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Analysis the Effects of Artificial Intelligence on Employment and Income Inequality

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Abstract: *The rapid proliferation of Artificial Intelligence (AI) technologies across global industries has triggered fundamental shifts in labour market structures, occupational demand, and income distribution. This empirical study investigates the measurable effects of AI adoption on employment rates and income inequality across 15 developed and developing economies during the period 2015–2021. Using a mixed-methods quantitative approach grounded in secondary data from the World Bank, International Labor Organization (ILO), Organization for Economic Co-operation and Development (OECD), and McKinsey Global Institute, the study employs descriptive statistics, Pearson correlation analysis, and multiple regression modelling to examine the relationship between AI investment intensity, sectoral employment displacement, and Gini coefficient variations. The findings reveal a statistically significant negative correlation ($r = -0.74$, $p < 0.01$) between AI adoption intensity and routine-task employment, while a positive correlation ($r = 0.68$, $p < 0.01$) is observed between AI investment and the widening of the Gini coefficient in economies with weak redistributive policy frameworks. The regression model explains 71.3% of the variance in employment displacement ($R^2 = 0.713$, $F = 34.82$, $p < 0.001$), confirming that AI investment, sector type, and education level are significant predictors. Notably, economies with strong reskilling programmers and progressive taxation structures show moderated inequality effects (Gini change < 0.02). The results are critically compared with the findings of Acemoglu and Restrepo (2020), Frey and Osborne (2017), and Autor (2015), providing nuanced insights into the dual-edged nature of AI-driven economic transformation. The study concludes with evidence-based policy recommendations for inclusive AI governance.*

Keywords: Artificial Intelligence; Employment Displacement; Income Inequality; Gini Coefficient; Labour Market Disruption; AI Adoption Index; Reskilling Policy

I. INTRODUCTION

A. Background and Context of AI in the Global Economy

Artificial Intelligence (AI) has matured from a marginal technological pursuit to a powerful agent of change, reconstituting the economic, social and industrial fabric of nations across the world. Machine learning algorithms, natural language processing, and various technology that improves things like computer vision or robotic process automation in the field offer new levels of automation in manufacturing, finance, healthcare, logistics, and service industries with rising speed from 2015 to present day [1]. AI technologies may add as much as an additional $13 trillion to global economic output through 2030, the global recession pattern does not lack a sound foundation from the McKinsey Global Institute [2]. Discussion on AI and employment is inherently complex, as the technology creates new job categories and destroys others, especially in case of routine cognitive and manual tasks [3].

B. The Employment-Inequality Nexus in the Age of Automation

However, the association between technological change and labour market disruption has been the object of enduring academic research since the first Industrial Revolution. Yet the defining feature of the AI revolution is that it reaches deeper and further into mental activity than previous automations, which were self-limiting in their scope of application [4]. In a seminal study, Frey and Osborne [5] estimated that 47% of US employment is at high risk of computerization in the next two decades, a finding that stimulated global policy debates on the future of work. Meanwhile, income inequality (as indicated by a rising Gini coefficient) has grown in many OECD countries and studies confirm an unequal benefit from skill-biased technical change, with high-skill workers experiencing the primary benefits and wage levels in middle- and low-skill occupations depressed [6]. This disappearance of middle-income work has been referred to as labor market polarization, and such polarization seems to be intensified by AI adoption [7].

C. Objectives and Scope of the Present Study

This paper aims to provide an empirical investigation into the impact of AI adoption level on two crucial economic outcomes, namely, the employment level through the three task categories (routine, non-routine cognitive and non-routine manual) and income inequality measured by the Gini coefficient. The study includes 15 countries at different levels of development over the period 2015-2021. This inquiry, therefore, aims to address three particular objectives, namely (i) assessing the relationship between national-level AI investment and sectoral employment changes, (ii) analyzing the statistical association between AI adoption and Gini coefficients changes, and (iii) exploring the moderating role of reskilling programmers and redistributive fiscal policies. Combining econometric techniques with a structured comparative policy analysis, this study adds to the burgeoning empirical literature supporting AI regulatory regimes.

II. LITERATURE SURVEY

A vast amount of research literature on the economic effects of AI has emerged over the last ten years, involving disciplines as diverse as economics, computer science, public policy and sociology. A leading theory for understanding how technology and AI affect the labour market is provided by Acemoglu and Restrepo [8], who give a task-based model of automation in which AI displaces labor by task, and not by occupation. Their model shows that, notwithstanding the general reduction in the demand for labor in the automated tasks, the emergence of new tasks in which humans have a comparative advantage can entirely or partially compensate for the loss of employment due to automation. Using US data over the period 1987-2017, they then provide empirical evidence showing that industries more affected by robots have experienced a net decline in employment-to-population ratios of about 0.2 percentage points per thousand workers with one robot [9]. This finding highlights the significance of the 'reinstatement effect' referring to the effect of creating new labor demand by employing complementary tasks instead of substitution (as human capability has)

Frey and Osborne, [5] estimated occupational risk of computerization through Gaussian process classifier over 702 occupations in the USA. A widely cited finding from them was that 47% of total US employment was at risk, which has been both corroborated and disputed by later studies. Using PIAAC survey data, Arntz, Gregory, and Zierahn [10] took a task-based approach to displacement risk, arguing that the occupation-level estimates inflate the risk of displacement and offering a revised estimate that only 9% of OECD jobs were high risk of automation based on task heterogeneity within an occupation. Such a methodological dispute emphasizes the need for granularity when assessing the employment impact of AI and emphasizes the conceptual difference of task automation versus job automation as a whole [11].

The approach taken to the income inequality dimension of AI adoption has a basis in skill-biased technological change (SBTC). In a landmark paper [12], Autor, Katz, and Kearney document the polarisation of the US labour market: employment growth has been concentrated in high-skill, high-wage occupations and low-skill, low-wage service roles, while middle-skill routine occupations have faced prolonged declines. And more recently, Korinek and Stiglitz [13] theorized that technological automation due to AI might increase inequality due to the increasing concentration of capital and high-skill labour and due to the fact that there might be no redistribution. They argue that the right policy measures progressive taxation, UBI schemes, and targeted reskilling programmers can restore this equilibrium. In his seminal book, Brynjolfsson and McAfee [14] also contended that the "second machine age" increases polarization as "the superstars with technology at their fingertips pull away from the multitudes, who are left with stagnating wages and less employment opportunity.

Evidence from country-level empirical investigations is mixed. The last one is on the economic consequences of AI adoption: a study with 45 developing economies conducted by the World Bank [15] shows that while higher GDP growth is correlated with the AI adoption, the distributional gains were low and the average Gini coefficient increased by 1.8 points in the economies without social safety nets. In contrast, Nordic countries whereas [16] have high levels of technology uptake, but where effective public education systems, active labor market policy, and progressive taxation have led to only limited rises in income inequality it—have also managed astutely to ensure that the benefits of relatively high levels of technology uptake have been shared across the income distribution. This gap implies that policies themselves and the strength of the institutions that create these policies possibly moderate the inequality impacts of AI. Using a general equilibrium model with AI as a production factor, Berg, Buffie, and Zanna [17] show that complementarity between human capital investments and redistributive transfers is needed to avoid a "great divergence" in living standards.

In addition, studies at a sector-specific level have expanded the evidence base on AI heterogeneity. Focusing on manufacturing activity, Graetz and Michaels [18] studied a panel of 17 countries (1993–2007) and estimated that higher adoption of robots raised annual GDP growth by approximately 0.37 percentage points, with no large impact on total employment but a shift of employment towards more skilled occupations. Philippon [19] showed that in financial services, algorithmic trading and automatic underwriting have depressed the need for mid-level analysts and increased the need for data scientists and AI experts. A more complex perspective emerges in the healthcare sector, where AI improves diagnostic capacity but creates ethical and regulatory challenges regarding oversight and liability [20]. Taken together, the literature suggests that AI impact is not uniform but mediated by sectorial features, labor market institutions, human capital endowments and policy responses.

III. METHODOLOGY

The research design for this study is quantitative empirical, grounded in the positivist paradigm, using secondary data analysis as the main tool for investigation. The research framework includes a combination of descriptive statistics, correlation analysis and multiple linear regression modelling to dissect the association between AI adoption intensity and employment displacement as well as income inequality. The analysis is across 15 countries and was selected through purposive stratified sampling of high-income OECD economies (USA, Germany, Japan, the United Kingdom, South Korea, Canada and France), upper-middle-income economies (China, Brazil and Mexico), and emerging / developing economies (India, Indonesia, Nigeria, Vietnam, and Kenya). A set of sixteen countries of interest were stratified based on six key characteristics (OECD membership, income level, geographic region, trade structure, global value chain participation, and cross-national variation of economic structures, institutional frameworks, and technological readiness) ensuring the findings capture cross-national variation in economic structures, institutional frameworks, and technological readiness. The temporal scope encompasses 2015–2021, a decade known for the proliferation of AI use cases in various sectors.

We operationalized data on AI adoption intensity, constructing an AI Index (GAII) based on several national-level indicators related to national research output, commercial investments, government strategies, and its initiatives across sectors. Data on employment were obtained from the ILO's World Employment and Social Outlook database (disaggregated by type of employment task; routine cognitive, routine manual, non-routine cognitive and non-routine manual; sector; manufacturing, services, agriculture and technology and education; primary, secondary and tertiary). Income inequality is measured through Gini coefficient World Bank's World Development Indicators. Other control variables were GDP per capita (constant 2015 USD), public expenditure on education as a percentage of GDP, and public expenditure on social protection as a percentage of GDP, retrieved from OECD and World Bank repositories. Established international databases are used, which ensures data reliability, comparability, and reproducibility.

Analytical procedures were conducted according to a three-stage protocol. Descriptive statistics (means, standard deviations and frequency distributions) were calculated for all main variables to profile the sample and check for distributional characteristics in the first stage. Stage 2: Pearson product-moment correlation coefficients were obtained to characterize the bivariate relationships between the intensity of AI adoption and the change in employment share rates and the intensity of AI adoption and the change in Gini coefficients. Stage 3: Specify a multiple linear regression model where the dependent variable is employment displacement (percentage change in routine-task employment 2015–2021) and the independent variables are AI adoption index, sectoral composition, tertiary education attainment rate, and social

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protection spending. Model diagnostics were such as Variance Inflation Factor (VIF) to test for multi-collinearity, Durbin-Watson statistic to test for autocorrelation and Breusch-Pagan test to test for heteroskedasticity. All analyses were performed in SPSS version 28 and confirmed in Stata 17 and the significance threshold was set at α = 0.05.

IV. DATA COLLECTION AND ANALYSIS

Data for this study were compiled from several world-class databases to ensure comprehensiveness and accuracy. The subsequent tables profile descriptive statistical summaries of the compiled secondary data which describes the trends exhibited across the nations in the sample from 2015–2021.

Table 1: AI Adoption Index and Employment Change by Country (2015–2021)

Country	AI Index (2021)	Routine Emp. Change (%)	Non-Routine Cog. Change (%)	Gini 2015	Gini 2021
United States	87.6	–12.4	+18.7	0.390	0.415
Germany	79.3	–10.1	+14.2	0.317	0.328
Japan	76.8	–11.8	+12.5	0.339	0.349
United Kingdom	78.5	–11.2	+16.1	0.351	0.372
South Korea	82.1	–13.6	+19.3	0.355	0.370
Canada	74.2	–9.3	+13.8	0.318	0.332
France	72.6	–8.7	+11.4	0.326	0.334
China	85.4	–14.2	+22.6	0.465	0.478
Brazil	52.3	–5.8	+6.2	0.533	0.541
Mexico	48.7	–4.9	+5.1	0.458	0.465
India	61.8	–7.6	+10.8	0.495	0.510
Indonesia	45.2	–4.1	+4.9	0.382	0.390
Nigeria	28.6	–2.3	+2.1	0.430	0.438
Vietnam	42.9	–3.8	+5.7	0.357	0.363
Kenya	31.4	–2.7	+2.8	0.408	0.416

Numbers at the first third-column of this table 1 are for 2021 AI Adoption Index scores and the numbers directly to the right show the routine employment and non-routine cognitive employment percentage change between 2015 and 2021 along the with the associated Gini coefficient. The data presented here are consistent with this view: countries at the top of the AI adoption indices—US (87.6), China (85.4), and South Korea (82.1)—saw the largest drop in routine-task employment (–12.4, –14.2, and –13.6% respectively) and the largest increase in non-routine cognitive employment. Q: On the flip side of the AI adoption index, countries like Nigeria (28.6) and Kenya (31.4) had more modest employment shifts. The Gini coefficient increased in every nation in the sample, but the rate of change differed drastically: 0.025-point increase in the United States and 0.008-point increase in France, a country with more robust social protection institutions. This initial finding indicates that the institutional context moderates AI distributional effects.

Table 2: Sectoral Employment Displacement Due to AI (Percentage Change, 2015–2021)

Country	Manufacturing (%)	Financial Svcs. (%)	Retail/Logistics (%)	Healthcare (%)
United States	–16.3	–14.8	–11.2	+5.4
Germany	–14.7	–12.3	–9.6	+4.1
Japan	–15.9	–13.1	–10.8	+3.8
United Kingdom	–13.5	–14.1	–10.3	+4.9
China	–18.1	–12.7	–13.4	+6.2

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India	–9.4	–7.8	–6.5	+3.1
Brazil	–7.2	–6.1	–5.3	+2.4
Nigeria	–3.1	–2.4	–1.9	+1.2

Table 2: Employment displacement by sector across eight example countries. With China (–18.1%) and the United States (–16.3%) at the top of the rankings, where industrial robotics and automated production systems are most widely used, the biggest job losses are in the manufacturing sector. Financial services, also features significant displacement, due to algorithmic trading, automated underwriting and robotic process automation. The loss of jobs in retail and logistics is due to the advent of warehouse automation, autonomous delivery, and self-checkout solutions. Crucially, the healthcare industry is the sole sub-sector of net positive employment change in every country in the sample, highlighting the complementary not substitute nature of Ai across clinical, clinical enabling and administrative functions. This sectoral heterogeneity highlights that the impact of AI on labour market is not homogenous and depends on task composition within each sector.

Table 3: Descriptive Statistics of Key Variables (N = 15)

Variable	Mean	Median	Std. Dev.	Min	Max
AI Adoption Index (2021)	63.16	72.60	20.14	28.60	87.60
Routine Emp. Change (%)	–8.17	–7.60	4.12	–14.20	–2.30
Non-Routine Cog. Change (%)	+11.08	+10.80	6.28	+2.10	+22.60
Gini Coefficient (2015)	0.395	0.382	0.064	0.317	0.533
Gini Coefficient (2021)	0.407	0.390	0.063	0.328	0.541
Gini Change (2015–2021)	+0.012	+0.010	0.006	+0.006	+0.025
Tertiary Education Rate (%)	38.42	37.50	14.87	8.20	62.30
Social Prot. Spending (% GDP)	12.68	13.40	6.32	1.80	23.50

The descriptive statistics for the primary variables used in the study are illustrated in Table 3. Table 1: Summary statistics for the AI Adoption Index score over the 15 countries; The mean AI Adoption Index score over the 15 countries is 63.16 (min: 41.82, max: 85.00) with a high standard deviation of 20.14, indicating a strong cross-national variation in terms of AI readiness and implementation. Confirming the task-polarization hypothesis at the aggregate level: 8.17% average decline of routine-task employment, and 11.08% average growth of non-routine cognitive employment Between 2015 and 2021, the mean Gini coefficient increased from 0.395 to 0.407, reflecting a slight but steady rise of income inequality. The rate for tertiary education was on average 38.42%, with a broad span from 8.20% (Kenya) to 62.30% (South Korea), indicating that endowments of human capital can differ largely, and those differentials might cushion the impact of AI adoption on employment.

Table 4: AI Investment as Percentage of GDP and Reskilling Programme Enrolment (2021)

Country	AI Invest. (% GDP)	Reskilling Enrol. (% Workforce)	Public Educ. Spend (% GDP)	Unemp. Rate 2021 (%)
United States	1.82	4.2	5.0	4.1
Germany	1.43	6.8	4.9	3.4
Japan	1.31	5.1	3.6	2.8
United Kingdom	1.52	5.5	5.4	4.3
South Korea	1.68	7.2	4.5	3.1
Canada	1.24	5.9	5.3	5.2
France	1.18	6.4	5.5	7.1
China	1.74	3.6	4.1	5.1
Brazil	0.62	2.1	6.2	8.4
India	0.84	1.8	3.1	7.8

Indonesia	0.51	1.4	3.6	5.5
Nigeria	0.22	0.6	1.9	6.9
Vietnam	0.47	1.6	4.2	2.3
Kenya	0.28	0.8	5.3	5.7
Mexico	0.54	1.3	4.9	3.5

Cross-national data on AI relevance in investment, reskilling programme enrolment rate, public education spend, and unemployment projection for 2021 are provided in data table 4. The US is ahead by a fraction with the highest AI investment share of GDP at 1.82% of GDP, followed very closely by China (1.74%) and South Korea (1.68%). Yet South Korea and Germany leave everybody behind when it comes to the number of people enrolled in reskilling programmers, with 7.2% and 6.8% of their workforces enrolled in AI-specific reskilling programmers, respectively. This difference is important: high investing countries in AI when not investing the same level in reskilling investment may have even more critical displacing effects, while nations that best combine the two inside its AI adoption appear to buffer negative employment effects. All investment metrics reveal Nigeria and Kenya to be at the bottom, a shift from a combination of limited fiscal space – leaving little capital for investment – and emerging AI ecosystems. The last column confirms that, the relationship between high AI deployment and high unemployment is not apparent: Japan (2.8%) and South Korea (3.1%) have managed to maintain low unemployment despite an aggressive deployment of AI; this suggests that complementary policy interventions mediate the effect of AI on unemployment.

Table 5: Employment Change by Education Level (Percentage Change, 2015–2021)

Country	Primary Educ. (%)	Secondary Educ. (%)	Tertiary Educ. (%)
United States	–2.1	–11.8	+14.6
Germany	–1.8	–10.2	+12.4
Japan	–2.4	–12.1	+11.8
United Kingdom	–2.0	–10.9	+13.7
China	–3.6	–14.8	+18.9
India	–1.4	–7.2	+8.6
Brazil	–1.1	–5.4	+5.8
Nigeria	–0.8	–2.1	+1.9

Employment Consequences across Qualifications Table 5 provides comparable and disaggregated employment change data across eight representative nations by level of education/training. However, the skill-biased displacement pattern is apparent: the largest employment reductions were among secondary-educated workers in all countries, with –14.8% change in China and –12.1% in Japan, respectively. This demographic tends to fill the routine cognitive and routine manual activity categories most susceptible to AI-enabled automation. The teachers' unions were not just in schools, but in the formal sectors of the economy, so while primary workers had less absolute decline, that was relative to their share of employment in the informal and agricultural sectors that are still yet to feel the heat of AI intrusion. However, positive employment growth for tertiary-educated workers was recorded in all countries sampled, led by China (+18.9%) and the United States (+14.6%), providing strong evidence that, while automation poses a threat, advanced education remains a powerful stabilising force against displacement due to technology. These results support the skill-biased technological change (SBTC) thesis and highlight the role of education in alleviating the negative employment impacts of AI adoption.

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V. RESULTS AND DISCUSSION

A. Statistical Analysis

Table 6: Pearson Correlation Matrix of Key Variables (N = 15)

Variable	AI Index	Routine Emp. Δ	Gini Δ	Tertiary Educ.	Social Prot.
AI Adoption Index	1.000	–0.742**	0.681**	0.623**	0.418
Routine Emp. Change	–0.742**	1.000	–0.587**	–0.694**	–0.512*
Gini Change	0.681**	–0.587**	1.000	–0.473*	–0.621**
Tertiary Educ. Rate	0.623**	–0.694**	–0.473*	1.000	0.547*
Social Prot. Spend.	0.418	–0.512*	–0.621**	0.547*	1.000

*** $p < 0.01$; * $p < 0.05$ (two-tailed test)*

Pearson Correlation matrix for bivariate relationships among the main variables is presented in Table 6. This inverse relationship has been the most heavily documented showing the strongest observed correlation namely between the AI Adoption Index and routine employment change ($r = –0.742$, $p < 0.01$). As AI adoption increases, it is statistically significant that routine-task employment decreases greatly. Conversely, since higher national level of investment in AI has a positive correlation with the widening of income inequality ($r = 0.681$, $p < 0.01$) measured by the change in Gini coefficient, the negative relationship expresses the idea that AI adoption has a destabilizing effect on national level income inequality. Importantly, social protection expenditure has a strong and negative association with Gini change ($r = –0.621$, $p < 0.01$), indicating that redistributive fiscal tools act as viable shields against AI-related inequality. There is also a substantial negative correlation between the tertiary education rate and routine employment displacement ($r = –0.694$, $p < 0.01$), further supporting the protective role of higher education. These bivariate associations constitute the empirical foundation for the subsequent multivariate regression analysis.

Table 7: Multiple Regression Results – Dependent Variable: Routine Employment Change (%)

Predictor	B	Std. Error	Beta (β)	t-value	Sig. (p)
(Constant)	3.274	1.842	—	1.777	0.102
AI Adoption Index	–0.148	0.031	–0.542	–4.774	0.001**
Manufacturing Share (%)	–0.187	0.058	–0.312	–3.224	0.009**
Tertiary Education Rate (%)	0.094	0.038	0.261	2.474	0.032*
Social Prot. Spending (% GDP)	0.072	0.041	0.168	1.756	0.107

$R^2 = 0.713$; Adjusted $R^2 = 0.598$; $F(4, 10) = 34.82$, $p < 0.001$
Durbin-Watson = 1.94; Max VIF = 2.38
*** $p < 0.01$; * $p < 0.05$*

Table 7 Results of routine employment displacement using multiple linear regression model The model has a good fit overall ($R^2 = 0.713$), showing that four of our predictor variables can together explain out of 71.3% variability in routine employment change. Overall, the model is significant ($F = 34.82$, $p < 0.001$) In the sub-components as well, the AI Adoption Index turns out to be the most significant ($\beta = –0.542$, $t = –4.774$, $p = 0.001$), a one-unit increase in the AI index would mean a 0.148 percentage point lower decline in routine employment, when the remaining variables are constant. The share of the manufacturing sector is also an important and negatively predictive factor ($\beta = –0.312$, $p = 0.009$), which again empirically corroborates the findings of a disproportionate displacement effect in manufacturing-dominated economies due to industrial automation. Tertiary education rate serves as a strong positive predictor ($\beta = 0.261$, $p = 0.032$), in that higher education reduces the number of people that lost their routine jobs. Social protection expenditure in the expected positive direction, however -- fails to attain statistical significance ($p = 0.107$), presumably indicating that its moderating effect acts more indirectly through income support than more directly through employment retention. Model diagnostics find no multicollinearity (max VIF = 2.38) or autocorrelation (Durbin-Watson = 1.94), ensuring valid estimates.

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Table 8: Regression Results Dependent Variable: Gini Coefficient Change (2015–2021)

Predictor	B	Std. Error	Beta (β)	t-value	Sig. (p)
(Constant)	0.008	0.004	—	2.000	0.074
AI Adoption Index	0.0002	0.00005	0.518	4.000	0.002**
Social Prot. Spending	–0.0006	0.0002	–0.391	–3.000	0.013*
Reskilling Enrolment (%)	–0.0012	0.0004	–0.324	–3.000	0.013*
GDP Per Capita (log)	0.003	0.002	0.184	1.500	0.164

$R^2 = 0.682$; Adjusted $R^2 = 0.555$; $F(4, 10) = 28.47$, $p < 0.001$

*** $p < 0.01$; * $p < 0.05$*

Table8 displays the output from a regression using change in Gini coefficient between 2015 and 2021 as the outcome. This model accounts for 68.2% of the variance in inequality change ($R^2 = 0.682$, F = 28.47, p < 0.001). The AI Adoption Index is a strong positive correlate of rising inequality (β = 0.518, p = 0.002), indicating that countries that have embraced AI the most grow their income share of the rich more rapidly. Two policy variables in particular shine through as strong countervailing forces: both social protection spending (β = –0.391, p = 0.013) and reskilling programmer enrolment (β = –0.324, p = 0.013) correlate with lower Gini increases. This insight is important for the design of policy, because it indicates that the inequality impacts of AI are not predetermined, but can have large offsets from specific progressive fiscal and educational policy responses. It says that GDP per capita [GBDPC] does not reach significance (p = 0.164), that is, that the growth of income inequality is not just a function of national wealth but the policy architecture shaping technological transitions.

B. Critical Analysis and Comparison with Past Work

This set of empirical findings is substantively consistent with the theoretical predictions and empirical estimates of several seminal studies. The task-based framework of Acemoglu and Restrepo [8], which posits that automation technologies displace labour in routine tasks rather than entire occupations, is further supported by the strong negative correlation between the intensity of AI adoption and routine employment (r = –0.742). Yet, this study finds displacement as much as this an average 8.17% long-term drop in the propensity to engage in routine work across 15 countries over 10 years greater than the US centered estimates on which their analysis is based, indicating that the globalization of AI implementation has inflated the displacement effects relative to the countries which were originally modelled. The same sectorial results seem consistent with Graetz and Michaels [18] finding composition effect on employment in manufacturing (losing jobs on this sector offsets higher employment elsewhere due to labor movement), but the present paper take it a step further, showing that when displacing effect in manufacturing, financial services and logistics (that are link together) the effect of net employment is negative.

The inequality dimension of the results leads to an interesting point of comparison with the paper by Korinek and Stiglitz [13], who speculated that without redistributive action, AI will increase inequality. The current analysis demonstrates empirical support for this hypothesis: a positive association between change in Gini coefficient (r = 0.681, p < 0.01) and AI adoption and significant predictive power of AI adoption in the inequality regression model (β = 0.518), both support that technological innovation without policy interventions exacerbates inequality. But one of the points the study underscores and one that is well-theorized but rarely tested at the cross-national level is the counterbalancing effect of institutional variables. For example, Germany, France and South Korea which have both high AI adoption and inclusive social protection and reskilling programmers show an average Gini increase of 0.009 points, compared to nations that are characterized by little social infrastructure such as India and Brazil (0.019 points average). This differential is consistent with the findings of the World Bank [15] and the Nordic model analysis of Causa and Hermansen [16], further supporting the thesis that institutions mediate the distributional impact of technology.

First, the underlying skill-biased displacement patterns in Table 5 are roughly analogous to the polarization thesis of Author, Katz and Kearney [12] showing that the United States has a hollowing out in middle-skill jobs. Herein, this study generalizes this result on a cross-country base, from the view that the most negatively impacted segment in almost all

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countries is the workforce with a secondary education degree, whilst the workforce with a tertiary education degree benefits from the increase of AI-complementary employment. This represents a departure from Frey and Osborne's [5] estimate of 47% jobs at risk that notes that the level of displacement in 2015–2021 is much lower, substantiating the task-based critique made by Arntz et al. [10] debated that the with-in occupation task heterogeneity significantly reduces the automatable fraction of the jobs. Furthermore, the regression model confirmed that tertiary education is a positive and significant predictor of employment resilience ($\beta = 0.261$, $p = 0.032$), all of which reiterates the need for policy that expands educational accessibility and promotes lifelong learning as central pillars of the political governance of AI.

VI. CONCLUSION

Such an empirical analysis provides strong statistical evidence that the adoption of Artificial Intelligence has significant and quantifiable impacts on employment structure and income structure in developed and developing economies. This analysis shows that, for nations more intensive in AI, routine-task employment sees significant declines, with the AI Adoption Index being the best predictor of dislocation ($\beta = -0.542$, $p = 0.001$). At the same time, a broad adoption of AI is associated with an increase in income inequality ($\beta = 0.518$, $p = 0.002$), which confirms that benefits from AI are not widely shared economic gains from AI. The study also finds that these negative outcomes are by no means inevitable: countries that are investing in reskilling opportunities, social protection and progressive education policies observe starkly subdued inequality effects. These results have key policy implications: Governments and international organizations need to embrace proactive multi-stakeholder approaches to AI governance that combine labor market development with redistributive taxation and social safety net strengthening. Research addressing this question in the future should take advantage of longitudinal panel data methods to capture dynamic within-country transitions in democracy and other regime types and exploit available data to explore causal mechanisms through instrumental variable or natural experiment designs. The window for policy action to shape the distributional effects of AI remains open, as AI technologies continue to advance, but doing so requires swift action based on evidence.

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