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The Relationship between Participation in Lifelong Learning Models and Reskilling of Workers Displaced by Artificial Intelligence in Cross River State Nigeria

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Abstract

The rapid adoption of Artificial Intelligence (AI) and automation has led to job displacement across several sectors in Nigeria. This study examined the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria. Guided by Human Capital Theory, the study adopted a quantitative correlational design with simple linear regression analysis. A sample of 228 workers displaced by AI-driven automation between 2022 and 2026 was selected using purposive and snowball sampling techniques. Data were collected using a validated 5-point Likert scale questionnaire with reliability coefficients of 0.84 and 0.88 for the participation and reskilling outcome scales respectively. Pearson Product Moment Correlation and Simple Linear Regression were used to analyze the data at a 0.05 level of significance. The findings revealed a strong positive and significant relationship between participation in lifelong learning models and reskilling outcomes, $r(226) = .61$, $p < .001$. Participation significantly predicted reskilling outcomes and accounted for 37.5% of the variance, $F(1, 226) = 135.47$, $p < .001$. The study concluded that engagement with AI-driven and competency-based lifelong learning platforms is a critical pathway for reskilling and employability among workers displaced by AI in Cross River State. It was recommended that government agencies, NGOs, and industry stakeholders should invest in accessible, scalable lifelong learning models to support workforce transition in the age of AI.

Keywords: Artificial Intelligence, Lifelong Learning Models, Reskilling Outcomes, Job Displacement, Workers Displaced By Ai, Cross River State, Workforce Development

Introduction

The rapid integration of artificial intelligence and automation into workplaces has significantly disrupted traditional job roles across the globe. In Nigeria, industries such as banking, manufacturing, customer service, and public administration are increasingly adopting AI-driven systems to improve efficiency and reduce labor costs. This technological shift has resulted in job displacement for many workers who lack the digital competencies required in the new economy.

In Cross River State, Nigeria, this challenge is particularly pronounced. As the state government and private organizations in Calabar, Ogoja, Ikom and other urban centers digitize operations and adopt AI-based tools, a growing number of workers, especially those in clerical, technical, and entry-level roles, have been displaced or rendered underemployed. The World Economic Forum (2025; 2026) estimates that reskilling will be critical for over 50% of the global workforce by 2027, yet access to structured and scalable reskilling pathways remains limited in many sub-national contexts in Nigeria.

Lifelong learning models, including AI-driven adaptive platforms, micro-credentialing systems, and competency-based online programs, have been proposed as viable strategies for reskilling displaced workers. These models offer personalized, flexible, and scalable learning that can bridge the skills gap created by automation. However, empirical evidence on the effectiveness of these models in the Nigerian context, and specifically in Cross River State, is sparse. It remains unclear to what extent participation in lifelong learning models translates to measurable reskilling outcomes for displaced workers in the state.

Given this gap, this study examines the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria. Understanding this relationship is critical for policymakers, educational institutions, and industry stakeholders seeking to design evidence-based interventions that support workforce transition in the era of AI.

Statement of the Problem

The rapid advancement and adoption of Artificial Intelligence (AI) technologies have transformed the nature of work across the world. While AI has improved productivity, efficiency, and innovation in various sectors, it has also contributed to the displacement of workers whose tasks can be automated or augmented by intelligent systems. As organizations increasingly adopt AI-driven technologies, many workers face the risk of skill obsolescence, reduced job security, and difficulties in adapting to emerging workplace demands.

In Nigeria, the growing integration of digital technologies and AI-enabled systems into sectors such as banking, telecommunications, manufacturing, education, and public administration has altered traditional work processes and competency requirements. Consequently, workers whose skills no longer align with evolving technological demands are increasingly required to acquire new knowledge and competencies to remain employable. Reskilling has therefore become a critical strategy for enhancing workforce adaptability and facilitating successful transitions into emerging job roles.

Lifelong learning has been widely recognized as a viable approach to promoting continuous skill development and workforce resilience in the face of technological change. Through formal, non-formal, and informal learning opportunities, individuals can acquire new competencies needed to navigate changing labour market conditions. Despite growing global recognition of the importance of lifelong learning for workforce adaptation, many workers continue to experience difficulties in accessing or effectively utilizing lifelong learning opportunities to support reskilling efforts.

Although several studies have examined the implications of AI for employment, digital transformation, and workforce development, limited empirical evidence exists regarding the influence of lifelong learning models on the reskilling outcomes of workers displaced by AI, particularly within the Nigerian context. Furthermore, there is a paucity of studies focusing on Cross River State, where the effects of technological change on workforce development remain underexplored. This gap in knowledge creates uncertainty regarding the extent to which lifelong learning models contribute to successful reskilling outcomes among workers affected by AI-driven displacement.

It is against this backdrop that this study seeks to examine the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by Artificial Intelligence in Cross River State, Nigeria.

Research question

Q1. To what extent does participation in lifelong learning models predict reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria?

Hypothesis

Ho1. There is no significant relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria.

Literature Review

Literature shows that AI is reshaping rather than outright replacing jobs, with augmentation and reskilling as the dominant workforce strategy (Microsoft, 2026; NTT DATA, 2026). Global reports indicate that top-performing organizations prioritize targeted reskilling to amplify skilled employees rather than displace them. AI-integrated learning ecosystems such as Coursera (2023), IBM Skills Build (IBM, 2023), and LinkedIn Learning (2023) use machine learning to personalize content and modular delivery. Simplilearn (2026) has scaled to over 6 million learners with AI-first libraries designed for individual and enterprise upskilling.

However, three gaps remain. First, most empirical studies focus on OECD countries with limited sub-national evidence from Africa. Second, there is a disconnect between employer offerings and employee access to upskilling (TriNet, 2025). Third, the direct predictive relationship between degree of participation in lifelong learning models and reskilling outcomes remains under-tested in developing economies. This study fills these gaps by providing evidence from Cross River State, Nigeria.

The literature on artificial intelligence and the future of work increasingly converges on one point: AI is not simply replacing jobs, but reshaping them through task automation and augmentation. Recent reports from the World Economic Forum and NTT DATA emphasize that top-performing organizations are prioritizing “augmentation, not replacement,” and are investing in targeted reskilling to amplify skilled employees rather than displace them (Microsoft, 2026; NTT DATA, 2026). The WEF’s 2030 scenarios further highlight that outcomes will depend less on technology alone and more on human capital strategies and investments made today (World Economic Forum, 2025).

Globally, several frameworks and platforms have emerged to support this transition. AI-integrated learning ecosystems such as LinkedIn Learning, IBM Skills Build, and Coursera AI use machine learning to personalize content and modular delivery, showing improvements in personalization, retention, and scalability (Coursera, 2023; IBM, 2023 and LinkedIn Learning, 2023). Simplilearn’s SkillUp platform has scaled to over 6 million learners with AI-first libraries designed for individual and enterprise upskilling

Simplilearn (Simplilearn, 2026). The IMF (2026) also identifies building effective lifelong learning systems as critical, noting that retraining must be widely accessible and aligned with emerging skill needs. However, three key gaps remain, especially for developing economies:

1. **Contextual Gap: Sub-national evidence in Africa**

Most empirical studies and policy recommendations focus on OECD countries, ASEAN, MENA, or global aggregates. The ILO notes that adoption remains uneven, with office and administrative sectors slower to adopt AI tools despite high exposure (International Labour Organization, 2026). In Nigeria, and specifically Cross River State, there is limited data on how displaced workers actually engage with lifelong learning models and whether participation translates to reskilling outcomes. Existing studies from Cambodia and general emerging market perspectives (Ly, 2026), suggest displacement should be viewed as part of a transformation cycle, but localized evidence is lacking.

2. **Implementation Gap: Access vs. Impact**

Reports show a disconnect between employer offerings and employee access. Only 44% of employers claim to offer formal AI/upskilling programs, while just 33% of employees confirm access (PMC, 2022; TriNet, 2025). Microsoft (2026) Work Trend Index also notes that 58% of users are producing work with AI they could not have a year ago, but institutional factors like culture and manager support account for 67% of AI impact. This suggests that simply providing platforms is insufficient. What is missing is evidence on how participation levels within lifelong learning models predict concrete reskilling outcomes at the individual level.

3. **Theoretical Gap: Human capital response to displacement**

From a Human Capital Theory perspective, learning and reskilling are rational responses to technological disruption. Studies show that organizations prioritizing structured reskilling initiatives experience higher worker retention following automation, and that AI literacy initiatives improve both innovation adoption and workforce confidence (Balakumar and Maria 2020; Kanagarla, 2023; Alsultan and Rueff as cited by Ly, 2026). Yet, the relationship between degree of participation in AI-driven lifelong learning models and measurable reskilling outcomes remains under-tested, particularly with simple correlational designs that can inform policy.

Given these gaps, this study contributes by examining the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by AI in Cross River State, Nigeria. This context is important because the state is experiencing digitization in banking, public service, and SMEs, but lacks coordinated lifelong learning infrastructure compared to leaders like Finland, Ireland, and Denmark.

Methodology

This study adopted a quantitative, correlational research design. A correlational design was deemed appropriate because the study sought to determine the nature and magnitude of the relationship between two continuous variables, and to assess the predictive power of one variable on the other. Specifically, the study examined the extent to which participation in lifelong learning models predicts reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria. Simple linear regression was used to test the predictive relationship. The study was conducted in Cross River State, located in the South-South geopolitical zone of Nigeria. The state has experienced increased adoption of AI and automation in banking, telecommunications, public administration, and SMEs, particularly in Calabar, Ogoja, and Ikom. This context makes it relevant for examining reskilling needs among displaced workers.

The target population comprised workers in Cross River State who were displaced from formal employment between 2022 and 2026 due to AI-driven automation and digitalization. Because no centralized database of AI-displaced workers exists, the accessible population was identified through professional associations, trade unions, and NGO reskilling programs in the state.

A sample size of 250 was determined using Cochran's (1977) formula. A purposive sampling technique was first used to identify eligible participants who confirmed job displacement due to AI or automation. This was followed by snowball sampling to reach additional participants through referrals. This approach was necessary given the dispersed and informal nature of the target population.

Data were collected using a structured questionnaire titled "Participation in Lifelong Learning Models and Reskilling Outcomes Questionnaire" (PLLM-ROQ). The instrument was developed by the researcher based on a review of relevant literature on lifelong learning and workforce reskilling. The questionnaire consisted of three sections. Section A elicited demographic information including age, gender, educational level, industry prior to displacement, months since displacement, and current employment status. Section B measured Participation in Lifelong Learning Models with 4 items. Section C measured Reskilling Outcomes with 4 items. Both Sections B and C used a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Sample items include: "I regularly used AI-driven lifelong learning platforms for reskilling" and "I have acquired new competencies that make me more employable."

To ensure content and face validity, the draft instrument was reviewed by three experts in Educational Technology and Human Resource Management. Their inputs were used to revise item wording and clarity. A pilot test was conducted with 30 AI-displaced workers in Akwa Ibom State outside the study area. Data from the pilot were subjected to reliability analysis using Cronbach's Alpha. The reliability coefficients obtained were 0.84 for the Participation scale and 0.88 for the Reskilling Outcomes scale, indicating acceptable internal consistency (Nunnally and Bernstein, 1994).

With ethical approval from the Research Ethics Committee, research assistants administered the questionnaire both physically and online via Google Forms between. Participants were provided with an informed consent form and assured of confidentiality. A total of 250 questionnaires were distributed, out of which 228 were returned and found usable, representing a 91.2% response rate. University of Calabar, July 2026.

Data were coded and analyzed using IBM SPSS Statistics Version 27. Descriptive statistics including frequencies, percentages, means, and standard deviations were used to summarize demographic characteristics and the levels of the study variables. To answer the research question, Pearson Product Moment Correlation was computed to determine the strength and direction of the relationship between participation in lifelong learning models and reskilling outcomes. To test the hypothesis, Simple Linear Regression analysis was conducted. The level of significance was set at 0.05. Assumptions of linear regression including normality, linearity, and homoscedasticity were checked prior to analysis.

This study is anchored on Human Capital Theory. Human Capital Theory posits that individuals' knowledge, skills, competencies, and experience constitute a form of capital that can be invested in and that yields economic returns. According to Becker (1964), investment in education, training, and skill development increases workers' productivity and earnings potential. The theory argues that in periods of technological change, workers who continually update their skills through learning are better positioned to adapt, remain employable, and capture new economic opportunities created by that technology.

Two core propositions of the theory are relevant to this study:

1. **Skill Investment and Productivity:** Workers who invest in lifelong learning acquire new competencies that increase their human capital. This increased capital directly translates to improved job performance and employability in a changing labor market.
2. **Adaptation to Technological Change:** Technological disruptions such as artificial intelligence devalues some existing skills while creating demand for new ones. Human Capital Theory suggests that the negative effects of displacement can be mitigated when workers engage in continuous reskilling. Thus, participation in learning models becomes the mechanism through which displaced workers rebuild their human capital.

In the context of this study, participation in lifelong learning models represents the investment in human capital. These models include AI-driven platforms, micro-credential programs, and competency-based training that provide displaced workers with new technical and digital skills.

Reskilling outcomes represent the return on that investment. They are measured as the extent to which displaced workers acquire new job-relevant competencies, improve employability, and gain confidence to re-enter the labor market after AI-driven displacement.

Therefore, Human Capital Theory provides the lens for understanding why participation in lifelong learning models should significantly predict reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria. The theory suggests that without deliberate investment in learning, displaced workers will experience a depreciation of their human capital, leading to prolonged unemployment. Conversely, active engagement with lifelong learning models will lead to the accumulation of new skills and better labor market outcomes. Human Capital Theory is therefore appropriate for this study because it explains the economic rationale for reskilling in the age of AI, positions lifelong learning as an investment rather than a cost and provides a basis for recommending policy interventions by government and industry to fund and scale learning models for displaced workers.

Results of findings

From the demographic characteristics of respondents, a total of 228 questionnaires were analyzed. The majority of the respondents were aged 25-34 years (42.5%), male (56.1%), and had a Bachelor's degree (48.7%). Most were displaced from Banking/Finance (31.6%) and Customer Service (24.1%). 39.9% reported being displaced 4-6 months ago, and 44.3% were currently seeking employment.

Table 1 presents the means and standard deviations for the study variables. The mean score of 3.42 for participation indicates a moderate level of engagement with lifelong learning models. The mean of 3.56 for reskilling outcomes indicates that respondents perceived moderate to high improvement in their skills.

Table 1

Descriptive Statistics for Study Variables (N = 228)

S/N	VARIABLES	N	$\overline{X}$	S.D
1.	Participation in Lifelong Learning Models	228	3.56	0.81
2.	Reskilling Outcomes	228	3.56	0.76

Note: Scale range = 1 to 5

Hypothesis one

H0: There is no significant relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria.

The two variables in this hypothesis were participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State. Simple Linear Regression analysis was used to test this hypothesis. The result of the analysis was presented in Table 2. Table 2 presents the summary of simple linear regression predicting reskilling outcomes from participation in lifelong learning models in Cross River state, Nigeria. The result in Table 2 shows that the analysis of variance in the regression output produced an F-ratio of 135.467 ($p< 0.001$), which is statistically significant at 0.05 probability level with 1:226 degrees of freedom. This means that the data for participation in lifelong learning models fits the model better than if participation in lifelong learning models was not added to the model, which means that participation in lifelong learning models contributed to the observed variance in reskilling outcomes among workers displaced by artificial intelligence in Cross River State. The result in Table 2 also shows a regression coefficient (R) of 0.612 and a coefficient of determination (R^2) of 0.375. This implies that 37.5% of the variation in reskilling outcomes among workers displaced by artificial intelligence in Cross River State is accounted for, by the variation in participation in lifelong learning models in Cross River State. Thus 62.5% of the variance in reskilling outcomes among workers displaced by artificial intelligence in Cross River State is attributed to the effect of other variables not considered in this study.

Similarly, the result of the regression weights of the predictor variable (participation in lifelong learning models) in Table 2 shows positive coefficients (B and Beta) of 0.57 and 0.61 respectively. This means that participation in lifelong learning models has a direct positive influence on reskilling outcomes among workers displaced by artificial intelligence in Cross River State, and a unit increase in participation in lifelong learning models in Cross River State would lead to a 0.56-unit improvement in reskilling outcomes among workers displaced by artificial intelligence in Cross River State. Accordingly, the result in Table 2 shows a t-value of 11.64 ($p<0.001$). This implies that participation in lifelong learning models contributed significantly to the variation in reskilling outcomes among workers displaced by artificial intelligence in Cross River State. With this result therefore, hypothesis one (the null hypothesis) is rejected. This means that participation in lifelong learning models significantly predicts reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria.

Table 2

Summary of simple linear regression predicting reskilling outcomes from participation

R	R-Square	Adjusted R-Square		Std. Error of the Estimate	
.612	.375	.372		.60214	
Model	Sum of Squares	Df	Mean Square	F-ratio	Sig.
Regression	49.112	1	49.112	135.467	.001
Residual	81.888	226	12.450		
Total	131.000	227			
Variable	B	Std. Error	Beta	T	Sig.
Constant	1.60	0.19		8.62	.001

Participation in lifelong learning models	.57	.05	.61	11.64	.001

a. Criterion: Reskilling outcomes.
b. Predictors: (constant), Participation in lifelong learning models.

Source: IBM SPSS Statistics Version 27.

Discussion

The purpose of this study was to examine the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria.

The finding of a strong positive and significant correlation, $r = .612$, $p < .001$, indicates that as workers' engagement with lifelong learning models increases, their perceived reskilling outcomes also increase. This aligns with Human Capital Theory (Becker, 1964), which posits that investment in education and skills enhances individual productivity and employability. The result also supports recent global reports and findings that emphasize "augmentation, not replacement" as the primary workforce strategy in the age of AI, where targeted reskilling is essential for displaced workers to remain relevant (Microsoft, 2026; Kanagarla, 2023; IFM, 2026).

The regression analysis further revealed that participation in lifelong learning models explained 37.5% of the variance in reskilling outcomes. This substantial effect size suggests that lifelong learning models are a key determinant of how well displaced workers adapt to new skill requirements. This finding corroborates studies which show that structured reskilling initiatives improve retention and workforce confidence after automation (Kanagarla, 2023). It also supports evidence from AI-integrated platforms that personalize learning and improve scalability and retention (Coursera, 2023; LinkedIn Learning, 2023). However, 62.5% of the variance remains unexplained. This suggests that other factors also play critical roles. These may include individual characteristics such as prior education and digital literacy, socio-economic factors such as access to internet and financial resources, structural factors such as labour market demand and quality of training programmes.

The moderate mean score of 3.42 for participation suggests that while some displaced workers in Cross River State are engaging with platforms such as Coursera, ALX, and NGO skill-up programs, access and consistent use remain challenges. This reflects the implementation gap noted in the literature where only about 44% of employers offer formal upskilling, and employee access is even lower. Given that 44.3% of respondents were still seeking employment, the predictive power of lifelong learning participation becomes even more critical for policy.

In the context of Cross River State, where digitization is accelerating in banking and public service, the results imply that without deliberate investment in lifelong learning infrastructure, displaced workers risk long-term unemployment. The findings extend the literature by providing sub-national evidence from Nigeria, a context that has been underrepresented in global AI and reskilling discourse.

In conclusion, this study provides empirical evidence that participation in lifelong learning models is a significant predictor of reskilling outcomes for AI-displaced workers. Therefore, scaling access to flexible, AI-driven learning ecosystems is not optional but necessary for workforce resilience in Cross River State.

Conclusion

This study examined the relationship between participation in lifelong learning models and reskilling outcomes among workers displaced by artificial intelligence in Cross River State, Nigeria. The findings revealed a strong, positive, and significant relationship between the two variables. Furthermore, participation in lifelong learning models significantly predicted reskilling outcomes and accounted for 37.5% of the variance in the outcome variable.

The results demonstrate that engagement with AI-driven, adaptive, and competency-based lifelong learning platforms is a critical mechanism for helping displaced workers rebuild skills and improve employability in the context of technological disruption. In Cross River State, where automation is increasingly affecting banking, customer service, and public sector jobs, lifelong learning models provide a scalable pathway for workforce transition.

The study therefore concludes that lifelong learning is not a supplementary activity but a strategic necessity for workers displaced by AI. Without deliberate investment in accessible and relevant reskilling ecosystems, the gap between technological advancement and human capital development will continue to widen.

Recommendations

Based on the findings of this study, the following recommendations are made:

1. **Government and Policy Makers:** The Cross River State Government, in collaboration with the Federal Ministry of Labour and the National Board for Technical Education, should establish a “Reskilling Fund” to subsidize access to AI-driven lifelong learning platforms for displaced workers. Public-private partnerships should be encouraged to scale this initiative.
2. **Industry and Employers:** Organizations adopting AI and automation should implement structured reskilling and upskilling programs as part of their workforce transition strategy. This aligns with the “augmentation, not replacement” approach emphasized by global AI leaders.
3. **Educational Institutions and EdTech Providers:** Universities, polytechnics, and platforms like Coursera, ALX, and Simplilearn should co-design localized, industry-relevant micro-credential programs tailored to the job market in Cross River State. Programs should focus on digital literacy, data analysis, and human-AI collaboration skills.
4. **Workers and Professional Associations:** Displaced workers are encouraged to proactively engage with lifelong learning models. Trade unions and professional associations should serve as hubs for disseminating information about free and low-cost reskilling opportunities.

However, this study was limited to Cross River State and used self-reported measures. Future studies should adopt a longitudinal design and include objective measures of employment outcomes. Future studies should also consider a multiple regression model that will include the variables that the remaining 62.5% of the variance this study could not explain to better the full range of predictors of reskilling outcomes among AI-displaced workers in Cross River State. Comparative studies across other Nigerian states are also recommended.

Definition of Key Terms

1. **Artificial Intelligence**

Operationally defined as the use of computer systems, machine learning, and automation technologies by organizations in Cross River State to perform tasks previously done by humans between 2022 and 2026. In this study, it refers to AI tools that led to the displacement of workers from their previous roles in sectors such as banking, customer service, manufacturing, and public administration.

2. **Lifelong Learning Models**

Operationally defined as structured, accessible platforms and programs engaged in by displaced workers to acquire new skills after job loss. In this study, this includes AI-driven platforms like Coursera, ALX, IBM SkillsBuild, micro-credential programs, competency-based online courses, and vocational training attended within the last 24 months. It will be measured using the 4-item "Participation in Lifelong Learning Models" subscale of the PLLM-ROQ.

3. **Reskilling Outcomes**

Operationally defined as the extent to which displaced workers have acquired new technical and digital competencies, improved job search confidence, and perceived employability after participating in learning programs. In this study, it is measured using the 4-item "Reskilling Outcomes" subscale of the PLLM-ROQ on a 5-point Likert scale.

4. **Job Displacement**

Operationally defined as the involuntary loss of formal employment between 2022 and 2026 that occurred directly as a result of the introduction of artificial intelligence and automation technologies in the worker's previous workplace in Cross River State.

5. **Workers Displaced by AI**

Operationally defined as adults aged 18 years and above who were in full-time employment in Cross River State before 2022, and who lost their jobs due to AI/automation, and are currently unemployed, underemployed, or seeking new employment as of 2026.

6. **Cross River State**

Operationally defined as the geographical location and context for this study. It refers to the South-South state in Nigeria where participants were recruited, including major urban centers such as Calabar, Ogoja, and Ikom where AI adoption in organizations is most visible.

7. **Workforce Development**

Operationally defined as the process of improving workers' skills and competencies through lifelong learning interventions to make them fit for current and future labor market demands. In this study, it refers to government, industry, and institutional efforts aimed at reskilling AI-displaced workers for re-employment.

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