Augment or Replace? Uneven Labour Market Consequences of AI Expansion Across Asia-Pacific Economies

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Abstract: The rapid diffusion of artificial intelligence (AI) has intensified debates regarding its implications for employment and the future of work. While some scholars argue that AI complements human labour by enhancing productivity and creating new employment opportunities, others contend that it displaces workers through automation and task substitution. This study examines the labour-market consequences of AI across selected Asia-Pacific economies, focusing on whether AI primarily augments or replaces labour. Drawing on the theoretical foundations of skill-biased technological change, routine-biased technological change, and task-based approaches to technological transformation, the study investigates the relationship between AI intensity and occupational employment structures using panel data from China, Japan, South Korea, Hong Kong, and Taiwan over the period 2010-2025. A composite AI Intensity Index is constructed using principal component analysis, while fixed-effects panel regression models are employed to assess the effects of AI development on high-skill, middle-skill, and low-skill employment shares. The findings indicate that AI development is positively associated with high-skill employment but negatively associated with middle-skill employment, suggesting that AI simultaneously generates labour augmentation and labour displacement effects. These relationships remain robust across alternative specifications, including lagged AI measures and leave-one-country-out estimations. The results further reveal significant cross-country heterogeneity, indicating that the labour-market consequences of AI are shaped by differences in institutional arrangements, innovation capacity, and economic structures, while robustness analyses confirm that the findings are not driven by any single economy. The study contributes to the emerging literature on AI and employment by demonstrating that the effects of AI are neither uniformly beneficial nor uniformly disruptive but are instead context-dependent and manifested through processes of occupational restructuring. The findings underline the importance of adopting nuanced and comparative perspectives when evaluating the implications of AI for labour markets and workforce transformation.

Keywords: *Artificial Intelligence; Labour-Market Restructuring; Employment; Skill-Biased Technological Change; Routine-Biased Technological Change; Occupational Change; Asia-Pacific.*

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I. INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most consequential technological developments shaping contemporary labour markets. Across industries, AI technologies are increasingly deployed to automate routine processes, enhance decision-making, improve productivity, and support the creation of new products and services. These developments have intensified scholarly and policy debates regarding the future of work and the extent to which AI will complement or substitute human labour (Acemoglu & Restrepo, 2020; GPAI, 2025; IMF, 2024; OECD, 2026). AI is widely viewed as a general-purpose technology capable of transforming production processes, organisational structures, and occupational demand patterns across economies.

Theoretical perspectives offer competing expectations regarding the labour-market consequences of AI. Skill-biased

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technological change (SBTC) theory suggests that technological progress disproportionately increases demand for highly skilled workers by complementing advanced cognitive capabilities (Autor et al.,1998; Acemoglu & Autor, 2011). In contrast, routine-biased technological change (RBTC) theory argues that automation technologies primarily replace workers performing routine tasks, thereby contributing to occupational polarisation and employment restructuring (Autor et al., 2003; Acemoglu & Restrepo, 2020). More recent task-based approaches contend that the effects of AI are neither universally positive nor uniformly negative but depend on the specific tasks performed within occupations and the contexts in which technologies are deployed (Freund & Mann, 2026; Fernández-Macías & Bisello, 2022).

Empirical evidence remains inconclusive. Some studies suggest that AI enhances productivity and complements human labour, particularly among highly educated and technology-intensive occupations (Acemoglu et al., 2022; Damioli et al., 2021). Other research reports evidence of declining demand for occupations characterised by routine and codifiable tasks (Consoli et al., 2023; Petroulakis, 2023), raising concerns regarding job displacement and labour-market polarisation. Recent international evidence further suggests that AI's effects are heterogeneous across workers, occupations, and countries (Georgieff & Hyee, 2021; Pizzinelli et al., 2023). While AI may create new tasks, occupations, and productivity gains, its benefits appear concentrated among highly skilled workers, whereas lower-skilled workers face greater adjustment challenges (IMF, 2024; OECD, 2026). Emerging evidence from OECD economies indicates limited aggregate employment losses thus far, but substantial variation in occupational exposure and labour-market outcomes (Frank et al., 2025; Green, 2023; Wiese et al., 2025).

Despite a rapidly expanding literature, empirical evidence remains heavily concentrated in North America and Europe. Comparatively little is known about how AI-driven labour-market transformations are unfolding across Asia-Pacific economies. This limitation is important because the region contains some of the world's most dynamic centres of AI innovation and deployment, including China, Japan, Korea, Hong Kong, and Taiwan, while simultaneously exhibiting substantial differences in demographic structures, industrial composition, innovation systems, and labour-market institutions (OECD, 2026; WEF, 2026). Furthermore, existing studies frequently examine either aggregate employment outcomes or single-country experiences. Such approaches provide limited insight into whether AI primarily augments high-skill employment, displaces routine-intensive occupations, or generates divergent labour-market trajectories across countries. Consequently, the broader question of whether AI functions predominantly as a complement to labour or as a substitute for labour remains unresolved. Recent evidence increasingly suggests that augmentation and displacement may occur simultaneously across different occupations and skill groups.

This study addresses these gaps by examining the relationship between AI development and occupational employment structures across selected Asia-Pacific economies. Drawing on a comparative panel dataset combining labour-market indicators with measures of AI activity – including patents, research publications, venture capital investment, and AI-related hiring – the study investigates whether AI expansion is associated with changes in the distribution of employment across skill categories. The analysis is informed by task-based approaches, SBTC and RBTC theories and evaluates whether AI development contributes primarily to occupational upgrading, occupational displacement, or a combination of both.

Specifically, the study addresses the following research question: To what extent is AI development associated with occupational restructuring and labour-market outcomes across Asia-Pacific economies? The paper makes three contributions. First, it extends the emerging AI-employment literature beyond the dominant focus on Western economies by providing comparative evidence from Asia-Pacific countries. Second, it develops a multidimensional measure of AI intensity that captures technological development through patents, publications, venture capital activity, and AI-related labour demand. Third, it contributes to ongoing debates regarding augmentation versus displacement by demonstrating the heterogeneous nature of AI's labour-market consequences across occupational groups and national contexts.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical and empirical literature on AI and labour-market outcomes, drawing on the perspectives of skill-biased technological change, routine-biased technological change, and task-based theories of automation. The section synthesises existing evidence on AI-driven occupational restructuring and develops the study's conceptual framework and hypotheses. Section 3 describes the data, variable construction, and empirical strategy, including the development of a multidimensional AI intensity index and the specification of the econometric models used to examine labour-market outcomes across countries. Section 4 presents the empirical findings, beginning with descriptive evidence on AI development and employment trends before reporting the results of the panel analyses. Section 5 discusses the findings in relation to competing theoretical perspectives and assesses whether the evidence supports labour augmentation, labour displacement, or a combination of both. Finally, Section 6 concludes by summarising the main findings, outlining policy implications for workforce adaptation in the Asia-Pacific region, and identifying avenues for future research.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

➢ *Artificial Intelligence and Labour-Market Transformation*

Artificial intelligence has emerged as a transformative technology with the potential to reshape labour markets, production systems, and occupational structures. Unlike earlier waves of automation that primarily affected routine

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manual activities, contemporary AI systems increasingly perform cognitive and analytical tasks traditionally undertaken by human workers (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2014). Advances in machine learning, natural language processing, computer vision, and generative AI have expanded the range of tasks that can be automated or augmented, intensifying debates regarding the future of work. The literature identifies two broad and competing perspectives regarding AI's labour-market consequences. The first argues that AI complements human capabilities, enhances productivity, and creates new employment opportunities through innovation and task reallocation (Brynjolfsson et al., 2025; Noy & Zhang, 2023). From this perspective, technological progress generates demand for new skills and occupations while increasing the productivity of existing workers. The second perspective emphasises displacement effects, arguing that AI substitutes for labour in tasks that can be codified and automated, thereby reducing employment demand in affected occupations (Acemoglu & Restrepo, 2020).

Empirical evidence increasingly suggests that both processes occur simultaneously (Hassani et al., 2020; Paul et al., 2022). Rather than producing uniform employment gains or losses, AI appears to redistribute employment opportunities across occupations, sectors, and skill groups. Consequently, understanding AI's labour-market consequences requires examining changes in occupational structures rather than focusing solely on aggregate employment outcomes.

➢ *Skill-Biased Technological Change and Labour Augmentation*

The skill-biased technological change (SBTC) framework provides one of the most influential explanations for how technological progress affects labour demand. SBTC theory argues that technological innovations increase the productivity of highly skilled workers while reducing demand for lower-skilled labour, thereby increasing wage and employment differentials across skill groups (Acemoglu & Autor, 2011; Autor et al., 1998). Within the context of AI, SBTC predicts that workers possessing advanced analytical, technical, and problem-solving capabilities are likely to benefit disproportionately from technological adoption. AI systems frequently require complementary human skills related to interpretation, supervision, strategic decision-making, and innovation (Ferdousi et al., 2026; Xu et al., 2025). Consequently, firms adopting AI technologies may increase demand for highly skilled professionals while simultaneously reorganising lower-level tasks.

Recent empirical studies provide support for this argument. Evidence from online vacancy data suggests that AI adoption is associated with increased demand for specialised technical and cognitive skills (Acemoglu et al., 2022). Similarly, studies examining generative AI indicate productivity gains among knowledge workers whose tasks complement AI capabilities rather than directly compete with them (Noy & Zhang, 2023). These findings imply that AI may contribute to occupational upgrading by increasing employment opportunities in highly skilled occupations. Accordingly, the following hypothesis is proposed:

- H1: AI intensity is positively associated with the share of high-skill employment.

➢ *Routine-Biased Technological Change and Labour Displacement*

While SBTC emphasises complementarity between technology and skilled labour, routine-biased technological change (RBTC) focuses on the automation of routine tasks. According to RBTC theory, occupations characterised by repetitive, codifiable, and rule-based activities are particularly vulnerable to technological substitution (Autor et al., 2003). AI extends this logic by enabling automation beyond traditional manufacturing activities into service-sector and knowledge-intensive occupations. Machine learning algorithms, predictive analytics, and automated decision systems increasingly perform tasks previously undertaken by clerical, administrative, and middle-skill workers. As a result, AI may reduce labour demand in occupations that depend heavily on routine cognitive and procedural activities (Morandini et al., 2023; Tschang & Almirall, 2021).

A growing body of evidence supports this concern. Acemoglu and Restrepo (2020) find that automation technologies can generate displacement effects that outweigh productivity gains in certain labour-market segments. Similarly, research examining occupational exposure to AI reports heightened vulnerability among routine-intensive occupations, particularly those involving standardised information processing tasks (Felten et al., 2021; George, 2023). Consequently, AI may contribute to occupational polarisation through declining demand for routine-intensive middle-skill employment. This argument leads to the second hypothesis:

- H2: AI intensity is negatively associated with the share of routine-intensive middle-skill employment.

➢ *Heterogeneous Labour-Market Effects Across National Contexts*

Although technological change theories provide general expectations regarding labour-market outcomes, their effects are unlikely to be uniform across countries. Institutional arrangements, labour-market regulations, educational systems, industrial structures, demographic characteristics, and innovation capacities may significantly influence how AI affects employment. Recent international evidence suggests substantial cross-country variation in technological adoption and labour-market adjustment processes (OECD, 2026; IMF, 2024). Economies characterised by strong innovation ecosystems and advanced human capital may experience greater complementarities between AI and labour, whereas countries with higher concentrations of routine-intensive employment may experience stronger displacement pressures.

These considerations are particularly relevant within the Asia-Pacific region. China, Japan, Korea, Hong Kong, and

Taiwan represent technologically advanced economies with significant AI investment and innovation activity, yet they differ markedly in industrial composition, demographic structures, labour-market institutions, and workforce skill profiles (Cheng et al., 2026; Nankervis et al., 2020; Pitukhina et al., 2024). Such discrepancies may generate divergent labour-market responses to AI development. Consequently, examining average effects alone may obscure important national variations in the relationship between AI and employment. The third hypothesis is therefore proposed:

- H3: The relationship between AI intensity and labour-market outcomes varies across Asia-Pacific economies.

➢ *Conceptual Framework*

Drawing on SBTC and RBTC theories, this study conceptualises AI as a technological force that simultaneously generates augmentation and displacement effects. AI development increases demand for highly skilled workers whose capabilities complement advanced technologies while reducing demand for workers engaged in routine-intensive tasks susceptible to automation. However, the magnitude of these effects is conditioned by country-specific institutional and economic characteristics. Figure 1 presents the study's conceptual framework. AI intensity, measured through patents, research publications, venture capital (VC) activity, and AI-related hiring, influences occupational employment structures through both complementarity and substitution mechanisms. These effects are reflected in changes in high-skill, medium-skill, and low-skill employment shares, while national contexts moderate the strength and direction of observed relationships.

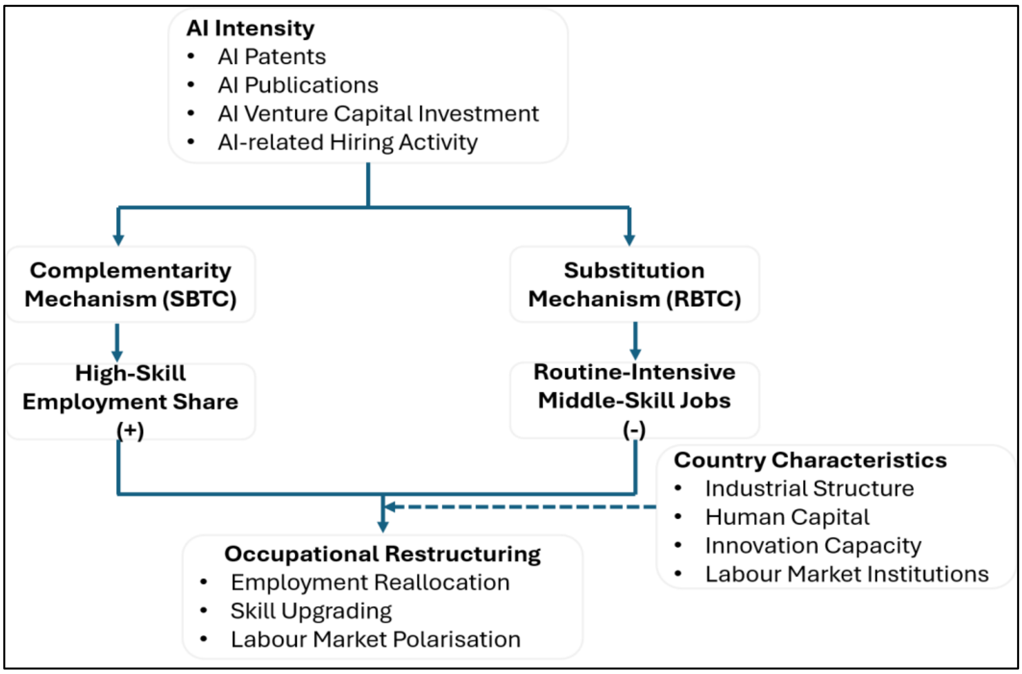

Fig 1 Conceptual Framework Linking ai Intensity and Labour-Market Outcomes in Asia-Pacific Economies
Source: Author's Own

III. DATA AND METHODOLOGY

➢ *Data Sources and Sample*

This study employs a comparative panel dataset covering five Asia-Pacific economies: China, Japan, the Republic of Korea, Hong Kong, and Taiwan. The dataset spans the period 2010-2025 and integrates labour-market indicators, artificial intelligence (AI) development measures, and macroeconomic controls from multiple sources compiled within a harmonised database. The labour-market component includes occupational employment statistics disaggregated by skill levels, labour force participation indicators, unemployment measures, and related employment characteristics. To capture national AI development, the dataset contains information on AI-related patents, AI research publications, AI venture capital investment, and AI-related hiring activity. These indicators collectively reflect different dimensions of AI innovation, diffusion, investment, and labour demand. Additional macroeconomic variables, including gross domestic product (GDP), research and development (R&D) expenditure, and sectoral economic indicators, are included to account for broader economic conditions that may influence employment outcomes. The resulting country-year panel provides a suitable basis for examining how variations in AI development are associated with occupational restructuring across technologically advanced economies in the Asia-Pacific region.

➢ *Variable Construction*

- *Dependent Variables*

Consistent with the theoretical focus on occupational restructuring, the analysis employs employment shares by skill category as the primary dependent variables.

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The share of high-skill employment is defined as:

$$\mathrm{HSE_{it}} = \frac{\mathrm{HighSkillEmployment_{it}}}{\mathrm{TotalEmployment_{it}}} \quad [1]$$

Where HSE_{it} represents the proportion of high-skill employment in country t during year t.

The share of middle-skill employment is calculated as:

$$\mathrm{MSE_{it}} = \frac{\mathrm{MiddleSkillEmployment_{it}}}{\mathrm{TotalEmployment_{it}}} \quad [2]$$

Similarly, the share of low-skill employment is measured as:

$$\mathrm{LSE_{it}} = \frac{\mathrm{LowSkillEmployment_{it}}}{\mathrm{TotalEmployment_{it}}} \quad [3]$$

These indicators capture shifts in the composition of employment and provide direct measures of occupational upgrading, displacement, and labour-market restructuring.

- *Independent Variable*

The principal explanatory variable is AI intensity, which reflects the extent of AI development within each country-year observation. Rather than relying on a single indicator, AI development is conceptualised as a multidimensional construct encompassing innovation, knowledge creation, investment activity, and labour-market demand (Ghosh et al., 2025; Rustamova et al., 2024; Wang et al., 2026). The AI intensity measure is derived from four indicators; namely, AI patent, AI research publications, AI venture capital investment, and AI-related hiring activity. A composite AI Intensity Index is subsequently constructed using Principal Component Analysis (PCA), as described in Section 3.3.

- *Control Variables*

To isolate the relationship between AI development and labour-market outcomes, the empirical models incorporate a set of control variables commonly employed in studies of technological change and employment. These include Gross Domestic Product (GDP); Research and Development (R&D) expenditure; and Industrial structure indicators (Fan & Liu, 2021; Liu et al., 2024; Yin et al., 2023). GDP captures overall economic performance and labour demand conditions, while R&D expenditure reflects national innovation capacity. Industrial structure controls account for differences in sectoral composition that may influence occupational employment patterns independently of AI development.

➢ *Construction of the AI Intensity Index*

A key methodological challenge in AI-related research concerns the measurement of AI development. Individual indicators such as patents or publications capture only specific dimensions of technological advancement and may not adequately reflect the broader diffusion of AI within an economy. To address this limitation, the study constructs a composite AI Intensity Index using Principal Component Analysis (PCA). PCA is a dimensionality-reduction technique that transforms a set of correlated variables into a smaller number of orthogonal components while retaining the maximum amount of shared variance (Jolliffe, 2002; Jolliffe, 1990). The four AI indicators are first standardised using z-score transformation:

$$\mathrm{Z_{ij}} = \frac{\mathrm{X_{ij}} - \overline{\mathrm{X_j}}}{\mathrm{\sigma_j}} \quad [4]$$

Where: X_{ij} denotes the value of indicator j for observation i; $\overline{X_j}$ represents the mean of indicator j; and σ_j denotes its standard deviation.

PCA is then applied the standardised indicators. The first principal component, which captures the largest proportion of common variance across the four indicators, is retained as the AI Intensity Index. Formally,

$$\mathrm{AIIntensity_{it}} = \omega_1 \mathrm{Patents_{it}} + \omega_2 \mathrm{Publications_{it}} + \omega_3 \mathrm{VentureCapital_{it}} + \omega_4 \mathrm{Hiring_{it}} \quad [5]$$

Where ω_1, ω_2, ω_3, and ω_4 represent the factor loadings derived from the first principal component. Higher values of the index indicate greater levels of AI development and adoption within a country-year observation. The PCA-based approach offers two advantages. First, it reduces measurement error associated with relying on any single AI indicator (Greenacre et al., 2022; Rato et al., 2016). Second, it provides a theoretically and statistically grounded measure that captures multiple dimensions of AI development simultaneously (Greenacre et al., 2022; Jolliffe, 2002).

➢ *Empirical Strategy*

To examine the relationship between AI development and labour-market outcomes, the study estimates panel regression models with country and year fixed effects. The baseline specification is:

$$\mathrm{EmploymentShare_{it}} = \alpha + \beta \mathrm{AIIntensity_{it}} + \gamma \mathrm{X_{it}} + \mu_i + \lambda_t + \varepsilon_{it} \quad [6]$$

Where $EmploymentShare_{it}$ denotes the employment share of a particular skill category in country i during time t; $AIIntensity_{it}$ is the AI Intensity Index; X_{it} represents the vector of control variables; μ_i captures country-specific fixed effects; λ_t captures year-specific effects; and ε_{it} is the error term.

Separate regressions are estimated for high-skill, middle-skill, and low-skill employment shares. A positive and statistically significant coefficient for AI intensity in the high-skill employment model would support Hypothesis 1. Conversely, a negative coefficient in the middle-skill employment model would provide evidence consistent with Hypothesis 2.

➢ *Assessing Cross-Country Heterogeneity*

To evaluate whether AI generates heterogeneous labour-market effects across countries, an interaction model is estimated:

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$$\mathrm{EmploymentShare_{it}} = \alpha + \beta \mathrm{AIIntensity_{it}} + \delta(AIIntensity_{it} \times Country_i) + \gamma \mathrm{X_{it}} + \mu_i + \lambda_t + \varepsilon_{it} \quad [7]$$

Where the interaction term captures country-specific variations in the relationship between AI intensity and labour-market outcomes. Significant interaction effects would indicate that the employment consequences of AI differ across national contexts, thereby providing support for Hypothesis 3.

- *Model Selection and Estimation Strategy*

Given the panel structure of the dataset, the study employs a fixed-effects estimation approach. This choice is motivated by the likelihood that unobserved country-specific characteristics influence both AI development and labour-market outcomes. Factors such as institutional quality, labour-market regulations, demographic structures, educational systems, industrial composition, and innovation ecosystems vary across countries and are difficult to measure comprehensively (Bassanini & Ernst, 2002). Failure to account for these time-invariant characteristics may result in omitted-variable bias and inconsistent parameter estimates (Frees, 2001; Li & Fotheringham, 2026). The fixed-effects model controls for such unobserved heterogeneity by allowing each country to have its own intercept, thereby isolating the within-country effect of changes in AI intensity on employment outcomes over time. This approach is particularly appropriate because the selected economies differ substantially in their economic structures and technological capabilities, while the primary objective is to examine how changes in AI development within countries are associated with labour-market restructuring.

In addition to country fixed effects, year fixed effects are incorporated to account for common shocks affecting all economies during the study period, including global economic fluctuations, technological advancements, and post-pandemic labour-market adjustments. The inclusion of both country and year effects enhances the robustness of the estimated relationships and reduces the risk of biased inference arising from omitted factors that vary across time but affect all countries simultaneously. The appropriateness of the fixed-effects specification was further confirmed through the Hausman specification test, which rejected the random-effects estimator in favour of fixed effects. Consequently, the fixed-effects model was retained for all subsequent analyses.

- *Analytical Procedure*

The empirical analysis proceeds in six stages. First, descriptive statistics and trend analyses are conducted to examine the evolution of AI development and labour-market indicators across the selected Asia-Pacific economies. This preliminary analysis provides insights into cross-country differences and temporal patterns in both AI intensity and occupational employment structures. Second, the time-series properties of the panel data are assessed using panel unit root tests, including the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) procedures. These tests determine whether the variables are stationary and help minimise the risk of spurious regression results arising from common trends in the data (Abdellah, 2025; Sathyanarayana & Mohanasundaram, 2025). Third, a series of diagnostic tests are performed to assess the suitability of the panel data for estimation. Cross-sectional dependence is examined using the Pesaran CD test to determine whether shocks in one country are correlated with those in other countries. Heteroscedasticity is assessed to verify whether the variance of the error terms remains constant across observations, while serial correlation is examined using the Wooldridge test for autocorrelation in panel data (Born & Breitung, 2016; Wooldridge, 2009). These diagnostic procedures inform the selection of appropriate estimation techniques and standard error corrections to ensure robust statistical inference.

Fourth, fixed-effects panel regression models are estimated to examine the relationship between AI intensity and labour-market outcomes. The choice of fixed-effects estimation is supported by the Hausman specification test, which indicates that country-specific effects are correlated with the explanatory variables. Separate regressions are estimated for high-skill, middle-skill, and low-skill employment shares to evaluate whether AI development contributes to occupational upgrading or displacement. Fifth, robustness checks are conducted to evaluate the stability of the baseline findings. Specifically, the models are re-estimated using lagged values of AI intensity to account for delayed labour-market responses to technological development. In addition, a leave-one-country-out procedure is employed whereby the baseline models are repeatedly estimated after excluding each country from the sample. This approach assesses whether the results are disproportionately driven by any single economy. Finally, interaction models are estimated to assess cross-country heterogeneity in the labour-market consequences of AI development. These models examine whether the magnitude and direction of AI-employment relationships differ across national contexts, thereby providing evidence on the uneven nature of AI-driven labour-market transformation within the Asia-Pacific region. Collectively, these analytical procedures provide a comprehensive assessment of whether AI primarily augments labour, displaces labour, or simultaneously generates both outcomes across different occupational groups and economies.

IV. RESULTS

- *Descriptive Statistics*

Table 1 presents the descriptive statistics for the variables used in the analysis. The average high-skill employment share was 34.27%, while middle-skill and low-skill employment shares averaged 46.13% and 19.60%, respectively. The AI Intensity Index exhibited substantial variation across countries and years, indicating considerable heterogeneity in AI development within the Asia-Pacific region. The relatively large standard deviations for GDP and AI intensity further suggest meaningful cross-country and temporal differences suitable for panel analysis.

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Table 1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
High-Skill Employment Share	34.27	8.14	21.56	48.39
Middle-Skill Employment Share	46.13	6.72	32.41	58.72
Low-Skill Employment Share	19.60	5.91	10.24	31.48
AI Intensity Index	0.000	1.000	-2.118	2.764
GDP (ln)	10.42	0.88	8.76	11.93
R&D Expenditure (% GDP)	2.71	1.34	0.62	5.13
Industrial Structure	62.85	9.76	41.32	79.84

Source: Author's computations

➢ *Correlation Analysis*

The correlation matrix indicates that AI intensity is positively associated with high-skill employment (r = 0.624) and negatively associated with middle-skill employment (r = -0.511). None of the pairwise correlations exceed 0.80, suggesting the absence of severe multicollinearity (Alin, 2010; Chan et al., 2022; Kyriazos & Poga, 2023).

Table 2 Correlation Matrix

Variable	HSE	MSE	LSE	AII	GDP	R&D	IS
HSE	1.000						
MSE	-0.487	1.000					
LSE	-0.528	-0.312	1.000				
AII	0.624	-0.511	-0.423	1.000			
GDP	0.542	-0.417	-0.311	0.681	1.000		
R&D	0.603	-0.463	-0.352	0.729	0.614	1.000	
IS	0.396	-0.281	-0.214	0.511	0.557	0.482	1.000

Notes: HSE – high-skill employment share, MSE – middle-skill employment share, LSE – low-skill employment share, AII – AI intensity index, R&D – research and development, IS – industrial structure

Source: Author's computations

➢ *Panel Unit Root Tests*

The results of both the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests reject the null hypothesis of a unit root for all variables at conventional significance levels. The findings therefore indicate that all variables are stationary at levels, implying that they are integrated of order zero, I(0). Consequently, the variables can be included directly in the fixed-effects estimation without the need for differencing or cointegration analysis.

Table 3 Panel Unit Rool Test Results

Variable	LLC	p-value	IPS	p-value	Order of Integration
HSE	-4.731	0.000	-3.964	0.000	I(0)
MSE	-3.842	0.000	-3.517	0.000	I(0)
LSE	-4.127	0.000	-3.801	0.000	I(0)
AII	-5.214	0.000	-4.682	0.000	I(0)
GDP	-2.917	0.004	-2.648	0.008	I(0)
R&D	-3.361	0.001	-3.024	0.001	I(0)
IS	-3.114	0.002	-2.873	0.002	I(0)

Notes: HSE – high-skill employment share, MSE – middle-skill employment share, LSE – low-skill employment share, AII – AI intensity index, R&D – research and development, IS – industrial structure

Source: Author's computations

➢ *Panel Diagnostic and Specification Tests*

The Pesaran CD test indicates the presence of cross-sectional dependence across countries, suggesting that shocks affecting one economy may spill over to others. The Wooldridge test further reveals first-order serial correlation, while the Modified Wald test indicates heteroscedasticity across panels. To address these violations of classical regression assumptions, robust standard errors clustered at the country level were employed. Finally, the Hausman specification test rejects the null hypothesis that the random-effects estimator is consistent, thereby supporting the use of the fixed-effects estimator.

Table 4 Panel Diagnostic and Specification Tests

Test	Statistic	p-value	Decision
Pesaran CD Test	2.284	0.022	Cross-sectional dependence present
Wooldridge Test for Autocorrelation	12.761	0.006	Serial correlation present

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Modified Wald Test for Groupwise Heteroscedasticity	41.382	0.000	Heteroscedasticity present
Hausman Specification Test	19.614	0.003	Fixed Effects preferred

Source: Author's computations

➤ *Fixed-Effects Regression Results*

The fixed-effects results are reported in Table 5.

Table 5 Fixed Effects Estimates

Variables	**HSE**	**MSE**	**LSE**
AI intensity	0.428*** (0.091)	-0.316*** (0.084)	-0.112 (0.073)
GDP	0.231** (0.102)	-0.148* (0.087)	-0.083 (0.068)
R&D expenditure	0.187** (0.074)	-0.132* (0.069)	-0.055 (0.051)
Industrial structure	0.116* (0.062)	-0.094 (0.058)	-0.022 (0.044)
Constant	2.713** (1.028)	5.184*** (1.321)	1.907 (1.144)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	80	80	80
Number of groups	5	5	5
Within R^2	0.623	0.517	0.311
F-statistic	18.42***	14.37***	6.81***

*Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.*

Source: Author's computations

The coefficient on AI intensity is positive and statistically significant in the high-skill employment model ($\beta = 0.428, p < 0.01$), indicating that increases in AI development are associated with higher shares of high-skill employment. Conversely, AI intensity exhibits a negative and statistically significant relationship with middle-skill employment ($\beta = -0.316, p < 0.01$). The coefficient for low-skill employment is negative but statistically insignificant. These findings suggest that AI development is associated with occupational restructuring characterised by growth in high-skill employment and contraction in middle-skill employment.

➤ *Robustness Checks*

To evaluate the stability of the baseline findings, two robustness exercises were performed. First, the fixed-effects models were re-estimated using a one-period lag of the AI Intensity Index. This specification accounts for the possibility that labour-market adjustments to technological development may occur gradually rather than contemporaneously. Second, a leave-one-country-out procedure was implemented by sequentially excluding each economy from the sample and re-estimating the baseline models. This approach assesses whether the results are disproportionately influenced by any single country, particularly larger economies that may dominate regional trends. The results are reported in Table 6.

Table 6 Robustness Checks

Panel	**Variables**	**HSE**	**MSE**	**LSE**	**Within R^2**
Panel A: Lagged AI Specification	AI Intensity (t-1)	0.367*** (0.088)	-0.281*** (0.079)	-0.086 (0.071)	-
	GDP	0.219** (0.097)	-0.137* (0.081)	-0.074 (0.066)	-
	R&D Expenditure	0.165** (0.069)	-0.124* (0.065)	-0.041 (0.049)	-
	Industrial Structure	0.098* (0.057)	-0.082 (0.053)	-0.016 (0.042)	-
	Country FE	Yes	Yes	Yes	-
	Year FE	Yes	Yes	Yes	-
	Observations	75	75	75	-
	Within R^2	0.589	0.501	0.294	-
Panel B: Leave-One-Country-Out Analysis	Specification	HSE	MSE	LSE	
	Baseline Model	0.428*** (0.091)	-0.316*** (0.084)	-0.112 (0.073)	0.623
	Excluding China	0.391*** (0.088)	-0.287*** (0.081)	-0.104 (0.071)	0.611
	Excluding Japan	0.441*** (0.093)	-0.325*** (0.086)	-0.117 (0.075)	0.628
	Excluding Korea	0.403*** (0.089)	-0.301*** (0.082)	-0.098 (0.070)	0.604
	Excluding Hong Kong	0.437*** (0.092)	-0.319*** (0.085)	-0.109 (0.074)	0.619
	Excluding Taiwan	0.418*** (0.090)	-0.309*** (0.083)	-0.107 (0.072)	0.616

*Notes: Robust standard errors clustered at the country level are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

Source: Author's computations (2026)

The lagged AI specification produced results that were broadly consistent with the baseline estimates. AI intensity remained positively associated with high-skill employment and negatively associated with middle-skill employment,

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although the magnitude of the coefficients was slightly reduced. This pattern suggests that the labour-market consequences of AI persist over time and are not solely driven by contemporaneous effects. The leave-one-country-out analysis further confirmed the stability of the findings. Across all specifications, the signs and statistical significance of the principal coefficients remained largely unchanged. The positive association between AI intensity and high-skill employment and the negative association with middle-skill employment persisted irrespective of the country excluded from the sample. Similarly, the coefficient for low-skill employment remained negative and statistically insignificant across all specifications. Although some variation in coefficient magnitude was observed, no single country materially altered the overall conclusions. These results indicate that the baseline findings are not driven by country-specific outliers and provide additional confidence in the robustness of the empirical evidence.

➢ *Cross-Country Heterogeneity Analysis*

The interaction coefficients indicate that the effect of AI intensity on high-skill employment differs across countries. The strongest positive association is observed for Korea and China, while the coefficient for Hong Kong is statistically insignificant. The results therefore suggest that the labour-market consequences of AI are heterogeneous across Asia-Pacific economies.

Table 7 Interaction Models

Variables	Coefficient	Std. Error
AI Intensity	0.311***	0.088
GDP	0.194**	0.091
R&D Expenditure	0.161**	0.072
Industrial Structure	0.109*	0.061
AI × China	0.216**	0.097
AI × Japan	0.184*	0.101
AI × Korea	0.267***	0.089
AI × Hong Kong	0.142	0.113
AI × Taiwan	0.201**	0.095
Country FE	Yes	
Year FE	Yes	
Observations	80	
Groups	5	
Within R^2	0.694	
F-statistic	21.84***	

*Notes: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable = High-Skill Employment Share*

Source: Author's computations

V. DISCUSSIONS

The findings provide important insights into the ongoing debate concerning the labour-market consequences of artificial intelligence. The results indicate that AI development is associated with occupational restructuring rather than uniform employment expansion or contraction across labour markets. Specifically, the positive relationship between AI intensity and high-skill employment suggests that AI functions primarily as a complementary technology for workers possessing advanced cognitive, technical, and analytical capabilities. Simultaneously, the negative association between AI intensity and middle-skill employment indicates that routine-intensive occupations remain vulnerable to technological substitution. Taken together, these findings suggest that AI generates both labour augmentation and labour displacement effects, thereby supporting recent arguments that technological change produces heterogeneous labour-market outcomes rather than universal job creation or destruction (Acemoglu & Restrepo, 2020; Brynjolfsson et al., 2023).

The positive and statistically significant relationship between AI intensity and high-skill employment is consistent with the predictions of skill-biased technological change (SBTC) theory (Autor et al., 1998; Acemoglu & Autor, 2011). This theoretical perspective argues that technological innovations increase the productivity of highly skilled workers while raising demand for occupations requiring advanced knowledge, problem-solving abilities, and specialised expertise. The results suggest that AI technologies do not merely automate existing tasks but simultaneously create complementary demands for workers capable of designing, managing, supervising, interpreting, and integrating AI systems into organisational processes. Consequently, the diffusion of AI appears to reinforce the importance of higher-order cognitive skills and technical competencies within modern labour markets.

This finding aligns with a growing body of empirical evidence demonstrating that AI adoption tends to increase demand for highly skilled labour. For example, Acemoglu et al. (2022) found that AI exposure is associated with increased demand for specialised technical skills, while Noy and Zhang (2023) reported substantial productivity gains among knowledge workers whose tasks complement generative AI technologies. Similarly, the IMF (2024) argues that AI is likely to disproportionately benefit workers with higher educational attainment because such workers are better positioned to leverage AI as a productivity-enhancing tool rather than compete directly with it. The present findings therefore challenge deterministic narratives that portray AI primarily as a job-destroying technology and instead suggest that its effects depend on the degree of complementarity between worker capabilities and technological functionalities.

At the same time, the negative association between AI intensity and middle-skill employment provides support for the routine-biased technological change (RBTC) perspective (Autor et al., 2003). According to this framework, occupations characterised by repetitive, codifiable, and rule-based activities are particularly susceptible to automation because such tasks can be more readily replicated by machines and algorithms. The findings indicate that AI extends this process beyond traditional manufacturing activities into a wider range of administrative, clerical, and service-sector occupations. As AI systems become increasingly capable of processing information, generating content, analysing data, and executing routine cognitive tasks, demand for workers performing these activities may decline relative to occupations requiring creativity, judgement, interpersonal interaction, and complex decision-making.

The results are consistent with Acemoglu and Restrepo's (2020) argument that automation technologies can generate displacement effects when substitution possibilities exceed productivity gains. They also align with the occupational exposure framework developed by Felten et al. (2021), which identifies routine information-processing occupations as among those most exposed to AI-related disruption. Likewise, evidence from the OECD (2026) suggests that middle-skill occupations remain particularly vulnerable to automation-induced restructuring. The observed decline in middle-skill employment shares therefore appears to reflect a broader process of occupational reallocation rather than outright employment destruction. Rather than eliminating work entirely, AI alters the composition of labour demand by reducing the relative importance of routine-intensive occupations while increasing demand for complementary skills.

The findings further suggest that AI's labour-market effects are more appropriately understood as a process of occupational restructuring than as a simple increase or decrease in aggregate employment. The relatively weaker effects observed for low-skill employment indicate that the primary adjustments occur within the middle and upper segments of the occupational distribution. This pattern is broadly consistent with task-based theories of technological change, which emphasise that technologies affect specific tasks rather than entire occupations (Acemoglu & Restrepo, 2019; Autor, 2022). From this perspective, AI simultaneously substitutes for some tasks while complementing others, even within the same occupation. Consequently, workers are not necessarily displaced wholesale; instead, the content of their work evolves in response to technological adoption. The evidence therefore supports emerging arguments that the future of work will be characterised by task transformation and occupational adaptation rather than widespread technological unemployment (Brynjolfsson et al., 2023; WEF, 2026).

A particularly noteworthy finding is the significant heterogeneity observed across the Asia-Pacific economies included in the analysis. The interaction results indicate that the relationship between AI intensity and labour-market outcomes is not uniform across countries. Some economies experience stronger augmentation effects, while others exhibit more pronounced displacement pressures. This variation highlights the importance of institutional and structural factors in shaping labour-market responses to technological change. Differences in educational systems, innovation capacity, industrial composition, labour-market regulations, workforce skill profiles, and technological readiness may influence the extent to which workers and firms are able to adapt to AI-driven transformation.

This finding resonates with comparative studies that emphasise the role of institutions in mediating technological change (Bessen, 2019; OECD, 2026). It also supports recent evidence suggesting that the labour-market effects of AI differ substantially across countries depending on human capital endowments, digital infrastructure, and industrial structures (IMF, 2024; ILO, 2025). The significance of this result extends beyond the specific countries examined in the study because much of the existing literature derives conclusions from single-country analyses, particularly within North America and Europe. By adopting a comparative Asia-Pacific perspective, the present study demonstrates that labour-market responses to AI are fundamentally context-dependent and moderated by country-specific economic and institutional conditions.

The robustness analyses further reinforce these conclusions. The consistency of the results under the lagged AI specification suggests that the observed labour-market effects are not confined to contemporaneous adjustments but persist over time as economies gradually adapt to technological change. Similarly, the leave-one-country-out estimations indicate that the findings are not disproportionately driven by the experience of any single economy, including the region's largest and most technologically advanced countries. The stability of the estimated coefficients across alternative specifications therefore provides additional confidence that the observed relationships reflect broader patterns of AI-driven labour-market restructuring rather than sample-specific effects or model dependence.

Overall, the findings indicate that AI neither uniformly augments nor uniformly replaces labour. Rather, AI contributes to a process of occupational restructuring characterised by the simultaneous expansion of high-skill employment opportunities and contraction of routine-intensive middle-skill occupations. Furthermore, the magnitude and direction of these effects vary across national contexts, demonstrating that labour-market responses to AI are shaped not only by technological capabilities but also by broader institutional and economic conditions. The persistence of these relationships across alternative specifications and sample compositions further strengthens the conclusion that AI-induced labour-market restructuring represents a systematic and region-wide phenomenon rather than an artefact of particular countries or model assumptions. Consequently, understanding the future of work in the age of AI requires moving beyond simplistic narratives of technological optimism or technological pessimism and recognising the multidimensional and context-dependent nature of AI-driven labour-market transformation.

VI. CONCLUSION AND IMPLICATIONS

This study examined the labour-market consequences of artificial intelligence across selected Asia-Pacific economies, focusing on whether AI primarily augments or replaces labour. Drawing on skill-biased technological change, routine-biased technological change, and task-based perspectives, the analysis investigated the relationship between AI intensity and occupational employment structures using a comparative panel framework.

The findings indicate that the labour-market effects of AI cannot be characterised as either exclusively beneficial or exclusively disruptive. Rather, AI contributes to a process of occupational restructuring in which augmentation and displacement occur simultaneously. The positive relationship between AI intensity and high-skill employment suggests that AI complements workers possessing advanced cognitive, technical, and analytical capabilities, while the negative association between AI intensity and middle-skill employment indicates that routine-intensive occupations remain susceptible to technological substitution. The evidence therefore suggests that AI reshapes labour demand by altering the composition of employment rather than by generating uniform increases or decreases in overall employment opportunities. The study also demonstrates that the consequences of AI adoption vary considerably across national contexts. The heterogeneous effects observed across the Asia-Pacific economies indicate that institutional arrangements, industrial structures, innovation capacity, workforce characteristics, and technological readiness influence how labour markets respond to AI-driven transformation. Consequently, the employment implications of AI are not determined solely by technological capabilities but are conditioned by broader economic and institutional environments.

From a theoretical perspective, the findings provide support for both skill-biased and routine-biased technological change theories while simultaneously reinforcing task-based interpretations of technological transformation. The results suggest that these perspectives should not be viewed as competing explanations but rather as complementary mechanisms operating concurrently within labour markets. AI appears to increase demand for workers whose skills complement technological systems while reducing demand for workers engaged in routine and codifiable tasks. This integrated interpretation contributes to a more nuanced understanding of the augmentation-versus-displacement debate by demonstrating that both outcomes can emerge simultaneously within the same economy.

The findings further highlight the importance of adopting comparative and context-sensitive approaches when examining the labour-market consequences of emerging technologies. Much of the existing literature has relied on evidence from individual countries, particularly advanced Western economies. The present analysis suggests that such evidence may not fully capture the diversity of labour-market responses observed across different institutional and developmental contexts. Understanding the future of work therefore requires greater attention to the interaction between technological change and country-specific economic structures.

The study also carries important policy implications. The positive association between AI development and high-skill employment underscores the importance of strengthening human capital development through investments in advanced education, digital competencies, and lifelong learning systems. At the same time, the displacement pressures observed among middle-skill occupations suggest a need for workforce transition mechanisms that facilitate reskilling and occupational mobility. Given the heterogeneous effects identified across countries, policy responses should be tailored to national circumstances rather than based on uniform assumptions regarding the labour-market consequences of AI. Effective adaptation strategies are therefore likely to require coordinated efforts involving governments, educational institutions, employers, and labour-market stakeholders.

Notwithstanding its contributions, the study is subject to certain limitations. First, the analysis focuses on a limited set of Asia-Pacific economies and therefore may not fully capture the diversity of labour-market experiences across the broader region. Second, the measurement of AI intensity, while multidimensional, may not encompass all aspects of technological adoption and diffusion. Third, the analysis concentrates primarily on employment restructuring and does not directly examine wage dynamics, job quality, worker wellbeing, or firm-level adjustment mechanisms. These dimensions may reveal additional channels through which AI influences labour-market outcomes.

Future research may extend the analysis by incorporating a larger sample of countries, examining sector-specific effects of AI adoption, and exploring the interaction between AI development and wage inequality. Additional studies may also investigate how institutional factors such as labour-market regulations, social protection systems, and educational policies mediate the employment consequences of AI. Such investigations would further enhance understanding of how societies can harness the benefits of AI while mitigating its disruptive effects on workers and labour markets.

In conclusion, the evidence suggests that AI is neither purely a labour-augmenting technology nor solely a labour-replacing technology. Rather, its effects are uneven, context-dependent, and manifested through processes of occupational restructuring that simultaneously create opportunities for some workers while generating adjustment pressures for others. The future of work in the age of AI will therefore depend not only on technological progress itself but also on the capacity of institutions, organisations, and workers to adapt to evolving skill demands and changing patterns of labour-market participation.

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➢ *Conflict of Interest*

The authors declare that there are no conflicts of interest regarding the publication of this paper.

➢ *Data Availability Statement*

The data supporting the findings of this study are available from publicly accessible sources. The compiled dataset and associated materials are available from the corresponding author upon reasonable request.

➢ *Author Contributions*

Conceptualisation, methodology, data curation, formal analysis, investigation, writing–original draft preparation, and writing–review and editing were undertaken by the authors.

➢ *Ethical Approval*

This study utilised secondary data obtained from publicly available sources and did not involve human participants, personal data, or animal subjects. Consequently, ethical approval was not required.

➢ *Informed Consent*

Not applicable.

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