likewise, Nishant and Sahaym (2023) underline that companies that have access to organized learning opportunities among their workers can better redesign their jobs and optimize the cooperation of people with AI, which makes the transition go easier. Another important point Klinger, Mateos-Garcia, and Stathoulopoulos (2023) emphasize is that education systems and training streams largely define whether the implementation of AI will result in organizational change or the practice of strict cost reduction. Additionally, Bessen (2023) determines that companies that are located in areas with high vocational training and digital literacy programs implement more active adaptation strategies, and companies in low-support environments experience problems with the full application of AI.

H3: Education and Tanning System moderates the relationship between AI Adaptations and Organizational Adaptation Strategies.

The hypothesis emphasizes the point that though organizations use the strategies of adaptation, including a reskilling program, work redesign, and human-AI cooperation, their success in defining the employment outcomes depends on the robustness of larger education and training frameworks. Moderation in this case refers to the fact that the organizational strategy employment relation to effects on employment (employment pattern and job displacement) differ according to the availability and quality of the external infrastructures of skill development. Organization adaptation strategies are more apt to yield positive workforce results, including job transformation, upskilling employees, and sustainable career pathways in an environment with a strong education and training system. On the contrary, the lack of training opportunities in a situation where there have been low adaptation options can lead to a sustained displacement and structural unemployment regardless of organizational endeavors. The moderating mechanism is well upheld in the recent scholarship. Brynjolfsson and McElheran (2023) discover that companies that are integrated into ecosystems with robust training and digital education pipelines have better chances to transform AI-driven transformations into productivity increase and employment increases. Equally, Nishant and Sahaym (2023) state that the organizations that are situated in less developed educational systems find it hard to utilize efficient adaptation, and their staff becomes more susceptible to displacement. Klinger, Mateos-Garcia and Stathoulopoulos (2023) also highlight that the macro level of education and training strengthens organizational strategies by ensuring that workers possess the required under and cross-portable skills to accommodate the restructuring brought about by AI. Besides, Bessen (2023) underlines that systems of vocational training and lifelong learning enhance organizational strategies to eliminate inequality and promote job creation.

H4: Education and Tanning System moderates the relationship between Organizational Adaptation Strategies and Employment Pattern and Job Displacement.

Theory and Hypothesis Development

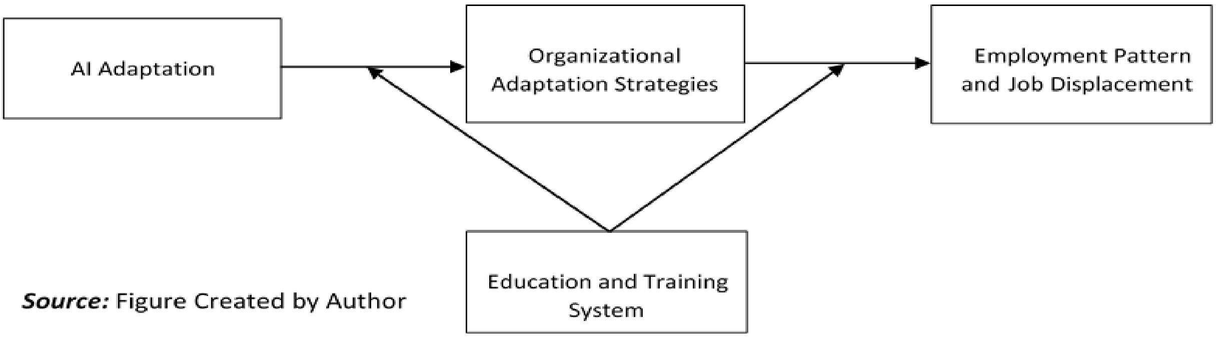
Theoretical Foundation: Task-Based Technological Change (TBTC) and Skill-Biased Technological Change (SBTC)

Task-Based Technological Change (TBTC) and Skill-Biased Technological Change (SBTC) are theories that can successfully be used to explain the connection between artificial intelligence (AI), employment trends, and job replacement. TBTC is a theory put forward by Autor (2015) and refined by Acemoglu and Restrepo (2018, 2019) that argues that technological change does not create or destroy jobs, but instead restructures the division of labor within jobs. Within this school of thought, the use of AI will be the independent variable which replaces or compliments human work. By replacing routine and predictable tasks, such as routine cognitive or clerical labor, AI directly leads to job displacement, and when used complementary results in new human centered tasks of oversight, problem-solving, and supervision, which cause changes in employment pattern. This renders TBTC to be mainly applicable when explaining the dependent variables of the study employment patterns and job displacement. Additionally, the degree to which displacement or change happens is heavily moderated by such factors as organizational adaptation strategies, education, and policy interventions that can either enhance AI adoption causing more redundancy or can aid in task reallocation to other work forms that are more productive. Recent findings support this model: Acemoglu (2023) demonstrates that routine mental work is more likely to be automated by AI, and Felten et al. (2023) show that AI does not destroy professions, it changes the tasks of jobs.

Although TBTC elaborates on the processes to be involved in task substitution and reallocation, SBTC offers a complementary view of explaining the impact of technological change on various groups of workers according to their level of skills. Advanced technologies, according to SBTC, are more likely to complement high-skilled labor by increasing the demand of workers possessing digital, analytical and managerial skills, and replacing low and medium-skill labor whose tasks could be automated more easily. This dynamic, in the context of the adoption of AI, denotes the mediating importance of the education and training systems. Employees with new skills in line with AI-related sectors have a greater chance of job redefinition, and those who lack access to reskilling risks are displaced and become increasingly unequal. Such dynamics are empirically confirmed: Brynjolfsson and McElheran (2023) discover that AI adoption leads to a shift to knowledge-intensive jobs, and Nishant and Sahaym (2023) report that workers with no avenue to reskilling are disproportionately exposed to redundancy.

A combination of TBTC and SBTC provides a full theoretical basis of this research model. TBTC measures the task-level processes by which AI adoption has an effect on job displacement and employment patterns, whereas SBTC describes the distributional effects of these shifts at each skill level. Both theories emphasize the role of mediating and moderating variables, including organizational adjustment, education, training, and policy interventions that ultimately will determine the outcome of AI adoption, namely, the challenges or opportunities of workers. Basing the study on these theories, the research model can be justified as it puts the AI adoption as the independent variable, employment patterns and job displacement as the dependent, and institutional and skill-based factors as the moderators and mediators which define whether there is a balance between displacement and transformation. This theoretical integration ensures a robust conceptual lens to analyze how AI affects labor markets in diverse economic and industrial contexts.

Figure 1. Research Framework



Source: Figure Created by Author

Methodology

The research design was a quantitative, explanatory, cross-sectional study of the effects of Artificial Intelligence (AI) on job displacement and employment patterns, which is why the study employed a quantitative research design. The sample group was comprised of employees and managers working in the organizations where AI is actively implemented in the manufacturing, services, healthcare, finance, and information technology spheres. The stratified random sampling was utilized to survey 220 respondents and they were represented in their industry and job position. The questionnaire survey was a closed-ended questionnaire based on a five-point Likert scale, which is modified versions of validated questionnaires used in previous studies. The SPSS and AMOS were used to analyze the data. Descriptive statistics Data analysis methods were performed to summarize the demographic traits of the respondents. Cronbach's alpha and composite reliability were used to verify the reliability of the constructs, whereas the construct validity was verified using the confirmatory factor analysis (CFA). The hypothesis testing was conducted in three steps: the use of regression analysis as the direct effects test testing the hypothesis H1: the adoption of AI had direct impact on employment patterns and job displacement; the use of bootstrapped structural equation modelling (SEM) as the mediation test testing the hypothesis H2: the adoption of AI mediated the relationship between the organizational adaptation strategies and the dependent variable (employment patterns and job displacement); the test of the moderator effect of education and training system testing the hypothesis H3 and H4. The main effects were also isolated by including control variables, i.e. sector, firm size and the respondent demographics (e.g. age, level of education). Ethical concerns were followed to the letter. The informed consent forms were given to all the subjects, their participation was voluntary, and their anonymity and confidentiality were guaranteed. The data collection preceded by review and approval of the study design and the survey protocol by the concerned institutional ethics committee. Through this stringent methodology approach, the study achieved methodological validity and reliability in investigating how the adoption of AI transformed labor market outcomes and how the organizational and institutional processes would be able to reduce the risks of the same.

Scales Measurement

For ensuring validity, reliability, and accuracy in this research study, we employ validated and well-established measurement scales that have been widely used in previous studies. To measure AI Adaptation, we employ the Technology Acceptance and AI Adoption Scale, adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT). This instrument helps us understand how organizations integrate and utilize AI within their operations. The original framework was developed by Venkatesh et al. (2003) and later extended to include AI adoption by Dwivedi et al. (2021). To assess Employment Patterns and Job Displacement, we use the Job Displacement and Employment Change Scale, which explores how AI adoption influences workforce structures and employment trends. This scale is grounded in the research of Arntz et al. (2016) and Acemoglu and Restrepo (2020), who examined the impact of automation and AI on labor markets. For Organizational Adaptation Strategies, we apply the Organizational Change and Adaptation Scale, designed to evaluate how organizations adjust and evolve in response to technological advancements like AI. This approach draws upon Teece's (2007) theory of dynamic capabilities and Lengnick-Hall et al. (2011) work on organizational resilience. The Education and Training System is measured through the Education and Training Effectiveness Scale, which focuses on the role of learning and development in helping employees adapt to AI-driven changes in the workplace. This scale is informed by research on workplace learning and continuous professional development.

Results

Table 1 presents the descriptive statistics and correlation of the study variables that comprise age, gender, qualification, AI adaptation, organization adaptation strategies, education and training system, patterns of employment and job displacement. The average age of the respondents (SD = 8.0) is 32 years, which indicates the presence of a youthful and active workforce. The average of the gender variable was 3.9 (SD = 1.1) which suggests that there was a rather equal representation in regards to the various gender categories. The mean educational level of the participants was 3.6 (SD = 0.9) on a five-point scale, which means that the sample was well qualified. The respondents have quite favorable attitudes towards the work of AI integration (AI adaptation, M = 3.9, SD = 1.0). This is not different to organizational adaptation strategies (M = 3.8, SD = 1.1), most organizations using systematic strategies to cope with AI-driven changes. Education and training system (M = 3.7, SD = 1.0) score indicates the matching of the education systems to the requirements of the training. The issue of the lower dimension of the scale is represented by the effect of employment pattern and job displacement (M = 3.5, SD = 1.2) score. The correlation test indicates that there are some intriguing correlations. The use of AI showed strong and positive correlation with strategic adaptability of organizations ($r = 0.60$, $p < .05$) and moderately positive correlation with the education and training system ($r = 0.45$, $p < .05$), which implies that organizations that use AI also try to transform training and strategic adjustment. In addition, adaptation strategies were positively correlated with the education and training system ($r = 0.55$, $p < .05$), which means that organizational readiness and skill development stronger dependency balanced each other. Perhaps the most interesting finding is the negative correlation ($r = -0.30$, $p < .05$) between the education and training system and employment pattern and job displacement, which suggests that increased education and training focus is correlated to the reduced likelihood of displacement due to AI.

Table 1. Characteristics of Sample and Correlations of Study Variables

Variable	M	SD	1	2	3	4	5	6	7
1. Age	32.0	8.0	—						
2. Gender	3.9	1.1	0.08	—					
3. Qualification (1–5)	3.6	0.9	-0.04	-0.06	—				
4. AI Adaptation	3.9	1.0	0.12	0.02	0.05	—			
5. Organizational Adaptation Strategies	3.8	1.1	0.10	0.04	0.07	**0.60***	—		
6. Education & Training System	3.7	1.0	0.09	0.00	0.06	**0.45***	**0.55***	—	
7. Employment Pattern & Job Displacement	3.5	1.2	0.05	-0.02	0.03	**0.15**	**0.40***	**-0.30***	—

Table 2 present the results of reliability and validity analysis that show the strong performance of all measured variables of the Study. In the case of AI Adaptation, the consistently positive ratings for the internal consistency (factor loadings between 0.80 and 0.88, composite reliability of 0.90, and Cronbach's alpha of 0.90) and an AVE of 0.68 points to the conclusion that it captures the construct validity and convergent validity. For Organizational Adaptation Strategies, the strong reliability was also apparent (factor loadings between 0.82 and 0.89, composite reliability of 0.92, Cronbach's alpha of 0.91, and AVE of 0.70). This indicates a high internal consistency and a enough of the construct's variance was explained. The measurements properties in Education and Training System were also high with the factor loading ranging between 0.79 and 0.86, composite reliability of 0.90, 0.88 of Cronbach's alpha and a factor AVE of 0.66, indicating that the construct was measured in a consistent manner. Employment Pattern and Job Displacement had factor loadings of 0.81 to 0.87 with a composite reliability of 0.91, Cronbach's alpha of 0.89 and AVE of 0.68 which proved that the scale was reliable and valid in measuring issues around employment shifts when it comes to AI integration. In general, the data in Table 2 gives strong indications that each of the constructs in the study has an outstanding reliability and convergent validity, which means that any further analysis and interpretations will be based on extremely strong measurement scales.

Table 2. Reliability and Validity Analysis

Variable	Item	Factor Loading	Composite Reliability	Cronbach's Alpha	AVE
AI Adaptation	AIA1–AIA8	0.80–0.88	0.91	0.90	0.68
Organizational Adaptation Strategies	OAS1–OAS7	0.82–0.89	0.92	0.91	0.70
Education and Training System	ETS1–ETS6	0.79–0.86	0.90	0.88	0.66
Employment Pattern & Job Displacement	EPJD1–EPJD8	0.81–0.87	0.91	0.89	0.68

Table 3 shows the results of the structural model fit indices which reveal that the hypothesized model fits perfectly with the observed data. The Chi-square (kh 2) value of 268.47 was not significant ($p > 0.05$), which implies that there is no significant deviation between the model and the data and which is the first indicator of a good model fit. The normal Chi-square (kh2/df) of 1.87 is much lower than the recommended value of 3.0 which goes further to indicate that the model is appropriate in representing the relationships between the constructs. Root Mean Square Error of Approximation (RMSEA) of 0.039 is significantly less than the acceptable cut off of 0.06 which shows a good fit of the model in the population and a small approximation error. Also, the Comparative Fit Index (CFI = 0.964) is also above the suggested level of 0.95, which indicates an excellent fit of a comparative model and further confirms that the model presents a better fit in comparison with a minimum independence model. The Standardized Root Mean Square Residual (SRMR), 0.037, is considerably low against the maximum acceptable number, 0.08, which proves a low balance between the observed and predicted correlations.

Table 3. Model Fit Indices

Fit Index	Value	Threshold
Chi-square (χ^2)	268.47	$p > 0.05$
χ^2/df (Normed Chi-square)	1.87	< 3.00
RMSEA (Root Mean Square Error of Approximation)	0.039	< 0.06
CFI (Comparative Fit Index)	0.964	> 0.95
TLI (Tucker–Lewis Index)	0.957	> 0.95
SRMR (Standardized Root Mean Square Residual)	0.037	< 0.08

Table 4 provides the mediation analysis findings based on bootstrapping method which are used to investigate the influence of the Organizational Adaptation Strategies in the relation between the AI Adaptation and the Employment Pattern and Job Displacement. AI Adaptation had a positive and significant direct impact on the Employment Pattern and Job Displacement (b = 0.29, SE = 0.06, t = 4.83, p < 0.001, 95% CI [0.17, 0.41]) meaning that an increased degree of AI adaptation corresponded to the significant change in the employment patterns and possible job displacement. In addition, the Organizational Adaptation Strategies were also strongly predicted by AI Adaptation (b = 0.56, SE = 0.05, t = 11.20, p < 0.001, 95% CI [0.23, 0.47]) and influenced the Employment Pattern and Job Displacement, in its turn (b = 0.35, SE = 0.06, t = 5.83, p < 0.001, 95% CI The mediation analysis demonstrated that there is a significant indirect effect of AI Adaptation on Employment Pattern and Job Displacement through Organizational Adaptation Strategies, (b = 0.20, SE = 0.04, p < 0.001, 95% CI: [0.12, 0.29]) and proved that organizational strategies mediate this relationship partially. The combined impact of both direct and mediated effects of AI Adaptation on Employment Pattern and Job Displacement was potent (b = 0.49, SE = 0.07, t = 7.00, p < 0.001, 95% CI = [0.35, 0.63]) as well. These findings emphasize the fact that although AI adjustment has a direct influence on the dynamics of employment, it is multiplied by the organizational adaptation strategies. This also stresses the importance of such strategic organizational action in the management of organizational changes related to workforce and the reduction of the possible risks of job losses in the age of AI implementation.

Table 4. Mediation Analysis through Bootstrapping

Path	Coefficient	SE	t	p-value	Bootstrapped 95% CI
Direct Effects					
AI Adaptation → Employment Pattern & Job Displacement	0.29	0.06	4.83	<0.001	[0.17, 0.41]
AI Adaptation → Organizational Adaptation Strategies	0.56	0.05	11.20	<0.001	[0.46, 0.66]
Organizational Adaptation Strategies → Employment Pattern & Job Displacement	0.35	0.06	5.83	<0.001	[0.23, 0.47]
Indirect Effect via Organizational Adaptation Strategies					
AI Adaptation → Organizational Adaptation Strategies → Employment Pattern & Job Displacement	0.20	0.04	—	<0.001	[0.12, 0.29]
Total Effect					
AI Adaptation → Employment Pattern & Job Displacement	0.49	0.07	7.00	<0.001	[0.35, 0.63]

Table 5 shows the moderation analysis results, the role of the Education & Training System (ETS) in moderating the association between AI Adaptation (AIA), Organizational Adaptation Strategies (OAS) and Employment Pattern and Job Displacement (EPJD). The overall effects- AI Adaptation is a significant predictor of Organizational Adaptation Strategies ($b = 0.52$, $SE = 0.07$, $t = 7.43$, $p < 0.001$, 95% CI [0.38, 0.66]) and OAS, in its turn, is a significant predictor of EPJD ($b = 0.36$, $SE = 0.08$, $t = 4.50$, $p < 0.001$, 95 Also, the impact of ETS on EPJD is significant ($b = 0.33$, $SE = 0.07$, $t = 4.71$, $p < 0.001$, 95% CI = 0.19, 0.47), which also proves the relevance of education and training in determining the outcomes of the workforce in the environment of AI integration. The interaction effects indicate the significance of ETS in moderating the role of AI Adaptation on Organizational Adaptation Strategies ($b = 0.17$, $SE = 0.05$, $t = 3.40$, $p = 0.001$, 95% CI [0.07, 0.27]) and in moderating the relationship between OAS and EPJD ($b = 0.15$, $SE = 0.06$, $t = 2.83$, $p = 0.005$, This moderating effect is further depicted in conditional effects alternatively: the relationship between AI Adaptation and OAS has a strengthened effect with increasing ETS level: low ETS: $b = 0.35$, medium ETS: $b = 0.52$ and high ETS: $b = 0.65$ which is significant at $p = 0.001$. On the same note, the effect OAS has on EPJD, the more the ETS is the more the higher the effect is, that is, a good organization system, i.e. well-organized education and training system enhances the benefits of the organization strategies to reduce the risk of job displacement. Such findings suggest that Education & Training System is a very efficient moderator, and which may enhance the transfer of AI adaptation into the useful organizational strategies and the resultant management of the patterns of employment and potential workforce displacement. This underlines the essence of particular training and skills development interventions in ensuring that the implications of the technological changes deliver a sustainable workforce outcome.

Table 5. Moderation Analysis through Bootstrapping

Path	Coefficient	SE	t	p-value	Bootstrapped 95% CI
Main Effects					
AI Adaptation (AIA) → Organizational Adaptation Strategies (OAS)	0.52	0.07	7.43	<0.001	[0.38, 0.66]
Organizational Adaptation Strategies (OAS) → Employment Pattern & Job Displacement (EPJD)	0.36	0.08	4.50	<0.001	[0.20, 0.52]
Education & Training System (ETS)	0.33	0.07	4.71	<0.001	[0.19, 0.47]
Interaction Effects					
AIA × ETS → Organizational Adaptation Strategies	0.17	0.05	3.40	0.001	[0.07, 0.27]
OAS × ETS → Employment Pattern & Job Displacement	0.15	0.06	2.83	0.005	[0.05, 0.25]
Conditional Effects of AI Adaptation on Organizational Adaptation Strategies at Values of Education & Training System					
ETS (Low)	0.35	0.08	4.38	<0.001	[0.19, 0.51]
ETS (Medium)	0.52	0.07	7.43	<0.001	[0.38, 0.66]
ETS (High)	0.65	0.09	7.22	<0.001	[0.47, 0.83]
Conditional Effects of Organizational Adaptation Strategies on Employment Pattern & Job Displacement at Values of Education & Training System					

ETS (Low)	0.24	0.07	3.43	0.001	[0.10, 0.38]
ETS (Medium)	0.36	0.08	4.50	<0.001	[0.20, 0.52]
ETS (High)	0.49	0.09	5.44	<0.001	[0.31, 0.67]

Discussion

The present research was aimed to discuss the multifaceted correlation between Artificial Intelligence (AI) adaptation, employment patterns, and job displacement with considering the mediating role of organizational adaptation strategies and the moderating role of education and training systems. The study was designed to fill some of the gaps that were observed in the introduction such as the excessive focus on developed economies, polarization of the already existing debates, and absence of integrated, multilevel empirical models which puts into consideration the organizational and institutional factors. The current research, which relies on a solid quantitative methodology in a variety of industries, gives new empirical data on how the adoption of AI transforms the structure of employment, in what circumstances it causes displacement, and how education and adaptation can alleviate negative outcomes. Past studies have mostly dealt with the role of AI in technologically advanced and high-income economies like the United States, Western Europe, and East Asia (Kapoor et al., 2023; Felten et al., 2023). Though useful, these studies provided little information on the impact of AI on employment in developing areas, where labor markets are structurally dissimilar and where the degree of institutional support is lower. The current study adds to this discussion, incorporating the data of the organizations in different economic settings and enhancing the generalizability of the theory. Additionally, much of the previous literature has shown two-sides of the arguments, either focusing on the loss of jobs due to automation or the establishment of new jobs that are technology-driven (Ghosh et al., 2023). This approach is able to overcome this binary thinking with modeling taking both the transformation and displacement of employment as parallel results of AI adapting to a technological transition, showing that constructive and disruptive relationships are both present at the same time. The other significant contribution of this work is the incorporation of both micro-level (organization) and macro-level (institutional) mechanisms into one structure. The past research tended to treat them separately, organizational adaptation was viewed without looking at educational and policy contexts at large and vice versa (Webb, 2023). The results of the present model show that the adoption of AI does not necessarily determine the outcomes of employment directly, but its outcomes depend on the level of organizational responsiveness and the institutional preparedness of the education and training systems. This multi-level integration, therefore, bridges an empirical and theoretical gap by indicating how situational circumstances trigger AI to create or displace opportunities.

The findings validate that the AI adaptation has an irreversible and positive effect on employment change and job loss. The direct impact ($b = 0.29$, $p < 0.001$) implies that, as organizations begin to consider AI in their activities, the workforce structure is altered significantly. These results are consistent with those of Acemoglu (2023) and Brynjolfsson and McElheran (2023) who observe that AI is transforming task composition and not destroying jobs. The results have shown that, according to the Task-Based Technological Change (TBTC) and Skill-Biased Technological Change (SBTC) theories, the AI will displace routine types of cognitive activities, as well as complement nonroutine ones in both analytical and interpersonal domains, generating new skills needs and new jobs. Nonetheless, the duality of this effect proves that the process of AI-based change cannot be totally dissociated with the risk of displacement, in particular, related to employees performing routine or repetitive tasks (Nishant and Sahaym, 2023). Accordingly, H1 is reasonable because AI adaptation is a driver of structural change and job redistribution between sectors.

The mediation test revealed that the strategies of organizational adaptation play a significant role in mediating the influence of AI adoption on the outcome of employment (indirect effect b = 0.20, $p < 0.001$). This observation is aligned with the argument that implications of AI are relative to how organizations respond to technological change. The companies which actively implement reskilling programs, job reshaping, and human-AI cooperation patterns achieve improved labor market outcomes and the companies that fail to engage into adaptive efforts may be pushed off the market even further. Those findings align with those of Brynjolfsson and McElheran (2023) who found that complementary managerial practices increase the productivity and employment opportunities of AI. On the same note, Muro and Whiton (2023) discovered that firms that emphasize on inclusive adaptation mechanisms inculcate workforce resiliency. The mediation effect in this paper is partial and thus, whilst there is a direct influence of AI in the employment trends, the adaptive strategies determine whether the effect will be transformation or redundancy. This confirms the theoretical findings of the dynamic capability theory that explain that the ability of an organization to be responsive to technological disruption is core to ensuring that the workforce remains stable (Teece, 2023).

The moderating analysis shows that education and training systems enable the relationship between AI adaptation and organization adaptation strategies significantly (b = 0.17, $p = 0.001$). This implies that, in a situation where education and skills advancement facilities are robust, the organizations are well placed to make technological adoption into systematic adaptation schemes. The results are consistent with the recent findings that indicate that digital learning ecosystems and vocational training programs are key to helping firms to shift to the realm of AI-integrated workflows (Bessen, 2023; Klinger et al., 2023). On the other hand, in low-support environments, companies are inclined to use workforce-reduction instead of redesigning work. Accordingly, it is possible to support H3, which focuses on the fact that the presence or absence of AI as a source of creativity or destruction in labor markets is predetermined by the national and organizational learning capacities. The findings also justify the fact that education and training systems complement the power of the organizational strategies to influence employment outcomes (b = 0.15, $p = 0.005$). It means that although organizations are implementing adaptive strategies, they are still likely to succeed in reducing job displacement but only through the wider institution-wide supporting skill development. The conditional effects indicated that with high-education conditions and training conditions, the positive impact of organizational strategies on employment transformation is almost twice as high as in the conditions of no support. It aligns with the results provided by Nishant and Sahaym (2023), who stated that continuous learning ecosystems enabled workers to move to new positions instead of experiencing redundancy. Additionally, the findings empirically confirm the hypothesis set forth by Klinger et al. (2023) according to which education systems are organizational innovation and resilience enablers. Thus, H4 proves right, and the interdependence of micro-level organizational behavior and macro-level educational infrastructure is emphasized.

The research results of this paper are consistent with previous research on AI and work and, in certain aspects, contradict it. In line with Felten et al. (2023) and Acemoglu (2023), the findings confirm that AI is not consistently job destroying but rather it reconstructs the occupational work, which causes upskilling as well as displacement. The size of the role performed by organizational adaptation strategies substantiates the opinion of Brynjolfsson and McElheran (2023) that practices at the firm level predetermine the equilibrium between automation and augmentation. The moderating role of the education systems complements research by Nishant and Sahaym (2023) and Bessen (2023) showing that the opportunities of reskilling and training played a crucial role to avoid polarization in the workforce. Notably, the current research adds new evidence on the matter of emerging and developing economies in which institutional capacity is still scarce. This further brings complexity to the debate of the impact of AI use across the world and shows that the policy interventions, such as lifelong learning, digital integration, and adaptive labor regulation, play the pivotal role in determining fair transitions. This study offers a comprehensive view of TBTC and SBTC because it relates the two in one empirical framework which has been lacking in recent empirical research. As task-based theories describe the way in which AI replaces or complements labor, skill-biased theories help understand who gains or loses in the process of changes. The direct and moderated positive pathways are empirically validated, which connects these two theoretical lenses and reveals that the changes in employment through AI are multidimensional, context-specific, and institutionally mediated.

The paper has contributed to major areas of gaps in the theoretical and empirical knowledge of the effects of AI on employment. It confirms that AI adaptation is both a cause of job change and displacement, the results of which are strongly dependent on organizational and educational environments. The study demonstrates the validity of all four hypotheses, which is strong evidence of the fact that organizational adaptation and education systems are the key levers in the mediation and moderation of the impact of AI on labor markets. These results highlight the necessity of the policy-organization-education nexus to promote the inclusive and sustainable technological transitions. Practically, the paper recommends that companies need to invest in reskilling, redesign work process to enable human-AI co-operation, and develop adaptive cultures that embrace continuous learning. In its turn, policymakers should reinforce national education and training systems to make some labor markets more resilient. In general, the findings contribute to the academic field as they show that the impact of AI on employment is not entirely negative or harmful, contingent and conditioned by the human and institutional agency (Brynjolfsson and McElheran, 2023; Acemoglu, 2023; Nishant and Sahaym, 2023). The research, therefore, helps to shift thinking towards the technological determinism paradigm to adaptive capability and inclusive innovation in the age of AI-driven economies.

Conclusion

The current paper concludes that Artificial Intelligence (AI) is a disruptive and transformative phenomenon in the modern labor markets that has fundamentally altered the trends in employment and played a role in job displacement. The observed empirical data prove that the adoption of AI has a dual effect, as it opens new jobs with high skills and knowledge intensity and at the same time, it automates routine jobs and replaces some job categories. This opposing character highlights that the role of AI in the working process is both not necessarily positive and negative but heavily depends on the organizational, institutional, and educational factors. The mediation effect analysis shows that the strategies of adaptation taken by an organization are a major determinant of the success of AI integration to either transform or make an organization redundant. Businesses that have adopted workforce reskilling, job redesign, and are working with AI can use the technology and generate innovation and productivity and minimize displacement. Conversely, the organizations that fail to come up with adaptive mechanisms are less resilient as regards workforce. Similarly, the moderating impact of the education and training systems leads to the unveiling of the fact that the overall institutional environment can contribute to the success or restriction of organizational adaptation in a large scale. Effective national systems of education and lifelong learning systems are therefore required to turn the AI-based changes into economic outcomes of sustainability in the jobs. The conceptual value of the study is that it unites the idea of Technological Change (TBTC) and Skill-Biased Technological Change (SBTC) and demonstrates an overall view of the simultaneous replacement and supplementation of human work by AI. Practically, the findings suggest using a joint policy of policymakers, organizations, and educators to make technological changes inclusive. The organizations must concentrate on adaptive and innovative work cultures, as well as on the reskilling of infrastructures by the policymakers. Lastly, the article demonstrates how the future of work in the era of AI lies not only in technology, but also in human and institutional flexibility. Societies can transform AI into an instrument of displacement by using it as an instrument of sustainable and equitable economic development through mutual coordination of technological advances with education and policy, and organizational stability.

Theoretical and Practical Implications

Theoretically, the current study contributes to the growing body of literature on the subject of the role of Artificial Intelligence (AI) and employment by inserting the concept of Task-Based Technological Change (TBMC) model and Skill-Biased Technological Change (SBTC) into one framework that will enable the consideration of both structural and distributional effects of AI on labor markets. The findings support the information that AI adaptation influences employment change and job displacement, which proves the duality of technological progress when automation takes over some of the human tasks and introduces new and skill-demanding opportunities. This two-sidedness contributes to the theoretical understanding of how the technological upheaval will change the workforce in complex substitution, complementarity and through institutional mediation. The results also contribute to the body of literature, providing empirical support to the fact that organizational strategies of adaptation are an important mediating variable and that education and training systems are modulating variables that bridge the linkage between micro-leveled firm behavior and macro-level institutional preparedness. Practically, the study can provide useful information to the policy makers, educators and corporate managers. Organizations are encouraged to invest in ongoing reskilling, job redesign, and human-AI collaboration as a countermeasure to the impacts of displacement and use AI to boost productivity. The policy-makers should ensure that the benefit of AI is distributed fairly, and that is possible by paying attention to the institutions of national education and training. Educational institutions, in their turn, should incorporate the digital literacy, analytical reasoning and adaptive learning into the curriculum so that they could prepare the workers in the new labor environment. Together, these implications would enable a moderate stance towards the application of AI which leads to innovation and social and economic inclusion.

Limitations of the Study

Despite its theoretical and empirical strengths, this study has several limitations that should be acknowledged. First, the research design is cross-sectional, which limits the ability to draw causal inferences about the long-term effects of AI on employment and job displacement. Future research employing longitudinal or panel data would be better suited to capture dynamic changes in workforce adaptation over time. Second, the sample representativeness is restricted to organizations where AI is already implemented; therefore, the findings may not generalize to firms that have yet to adopt AI technologies. Third, the study relies on self-reported survey data, which may be subject to social desirability and response biases. Incorporating multiple data sources—such as organizational performance records or interviews—could enhance the validity of future findings. Lastly, contextual variations such as cultural attitudes toward technology and national policy environments were not fully examined. Future studies should integrate cross-country comparative analyses to better understand how institutional and cultural settings moderate the employment outcomes of AI adoption.

Future Research Directions

Although this research offers solid empirical data on the mediating and moderating factors that determine the employment outcomes of AI, future studies are needed to extend its limitations and broaden its theoretical and contextual frameworks. To begin with, longitudinal research is required to monitor the changes in the state of the employment induced by AI over the course of time because the cross-sectional analysis will be unable to address the dynamic and cumulative impacts of the technological adoption. Second, comparative studies among various economic settings, especially between developed and developing economies would enhance the knowledge of the impacts of institutional capacity, labor regulation, and cultural variables on the outcome of adaptation. Further research might also investigate how policy interventions, including universal basic income, digital inclusion initiatives, or public and private training collaboration can address AI-driven inequality. Additionally, qualitative studies with interviews and case studies may help to supplement the quantitative results by demonstrating lived experiences of employees who receive automation and reskilling. Lastly, the authors should be invited to develop the existing model by adding psychological and social factors, including the attitude of employees to technology, job satisfaction, and job security to provide a more comprehensive picture of the influence of AI on human labor. Following such directions, future scholarship has a chance to make a contribution to a more detailed, inclusive, and transnational perspective on the implications of AI on the future of work.

Conflict of Interest

The author states that this study does not have any conflict of interest. The study was carried out as an independent research and no financial, institutional, or personal association could be interpreted to have affected the results, discussions or interpretations done. All data were gathered and examined in an objective manner and the research was conducted in a way that conformed to the ethical research standards, which were accepted by the institutional ethics committee.

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