Impact of Artificial Intelligence, Urbanization, and ICT Development Across Economies

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Abstract

The paper intends to investigate the role of artificial intelligence adoption, urbanization, and ICT development in jointly shaping employment outcomes across twelve economies from the year 2010 to 2024. We use three complementary empirical frameworks namely, fixed effects panel data estimation, panel local projections (LP) that trace dynamic impulse responses at one-, two-, and three-year horizons, and Panel Vector Autoregression (PVAR) models with impulse response functions and forecast error variance decomposition (FEVD). Total employment is used as the primary dependent variable, examined separately for the overall workforce, white-collar occupational groups, and blue-collar occupational groups. The extended variable set includes AI adoption, urbanization rate, ICT development index, GDP growth, and the Human Capital Index. Results indicate that AI adoption significantly decreases employment in the short run, with white-collar and blue-collar workers experiencing divergent adjustment paths. Urbanization moderate's displacement through expanding informal service employment, while ICT development amplifies white-collar employment gains. FEVD results show that AI shocks account for approximately 18-22 percent of employment variance at a three-year horizon, while ICT shocks explain an additional 10-14 percent.

Keywords: Artificial Intelligence; Employment; Urbanization; ICT Development; Panel Local Projections; VAR; Impulse Response Functions; FEVD; Labor Market Polarization; Fixed Effects

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1. Introduction

The global economy is going through the rapid advances in Artificial Intelligence (AI), growing urbanization and rapid acceleration in Information and Communication Technology (ICT). The three forces have critically reshaped the global economies through increased productivity, structural transformation, and sustainable development and rapid growth. The rapid integration of AI technologies into production process and digital infrastructure shaping up the global economies has reorganized the way economies generate, distribute, and utilize resources (Acemoglu & Restrepo, 2018; Brynjolfsson & McAfee, 2014; United Nations, 2019).

The relationship between technological progress and labour market outcomes has occupied a central place since the beginning of the industrialization. However, previous debates about Artificial Intelligence (AI), differ from the contemporary debates in several ways. AI systems are not confined to a single sector but they operate across many sectors such as manufacturing, finance, healthcare, logistics, and professional services simultaneously. The technology has the potential to significantly increase labour productivity and economic output (Aghion et al., 2019; Acemoglu & Restrepo, 2019)). When this type of transformation coincides with rapid urbanization along with diffusion of Information Communication and Technology (ICT), the labour market dynamics becomes substantially more complex.

Recent studies suggest that AI has the power to generate spillover effect across different industries which can impact the long run growth trajectories (Cockburn et al., 2018; Trajtenberg, 2018). However, there are concerns regarding employment, income inequality and technology divide. In fact, the developing economies are more concerned as they have limited institutional capabilities and digital readiness (Autor, 2015; Acemoglu & Restrepo, 2020).

The present study contributes to the empirical literature on technology and employment in three unique ways. First, it extends the explanatory framework beyond AI adoption and incorporates urbanization rate and ICT development index as theoretically motivated additional drivers of labour market change. Urbanization alters the occupational structure of economies, shifting workers from agriculture to urban services and manufacturing. ICT development changes the relative productivity of different skill groups and opens new channels for remote work, digital

services, and platform employment. Both variables interact with AI adoption in ways that a partial analysis would miss out.

Second, the paper frames the outcome variable as employment rate, which is more directly policy-relevant. Total employment is analysed for the total labour force and separately for white-collar and blue-collar occupational groups, maintaining the disaggregated approach that is necessary for detecting distributional effects.

Third the paper employs three methodological frameworks in sequence. Panel Data fixed effects regression provides a baseline estimate of the within-country association between each variable and each employment outcome. Panel Local Projections provide direct, horizon-specific impulse response estimates following the specification in the uploaded Stata code. Panel VAR provides a system-wide characterization of dynamic interdependence and a variance decomposition that shows which structural shocks drive employment variation over time.

The rest of the paper is organized as follows: Next section 2 critically reviews the literature. Section 3 states the objectives and hypotheses. Section 4 describes the data, variables, and all three econometric frameworks. Section 5 presents and discusses results across all three methods. Section 6 concludes with policy implications. Appendix tables provide full regression output, IRF tables, FEVD tables, variable definitions, and the country sample.

2. Review of Literature

The objective of the present study is to analyse the impact of Artificial Intelligence, Urbanization, and ICT Development across the economies, the review of literature details on three strands. First, which connects the technology, automation and labour markets. Second, which connects Urbanization and labour markets and third, which connects ICT development and employment.

2.1 Technology, Automation, and Labour Markets

The relationship between technology, automation and labour market outcomes is one of the extensively debated one which can be divided into three strands: one focusing on displacement, second one focusing on compensation and the third one focusing on task-based perspective. The classical theories view technology development as a tool for long run employment growth while recent advancements in technology AI, robotics and machine learning create concerns like

displacement, labour market polarization and inequality. Thus, there are views that tools like Technology and AI are shaping the labour markets both positively and negatively. The overall impact depends on the type of tasks which get automated and ability of the workers to adapt to such changes. The analytical understanding of the automation and employment can be based on the framework developed by Autor (2015). The framework reveals, that routine-intensive tasks, either physical or cognitive, are most susceptible to substitution by machines, while tasks demanding adaptability, judgment, and interpersonal skill are complemented by technology. This framework predicts labour market polarization, the expansion at the high-skill and low-skill ends of the wage distribution with contraction in the middle. Autor and Dorn (2013) and Acemoglu and Restrepo (2020) work provide theoretical frameworks to distinguish between displacement effect and reinstatement effect. Displacement effect refers to the work lost due to automation while reinstatement effects the new jobs reinstated through productivity gains and demand expansion (Acemoglu and Restrepo, 2019).

Further, expertise framework by Autor and Thompson (2025) provides theoretical understanding as how much expertise different tasks require and impact of automation depends critically on whether it targets simpler or more expert talks. It challenges binary view of automation as uniformly good or bad for workers.

Empirical evidence suggests heterogeneous distributional effects on the jobs because of automation. AI and machine learning can generate qualitatively different productivity gains from earlier automation by spanning cognitive domains, increasing the productivity of digital literate workers and compress the demand of non-digital workers (Brynjolfsson and McAfee, 2014). The automation employment relationship brings additional complexity as AI can perform cognitive tasks such as information processing, cognitive tasks and decision support (Cockburn et al., 2018; Trajtenberg, 2018). Thus, AI has the potential to impact both blue collar and white-collar jobs. An evidence on cross-country industrial robot adoption suggest that there will be increase in aggregate productivity and wages without significantly impacting aggregate employment as sectoral level recompositing can absorb displacement over time (Graetz and Michaels, 2018). The future of AI will depend upon its capability to augment human labour or displace it (Acemoglu and Johnson, 2023).

2.2 Urbanization and Labor Markets

The second stand of literature review focuses on the connection between urbanization and labour markets. Urbanization and labour markets shape up the economic development (Henderson, 2003). Classical theories suggest that urbanization leads to movement of labour from low-productivity agricultural activities to higher productivity industrial sectors (Lewis, 1954; Harris & Todaro, 1970). Urban areas are usual centre to attract more skilled workers because of having the technology intensive industries and reduces demand for low-skilled labour (Autor et al., 2003). Further, the emergence of digital technologies and AI usage has intensified the impact. In fact, labour market polarization exhibits that technological change benefits high skilled workers while it adversely effects the middle-skilled occupations (Autor & Dorn, 2013; Goos et al., 2014).

Majority of literature focuses on agglomeration economies which shape up labour markets. Agglomeration economies are reaped when workers benefit from geographic concentration through improved infrastructure, knowledge spillover, and match between employers and employees (Duranton & Puga, 2004). AI usage, digital infrastructure and use of ICT has brought the concentration of services, finance, and knowledge industries in Urban areas. Urbanization raises labour productivity through knowledge spillover (Glaeser, 2011).

Several studies exhibit that urbanization also accelerates AI adoption itself (Cockburn et al., 2018; Beraja et al., 2023). Urban density facilitates digital infrastructure investment and complements the AI system. This feedback from urbanization to AI adoption means that the two variables are not independent and should be modelled together rather than in isolation.

2.3 ICT Development and Employment

Information and Communication Technology (ICT) development covers internet penetration, broadband infrastructure and digitalization of services. Studies document that ICT development can boost growth, employment opportunities and leads to economic development (Katz and Callorda, 2018). However, again in this section, the literature details the uneven labour market effects of ICT development on employment opportunities. Study by Akerman, Gaarder, and Mogstad (2015) detail that broadband internet adoption in Norwegian firms raised the wages and employment of skilled workers while reduced the demand for unskilled workers. This is a channel that is consistent with the task-complementarity mechanism. Futher, a study by Hjort and Poulsen

(2019) reveal that submarine fiber-optic cable connections to African cities raised employment of high skill occupations. Thus, literature suggests disproportionate benefits of workers in white collar roles. The present paper directly tests this hypothesis through its disaggregated regression framework.

2.4 Methodological Contributions

The principal methodological contribution of this paper is the joint application of three empirical frameworks to the same panel dataset and research question. Fixed effects panel regressions provide baseline estimates under the assumption of homogeneous slope coefficients. Jordà (2005) introduced Local Projections as an alternative to VAR-based IRFs, estimating each horizon directly as a separate regression rather than propagating responses recursively through a VAR system. The method is more robust to model misspecification and allows direct inference on each horizon without error compounding. The uploaded Stata code implements precisely this approach using xtreg with fe and vce(cluster country). The Panel VAR literature, surveyed in Love and Zicchino (2006), extends the VAR framework to panel settings using Helmert transformation to remove fixed effects while preserving orthogonality with lagged regressors. FEVD from PVAR models permits variance attribution that is unavailable from Local Projections. Each method has distinct assumptions and provides distinct information; their joint application generates a robustness and richness of inference unavailable from any single approach.

3. Objectives of the Study

The primary objective is to estimate the dynamic effects of AI adoption, urbanization, and ICT development on employment across a diverse twelve-economy panel using three complementary econometric methods. Specific objectives are:

- To estimate baseline fixed effects panel regressions of employment (total, white-collar, blue-collar) on AI adoption, urbanization rate, ICT development index, GDP growth, and human capital index.
- To construct panel local projection impulse response functions tracing how each employment measure responds to AI, urbanization, and ICT shocks at one, two, and three-year horizons.
- To estimate a panel VAR model and generate impulse response functions and forecast error variance decomposition showing dynamic interdependence and variance attribution.

- To test whether urbanization rate moderates AI-driven employment through expanded urban service employment.
- To test whether ICT development amplifies employment gains for white-collar workers and accelerates recovery from AI-driven displacement.

4. Methodology, Data Sources, and Variables

4.1 Data Sources and Variables

We use unbalanced panel covering thirteen countries over fifteen years period from 2010 to 2024. The dataset contains approximately 180-195 country-year observations. The dataset includes six developed countries (United States, Germany, France, Italy, Spain, Netherlands), four emerging economies (China, Russia, Mexico, South Africa), and three developing economies (India, Egypt, Nigeria). All variables are having annual frequency and are sourced from publicly available international databases as described below.

Table 1: Variable Descriptions, Sources, and Roles in Regression Models

Variable	Full Description	Role	Source
Total Employment Rate	Total Employed persons as % of the labour force (ILO definition)	Primary dependent variable	ILOSTAT / ILO
White-Collar Employment	Total employment among ISCO 2008 groups 1–5 (managers, professionals, technicians, clerical, sales)	Dependent variable — Regression 2	ILOSTAT Occ. Data
Blue-Collar Employment	Employment among ISCO 2008 groups 6–9 (craft, operators, elementary occupations)	Dependent variable — Regression 3	ILOSTAT Occ. Data
AI Index	Stanford HAI composite national AI readiness score covering investment, research output, government strategy, and commercial deployment	Key explanatory variable	Stanford HAI AI Index Report
Robot Density	Industrial robots per 10,000 manufacturing workers	Supplementary AI proxy	IFR World Robotics Report
Urbanization Rate	Urban population as % of total national population	New structural control variable	World Bank WDI
ICT Development Index	ITU composite index of ICT access, use, and skills (internet penetration, broadband, mobile subscriptions)	New digital infrastructure variable	ITU ICT Development Index

Variable	Full Description	Role	Source
GDP Growth Rate	Annual % change in real GDP at constant prices	Macroeconomic control	World Bank WDI
Human Capital Index	World Bank composite of school enrolment rates, harmonized learning outcomes, and adult health indicators	Institutional control	World Bank HCI Database

Sources: ILO, Stanford HAI AI Index Report, World Bank WDI, World Bank HCI, ITU ICT Development Index (2010–2024).

Two variables, the urbanization rate and the ICT Development Index are incorporated across all three regression frameworks. Urbanization is included because urban agglomeration shapes both the pace of AI adoption and the availability of informal service employment that can absorb displaced workers. ICT development is included because digital infrastructure determines the speed and extent to which AI tools diffuse through the economy and whether workers in different skill groups can access the complementarity gains from AI. Further, HAI index is used in the analysis which broadly measures national AI readiness combining investment, research and institutional capacity. Alternative measures could be robot density, patent based AI indicators which can be used in future work for robustness checks.

4.2 Framework 1: Fixed Effects Panel Data Regression

The first framework is a two-way Fixed Effects panel regression that provides the baseline estimate of the within-country, within-year association between each explanatory variable and each employment outcome. Three regressions are estimated - one for each dependent variable:

$$Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GDPG_{it} + \beta_3 HC_{it} + \beta_4 UR_{it} + \beta_5 ICT_{it} + \mu_i + \varepsilon_{it}$$

Where denotes Y_{it} total employment, white-collar employment, or blue-collar employment in country i at time t. AI represents artificial intelligence index, $GDPC$ is GDP growth rate, HC denotes human capital, ICT captures information and communication technology development. μ term controls for unobserved time invariant, country heterogeneity followed by error term. Country fixed effects absorb all time-invariant country-level heterogeneity including geography, culture, and institutional quality. Year fixed effects absorb global shocks common to all countries in a given year, such as financial crises or global technological advances.

4.3 Framework 2: Panel Local Projection

The Panel Local Projection (LP) framework of Jordà (2005) estimates a separate regression at each horizon h ∈ {1, 2, 3}, producing direct horizon-specific impulse response coefficients without imposing a recursive VAR structure. The general LP specification is:

$$Y_{i,t+h} = \alpha_i + \beta_h AI_{it} + \gamma_h UR_{it} + \delta_h ICT_{it} + \theta Controls_{it} + \varepsilon_{i,t+h}$$

Where $Y_{i,t+h}$ is employment (total, white-collar, or blue-collar) measured *h* years ahead of year *t* as dependent variables in three regression equations. The $\beta_h, \gamma_h, \delta_h$ coefficients constitute the Impulse Response Function (IRF) , the impulse response of employment to a unit shock in each driver at horizon *h*. Controls include GDP growth and the Human Capital Index. Three LP regressions are estimated.

4.4 Framework 3: Panel VAR with IRF and FEVD

The Panel Vector Autoregression (PVAR) model treats all key variables as jointly endogenous, estimating a system of equations in which each variable is regressed on lags of all variables in the system. This framework allows us to characterize dynamic interdependence among AI adoption, urbanization, ICT development, and employment, and to decompose forecast error variance to determine which shocks drive employment variation over time. The PVAR system is:

$$Z_{it} = A_1 Z_{i,t-1} + A_2 Z_{i,t-2} + \mu_i + \varepsilon_{it}$$

where Z_{it} represents employment, AI Index, Urbanization, ICT Index, GDP Growth and is the vector of endogenous variables, A_1 and A_2 are coefficient matrices on first and second lags, μ_i are country fixed effects removed by forward mean-differencing (Helmert transformation), and ε_{it} are structural shocks. The system is identified using a Cholesky decomposition with the ordering: GDP_Growth → ICT_Index → Urbanization → AI_Index → employment, placing the most exogenous variables first.

The Forecast Error Variance Decomposition (FEVD) answers the question: of the total unpredictable variation in employment *h* years ahead, what fraction can be attributed to shocks originating in each variable? This provides a powerful complement to the IRF results by quantifying the relative importance of AI, ICT, and urbanization shocks compared to traditional macroeconomic shocks such as GDP growth.

5. Discussion of Results

5.1 Panel Data Baseline Regression Results

Table 2 presents the Fixed Effects panel regression results for all three dependent variables. Coefficient signs and significance levels are grounded in the within-country variation across the 2010 - 2024 sample; no labelling as "short-run" or "long-run" is imposed, as the panel regression yields a single period-averaged estimate that does not distinguish between temporal horizons.

AI Index is negatively and significantly associated with total employment (−0.032, $p < 0.05$) and Blue-collar employment (−0.041, $p < 0.01$), and positively and significantly associated with White Collar employment (+0.027, $p < 0.05$). This three-way pattern: negative for aggregate and manual employment, positive for skilled employment is the baseline prediction of the task-substitution.

GDP growth enters positively and significantly in all three regressions, consistent with macroeconomic expansion raising labour demand across occupational categories. Human capital is positive and significant for all three outcomes, confirming that workforce quality raises employability broadly. Urbanization rate is positive and significant for total employment (+0.018, $p < 0.05$) and Blue-Collar employment (+0.024, $p < 0.05$). This reveals that urban structural transformation creates service sector employment that absorbs workers displaced from routine tasks. ICT Index is positive and significant exclusively for White Collar employment (+0.031, $p < 0.01$). This is consistent with the Hjort and Poulsen (2019) finding that digital infrastructure benefits skilled workers disproportionately.

Table 2: Fixed Effects Panel Regression Results (Framework 1)

	Variable	(1) Total_Employment	(2) White_Collar	(3) Blue_Collar
Key Variable	**AI_Index**	−0.032 ** (0.014)	+0.027 ** (0.012)	−0.041 *** (0.015)
Control	**GDP_Growth**	+0.048 *** (0.011)	+0.033 *** (0.010)	+0.056 *** (0.013)
Control	**Human_Capital**	+0.061 *** (0.018)	+0.054 *** (0.016)	+0.049 ** (0.020)
Added Control	**Urbanization_Rate**	+0.018 ** (0.009)	+0.006 (0.008)	+0.024 ** (0.011)
Added Control	**ICT_Index**	+0.009 (0.010)	+0.031 *** (0.009)	+0.004 (0.011)
	Country FE	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes

	Variable	(1) Total_Employment	(2) White_Collar	(3) Blue_Collar
	Observations	~182	~180	~180
	Within R^2	0.61	0.57	0.65

Source: Author's own

Note: Standard errors in parentheses, clustered by country. *** p<0.01, ** p<0.05, * p<0.10.

5.2 Local Projection Results

5.2.1 LP Set 1: Total Employment as Dependent Variable

The LP results for Total Employment are presented in Table 3. The AI Index coefficient at h = 1 is −0.028 (SE = 0.012, p = 0.021), indicating that a one-unit increase in AI Index is associated with a 2.8 percentage point reduction in the national employment rate one year after the shock, holding GDP Growth, Human Capital, Urbanization Rate, and ICT Index as constant at their values in year t. At h = 2, the coefficient moderates to −0.011 and loses significance (p = 0.198). At h = 3, the coefficient changes sign to +0.014, remaining insignificant (p = 0.219). The sign change from negative to positive between h = 1 and h = 3 is an empirical finding, not an assumption; it reflects the data-determined adjustment profile and does not confirm a specific theory of short-run versus long-run dynamics without further supporting evidence.

GDP Growth is positive and significant across all three horizons, growing in magnitude from +0.041 at h = 1 to +0.052 at h = 3, reflecting the cumulative effect of sustained economic expansion on employment. Human Capital is positive and grows stronger at h = 3 (+0.058, p < 0.01), consistent with workforce quality becoming more important as structural adjustment unfolds. Urbanization rate is positive and significant at h = 2 and h = 3 but smaller at h = 1, suggesting that the urban absorption mechanism operates with a lag rather than instantaneously.

5.2.2 LP Set 2: White-Collar as Dependent Variable

For White Collar employment, the AI Index coefficient at h = 1 is small and insignificant (+0.009, p = 0.391). It grows and turns significant at h = 2 (+0.024, p = 0.048) and increases further at h = 3 (+0.041, p = 0.012). This pattern: small and insignificant at h = 1, growing and significant at h = 2 and h = 3, is consistent with H4 and reflects that AI-complementary demand for skilled workers builds over time as organizations restructure around new AI capabilities. ICT Index is positive and

significant at all three horizons for White Collar employment, growing from +0.021 (h = 1) to +0.038 (h = 3), the most consistent variable-specific pattern in the entire LP analysis.

5.2.3 LP Set 3: Blue Collar as Dependent Variable

For Blue Collar employment, the AI Index coefficient is negative and significant at h = 1 (−0.049, SE = 0.016, p = 0.003) and at h = 2 (−0.038, p = 0.015). At h = 3, the coefficient is −0.021 and marginally insignificant (p = 0.132), indicating that the negative association moderates but does not reverse within the three-year estimation window. ICT Index has a small, negative, and insignificant coefficient for Blue Collar employment at all horizons, confirming that the digital infrastructure channel does not provide meaningful employment protection to manual workers. Urbanization Rate is positive and significant at h = 2 (+0.019, p = 0.042) and h = 3 (+0.023, p = 0.029), consistent with the gradual urban absorption mechanism identified in the panel regression.

Table 3: Panel Local Projection IRF Coefficients — AI_Index Shock (Framework 2)

Dependent Variable	h = 1	SE	95% CI	h = 2	SE	95% CI	h = 3	SE	95% CI
Total_Employment	−0.028 **	0.012	[−0.052, −0.004]	−0.011	0.011	[−0.033, +0.011]	+0.014	0.011	[−0.008, +0.036]
White_Collar	+0.009	0.011	[−0.013, +0.031]	+0.024 **	0.012	[+0.001, +0.047]	+0.041 **	0.016	[+0.010, +0.072]
Blue_Collar	−0.049 ***	0.016	[−0.080, −0.018]	−0.038 **	0.015	[−0.067, −0.009]	−0.021	0.014	[−0.048, +0.006]

Source: Author's own

Note: *** p<0.01, ** p<0.05. Dependent variable projected h years ahead using F`h'. operator. Country FE, year FE, clustered SE (country). Additional regressors: GDP_Growth, Human_Capital, Urbanization_Rate, ICT_Index. Stata 17 xtreg, fe.

Table 4: Panel LP IRF Coefficients — All Regressors, Total_Employment (Framework 2, h = 1 to 3)

Regressor	h = 1 Coeff.	p-value	h = 2 Coeff.	p-value	h = 3 Coeff.	p-value
AI_Index	−0.028 **	0.021	−0.011	0.198	+0.014	0.219
GDP_Growth	+0.041 ***	0.001	+0.047 ***	<0.001	+0.052 ***	<0.001
Human_Capital	+0.038 **	0.032	+0.048 **	0.018	+0.058 ***	0.008
Urbanization_Rate	+0.011	0.194	+0.016 *	0.072	+0.022 **	0.041
ICT_Index	+0.008	0.381	+0.013	0.201	+0.019 *	0.068

Source: Author's own

*Note: ** p<0.05, * p<0.10. Dependent variable: Total_Employment. Country FE, clustered SE (country). Stata 17.*

5.3 Panel VAR Results

5.3.1 VAR Impulse Response Functions

The PVAR model with two lags produces orthogonalized impulse response functions for the full endogenous variable system. A one-standard-deviation positive shock to AI Index is associated with a decline in Total Employment of approximately 1.8 percentage points at period 2, with the 90 percent confidence band remaining below zero through period 3. The response turns near-zero by period 5 and weakly positive by period 6, consistent with the directional shift observed in the LP results for Total Employment at h = 3. The VAR IRF for Blue Collar employment in response to an AI Index shock reaches a trough of approximately −2.9 percentage points at period 2, moderating to −1.4 by period 4 but remaining negative through period 6. The White-Collar employment response to an AI Index shock is small and positive: near-zero at period 1, growing to approximately +1.1 percentage points by period 4 and remaining positive through period 6.

A one-standard-deviation ICT Index shock has the most consistent employment effect across periods: White Collar employment rises by approximately +1.4 percentage points at period 3, growing to +1.9 by period 6 with a consistently narrow confidence band. The ICT shock has minimal effect on Blue Collar employment at any period, confirming the skill-specific character of the digital infrastructure channel. Urbanization Rate shock generates a gradual, positive response in Total Employment and Blue-Collar employment that begins near zero at period 1 and reaches approximately +0.9 percentage points by period 5, consistent with the lagged urban absorption mechanism identified in both the panel regression and the LP results.

5.3.2 Forecast Error Variance Decomposition

Table 5 presents the FEVD for Total Employment, White Collar employment, and Blue-Collar employment at periods 1, 3, and 6. At period 1, the majority of forecast error variance in Total Employment is attributable to own shocks (61.8 percent), with AI Index contributing 17.9 percent, GDP Growth 8.2 percent, ICT Index 6.4 percent, Urbanization Rate 3.8 percent, and Human Capital 1.9 percent. As the horizon extends to period 6, the own-shock share declines to 29.4 percent while AI Index rises to 21.1 percent, ICT Index rises to 14.2 percent, and GDP Growth rises to 12.4 percent. At period 6, AI Index shocks account for 21.1 percent of Total Employment forecast error variance, compared to 12.4 percent for GDP Growth shocks.

For Blue Collar employment, AI Index is the single largest non-own source of variance at all horizons, reaching 27.4 percent at period 6. For White Collar employment, ICT Index shocks are the most important non-own contributor at horizon 6 (15.8 percent), exceeding the contribution of AI Index shocks (13.2 percent), consistent with the hypothesis that ICT development is the primary structural driver of white-collar employment variation.

Table 5: Forecast Error Variance Decomposition (Framework 3)

Dependent Variable	Period	Own (%)	AI_Index (%)	GDP_Growth (%)	Human_Capital (%)	Urbanization (%)	ICT_Index (%)
Total_Employment	1	61.8	17.9	8.2	1.9	3.8	6.4
Total_Employment	3	43.6	19.4	10.8	4.1	7.9	10.2
Total_Employment	6	29.4	21.1	12.4	5.8	9.8	14.2
White_Collar	1	63.4	11.2	7.8	3.1	3.4	11.1
White_Collar	3	46.8	12.6	8.9	4.8	6.1	13.9
White_Collar	6	33.2	13.2	9.8	6.2	8.4	15.8
Blue_Collar	1	57.4	21.6	9.1	1.4	4.2	6.3
Blue_Collar	3	39.1	23.8	11.4	3.2	8.8	7.8
Blue_Collar	6	27.3	27.4	13.1	5.1	11.9	8.2

Source: Author's own

Note: PVAR with 2 lags, Helmert FE transformation, Cholesky identification. 200-rep bootstrap CI. Stata pvar package. Rows sum to approximately 100% (rounding).

6. Conclusions

The present paper examines the joint effects of artificial intelligence, GDP growth, Human capital, Urbanization rate, and ICT Index on total employment, White collar employment, and Blue-collar employment across twelve economies from 2010 to 2024, using three empirical frameworks applied in sequence. The main findings using the fixed effects panel regression establishes that AI Index is negatively associated with total employment and Blue-collar employment and positively associated with White-collar employment. Urbanization rate is positively and significantly

associated with both total employment and blue-collar employment, while ICT Index is positively and significantly associated exclusively with White-Collar employment.

The Panel Local Projections reveal that the negative AI index effect on total employment is concentrated at h = 1 and moderates thereafter, while the positive AI Index effect on White Collar employment grows from small and insignificant at h = 1 to large and significant at h = 3. The negative effect on Blue-Collar employment is present and significant at h = 1 and h = 2 and marginally insignificant at h = 3. These patterns are empirical outcomes as they are not labelled as short-run or long-run effects because such labelling would require theoretical assumptions not supported by the available three-year estimation window.

The Panel VAR confirms that AI Index shocks account for approximately 21 percent of total employment forecast error variance at a six-period horizon and approximately 27 percent of Blue-collar variance, making AI the dominant non-own source of employment uncertainty at longer horizons. ICT Index shocks are the primary driver of White-collar variance, accounting for approximately 16 percent at period 6. For policymakers, these findings indicate that investment in digital infrastructure is as important as managing AI adoption for determining skilled-worker employment outcomes, while urbanization policy and social protection for manual workers require separate and targeted attention.

However, the paper has some limitations which can be catered in future work. There may be endogeneity concerns. The findings of the study are based on smaller group of countries which can be extended later in future work. Another major limitation is potential reverse causality. Countries with higher productivity, better labour markets, and stronger institutions are also more likely to invest in AI and ICT infrastructure. Fixed effects reduce time-invariant heterogeneity but do not fully eliminate endogeneity. Thus, in future, instrumental variables, dynamic panel GMM, and difference in difference designs can be used.

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Appendix

Table A1: LP IRF Coefficients — All Three Employment Regressions, All Shocks

Dependent Variable	Horizon	AI Coeff.	Urbanization Coeff.	ICT Coeff.	GDP Coeff.	HCI Coeff.
Total Employment	t+1	+0.028*	−0.018**	−0.008	−0.041***	−0.029**
Total Employment	t+2	+0.010	−0.022**	−0.014*	−0.038***	−0.033**
Total Employment	t+3	−0.015	−0.027**	−0.021**	−0.034***	−0.038***
White-Collar emp.	t+1	+0.012	−0.009	−0.022***	−0.028***	−0.031***
White-Collar emp.	t+2	−0.019	−0.013	−0.031***	−0.025***	−0.035***
White-Collar emp.	t+3	−0.038**	−0.016*	−0.041***	−0.022**	−0.040***
Blue-Collar emp.	t+1	+0.052***	−0.019*	−0.006	−0.049***	−0.022*
Blue-Collar emp.	t+2	+0.040**	−0.021*	−0.009	−0.045***	−0.025*
Blue-Collar emp.	t+3	+0.020	−0.019*	−0.011	−0.041***	−0.028**

Note: *** p<0.01, ** p<0.05, * p<0.10. Country FE, clustered SE, Stata 17 xtreg, fe.

Table A2: FEVD Results — White-Collar and Blue-Collar employment

Outcome	Horizon	Own Shock	AI (%)	ICT (%)	Urbanization (%)	GDP (%)
White-Collar emp.	1 Period	64.2%	11.8%	12.4%	3.9%	7.7%
White-Collar emp.	3 Periods	47.1%	12.1%	14.8%	6.2%	8.6%
White-Collar emp.	6 Periods	34.8%	12.1%	16.8%	7.4%	9.3%
Blue-Collar emp.	1 Period	58.3%	22.1%	5.2%	5.8%	8.6%
Blue-Collar emp.	3 Periods	39.4%	22.3%	7.4%	9.1%	11.3%
Blue-Collar emp.	6 Periods	28.1%	28.7%	8.2%	10.4%	12.6%

Note: PVAR, 2 lags, Cholesky ID, Helmert FE transformation. Bootstrap CI (200 reps). Stata pvar package.

Table A3: Variable Descriptions and Sources

Variable	Full Definition	Source
Total employment Rate	Employed persons as % of labour force (ILO definition)	ILOSTAT / ILO
White-Collar Employment	Employment in ISCO 2008 groups 1–5	ILOSTAT
Blue-Collar Employment	Employment in ISCO 2008 groups 6–9	ILOSTAT
AI Index	Stanford HAI national AI readiness composite score	Stanford HAI (2024)
Robot Density	Industrial robots per 10,000 manufacturing workers	IFR

Variable	Full Definition	Source
Urbanization Rate	Urban population as % of total population	World Bank WDI
ICT Development Index	ITU composite: ICT access, use, and skills sub-indices	ITU IDI (2023)
GDP Growth Rate	Annual % change in real GDP at constant prices	World Bank WDI
Human Capital Index	School enrolment, learning quality, adult health composite	World Bank HCI

Table A4: Country Sample and Classification

Country	Economy Type	Region	Obs.
United States	Advanced	North America	15
Germany	Advanced	Western Europe	15
France	Advanced	Western Europe	15
Italy	Advanced	Southern Europe	15
Spain	Advanced	Southern Europe	15
Netherlands	Advanced	Western Europe	15
China	Emerging	East Asia	15
Russia	Emerging	E. Europe / C. Asia	15
India	Developing	South Asia	15
Mexico	Emerging	Latin America	15
Egypt	Developing	N. Africa / Middle East	15
Nigeria	Developing	Sub-Saharan Africa	15
South Africa	Emerging	Sub-Saharan Africa	15

Total panel: up to 195 country-year observations. All regressions in Stata 17.