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OW AI-DRIVEN SKILL REALLOCATION SHAPES WAGE INEQUALITY AND PRODUCTIVITY IN EMERGING ECONOMIES

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Abstract

This study examines how artificial intelligence–driven skill reallocation relates to productivity and wage inequality in emerging economies. Using a synthetic panel of 400 observations across ten fictional economies, five sectors, and eight periods, it illustrates a quantitative framework for analysing technological adoption and labour market adjustment. Fixed effects models assess relationships among AI adoption, occupational reallocation, training access, digital readiness, productivity, and wage dispersion. These findings show positive associations between AI adoption, occupational reallocation, and productivity. Training access moderates the adoption–inequality relationship, with broader access associated with a smaller increase in wage dispersion. The interaction between digital readiness and adoption is statistically inconclusive. These findings reflect relationships embedded in the data-generating process rather than evidence about actual economies. The study demonstrates the importance of distinguishing adoption from exposure, occupational redistribution from complementary skill upgrading, and productivity growth from equitable wage outcomes. Future research should validate these potential relationships using observed worker and sector data and credible identification strategies.

Keywords: Blockchain, Family Takaful, Islamic Finance, Smart Contracts, Digital Payments Systems, Fraud Prevention, Pakistan's Regulatory Challenges

1. Introduction

1.1 Background

Artificial intelligence (AI) has emerged as an important force reshaping the relationship between technological change, labour demand, and economic development. Its significance extends beyond the automation of existing activities to the reorganisation of tasks, the changing value of workers' skills, and the creation of new forms of human–machine collaboration. A task-based perspective helps explain these changes: technologies can displace workers from particular production activities while also generating new tasks in which human labour retains a comparative advantage. Consequently, productivity growth and employment gains do not necessarily occur together; their relationship depends partly on whether labour-displacing changes are accompanied by opportunities for workers to enter new productive activities (Acemoglu & Restrepo, 2019; Akash, n.d.).

Within this study, AI-driven skill reallocation refers to changes in the deployment, demand, and development of workers' skills across tasks, occupations, firms, and sectors following AI adoption. This definition encompasses the movement of workers away from activities that AI can substitute for, the upgrading of skills needed to work with AI systems, and the reassignment of existing capabilities to newly

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valuable tasks. It therefore distinguishes skill reallocation from job displacement alone. The central analytical concern is not simply whether AI reduces employment in particular occupations, but whether workers can move into activities where their capabilities complement technology and support higher productivity (Akram et al., 2026; Al Kium et al., 2023).

The potential scale of this adjustment is substantial. Cazzaniga et al. (2024) estimate that approximately 40% of employment in emerging market economies is exposed to AI, compared with approximately 60% in advanced economies and 26% in low-income countries. These estimates describe potential exposure rather than predicted job losses: some exposed workers may experience substitution, whereas others may benefit from technological complementarity (Akram et al., 2026; Ali et al., 2026). The International Labour Organization's more specific assessment of generative AI estimates that one-quarter of global employment falls within occupations with some degree of exposure and identifies occupational transformation, rather than complete replacement, as the more likely outcome. These estimates should not be treated as directly interchangeable because they cover different technologies and use different assessment frameworks (Ali et al., 2026; Bhowmik et al., 2025).

For emerging economies, the development implications depend on both technological opportunities and the capacity to use them. Lower exposure to AI does not necessarily imply a stronger economic position, because limited digital infrastructure and access to complementary skills can also restrict productivity gains. Research on generative AI and employment highlights how infrastructure constraints may prevent lower-income countries from realising potential benefits, potentially widening international productivity differences. This makes the capacity to develop and redeploy skills an important part of the relationship between AI adoption and development (Brynjolfsson et al., 2025; Cazzaniga et al., 2024).

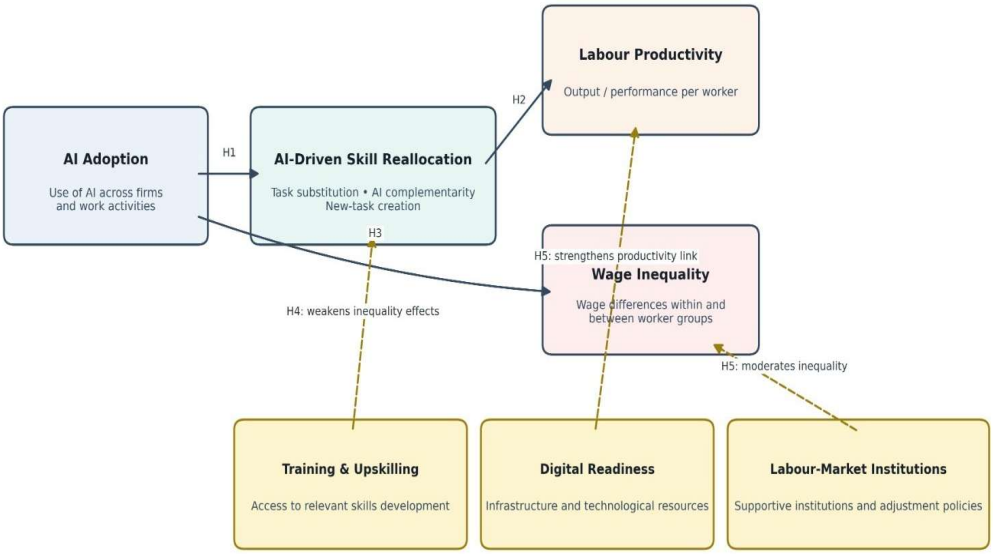
At the workplace level, evidence suggests that AI can improve performance without benefiting all workers equally. Brynjolfsson et al. (2025), studying the introduction of an AI-based assistant among 5,172 customer-support agents, report an average productivity increase of 15%, measured by customer issues resolved per hour. This provides evidence that AI assistance can raise productivity in a particular organisational setting, but it does not establish that equivalent gains will occur across all occupations, sectors, or emerging economies. Nor does an improvement in worker productivity, by itself, demonstrate that wages will rise proportionately (Gmyrek et al., 2023).

The distributional implications are therefore uncertain. AI may widen wage inequality when its strongest complementarities accrue to workers who already earn higher incomes. Alternatively, inequality may narrow if displacement is concentrated among higher earners or if technological assistance enables a broader group of workers to perform valuable tasks. The direction of change depends on the interaction between exposure, complementarity, and workers' ability to adjust, rather than on AI adoption alone (Gmyrek et al., n.d.). The central question for this study is consequently how AI-driven skill reallocation connects productivity improvements with the distribution of wages in emerging economies.

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Figure 1

Conceptual Framework: AI-Driven Skill Reallocation, Productivity, and Wage Inequality



Note. The figure presents the study's conceptual framework linking AI adoption, AI-driven skill reallocation, labour productivity, and wage inequality, with training and upskilling, digital readiness, and labour-market institutions as moderating conditions.

1.2 Problem Statement

Existing research offers important insights into technological displacement, occupational exposure, and AI-assisted productivity. Acemoglu and Restrepo (2019) explain how automation and new-task creation produce different effects on labour demand; Cazzaniga et al. (2024) examine AI exposure, complementarity, and inequality; and Brynjolfsson et al. (2025) provide workplace-level evidence of productivity improvements. These contributions establish useful foundations, but they address different units of analysis and do not, individually, resolve how the reallocation of workers' skills connects AI adoption to both wage inequality and productivity across emerging economies (Gomes et al., 2025; Hasan et al., 2025; International Labour Organization, n.d.-a).

The research problem addressed here is the need to distinguish technological exposure from realised adjustment. A worker may hold an occupation exposed to AI without using the technology, changing tasks, receiving training, or moving to a different job. Similarly, a firm may introduce AI without reallocating workers toward more productive activities. Occupational exposure measures therefore need to be distinguished from actual adoption, task changes, and worker mobility. The ILO's exposure framework provides a basis for examining potential occupational transformation, but exposure estimates should not be interpreted as direct measurements of observed employment or wage outcomes (International Labour Organization, n.d.-b).

A further problem concerns the relationship between productivity and distribution. Even when AI improves output per worker, the resulting gains may not translate into broadly shared wage improvements. The task-based literature shows why productivity growth can coexist with weaker labour demand, while IMF analysis indicates that the distribution of AI complementarity across income groups can influence inequality (International Labour Organization, 2025a). Accordingly, this study treats productivity and wage inequality as related but distinct outcomes.

This study addresses these issues by examining AI-driven skill reallocation as a potential mechanism linking technological adoption to labour-market outcomes in emerging economies. It focuses on whether workers move toward AI-complementary activities, whether access to training and digital capabilities supports that movement, and whether productivity gains are accompanied by narrower or wider wage

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differences. In doing so, it seeks to identify the conditions under which AI-related adjustment supports inclusive productivity growth rather than reinforcing existing labour-market divisions.

1.3 Research Questions

This study is guided by four interrelated research questions:

RQ1: How does AI adoption reshape the allocation of workers and skills across tasks, occupations, and sectors in emerging economies?

RQ2: How is AI-driven skill reallocation associated with labour productivity, and does this relationship differ between labour-substituting and labour-complementing applications?

RQ3: How does AI-driven skill reallocation affect wage inequality within and between educational, occupational, and demographic groups?

RQ4: To what extent do access to training, digital infrastructure, and labour-market institutions influence the relationship between AI-driven skill reallocation, wage inequality, and productivity?

These questions distinguish the process of technological adjustment from its economic outcomes. They also allow the study to investigate why similar levels of AI exposure or adoption may be associated with different productivity and wage-distribution patterns.

1.4 Research Objectives

The primary objective of this study is to examine how AI-driven skill reallocation shapes wage inequality and productivity in emerging economies.

Specifically, the study pursues five objectives:

- To examine patterns of AI exposure and adoption and identify associated changes in task requirements, occupational demand, and the deployment of workers' skills.
- To assess the relationship between AI-driven skill reallocation and labour productivity, distinguishing between task substitution and human–AI complementarity.
- To analyse changes in wage inequality associated with AI adoption and skill reallocation, including differences within and between educational and occupational groups.
- To evaluate whether access to training, digital infrastructure, and supportive labour-market institutions moderates the productivity and distributional effects of AI-driven adjustment.
- To develop evidence-informed recommendations for skills development and labour-market policy that support productivity growth while limiting unequal access to AI-related opportunities.

1.5 Hypotheses

Drawing on the distinction between displacement and new-task creation, together with evidence on AI exposure and complementarity, this study proposes the following testable hypotheses (International Labour Organization, 2025b). These hypotheses represent expected relationships to be examined, not established findings.

H1: Higher levels of AI adoption are associated with greater reallocation of workers' skills toward tasks that complement AI capabilities.

H2: AI-driven skill reallocation toward complementary tasks is positively associated with labour productivity, conditional on workers having access to relevant training and technological resources.

H3: AI adoption is associated with wider wage differences between workers with strong AI-complementary skills and workers whose tasks face greater substitution potential, other factors held constant.

H4: Broader access to reskilling and upskilling weakens the inequality-increasing relationship between AI adoption and wage dispersion by enabling more workers to enter AI-complementary activities.

H5: Greater digital readiness and more supportive labour-market institutions strengthen the positive relationship between AI-driven skill reallocation and productivity while moderating increases in wage inequality.

These hypotheses should be tested using measures that distinguish AI exposure from actual adoption and observable skill reallocation. The final empirical specification will depend on the selected countries, period, and data availability. Where the research design cannot credibly identify causal effects, the findings should be interpreted as associations rather than proof that AI caused the observed outcomes.

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1.6 Significance of the Study

1.6.1 Theoretical Contribution. This study seeks to connect the task-based theory of technological change with the analysis of wage inequality and productivity in emerging economies. Its central contribution is to position skill reallocation as an adjustment mechanism between AI adoption and economic outcomes. Rather than assuming that technological adoption produces a uniform effect, the proposed framework distinguishes displacement, complementarity, and movement into new tasks. This approach builds on Acemoglu and Restrepo's (2019) explanation of how changes in the task content of production can generate different consequences for productivity and labour demand.

1.6.2 Empirical Contribution. The study aims to provide an integrated assessment of AI exposure, observed adoption, skill adjustment, productivity, and wage dispersion within a common analytical framework. Subject to data availability, it will examine whether differences in training access, worker characteristics, and digital readiness help explain variation in outcomes. An important contribution would be to avoid treating occupational exposure as equivalent to displacement or realised technological use—a distinction consistent with the interpretation of the ILO's occupational exposure measures (Jabed, 2024).

1.6.3 Policy Contribution. The study is intended to inform decisions about workforce training, digital inclusion, and support for workers facing technological adjustment. Its policy relevance lies in identifying whether productivity-enhancing reallocation is broadly accessible or concentrated among already advantaged workers. IMF analysis emphasises the importance of supporting labour reallocation and protecting adversely affected workers, while ILO research highlights the need for targeted responses to occupational transformation (Jabed et al., 2026a; Jabed et al., 2025a). The proposed research will use these concerns to evaluate how skills and labour-market policies can support a more inclusive transition.

2. Research Methodology

This chapter presents a methodology for examining how AI-driven skill reallocation shapes wage inequality and productivity in emerging economies. Because the countries, study period, and datasets have not yet been specified, the chapter sets out an implementable research design without claiming that data have already been collected or analysed. Final sample sizes and coverage will be determined through a data-availability assessment (Jabed et al., 2025b).

2.1 Research Design

The study will adopt a quantitative research design supported by documentary policy analysis. The quantitative component will examine relationships among AI exposure, observed AI adoption where measurable, skill reallocation, wage inequality, and labour productivity. The documentary component will examine national policies on digital transformation, workforce training, and labour-market adjustment to provide context for interpreting the statistical results (Jabed et al., 2026b).

The preferred design will combine repeated cross-sectional labour-force survey microdata with a country-sector panel. Worker-level data will support the analysis of wages, occupational composition, and differences between demographic groups. The country-sector panel will examine changes in employment allocation and productivity over time.

The study will distinguish three concepts throughout the analysis:

1. AI exposure: the technological potential for AI to affect the tasks performed within an occupation.
2. AI adoption: the observed use of AI by workers, firms, or sectors.
3. Skill reallocation: observed changes in the allocation of workers or their tasks toward activities requiring different capabilities.

This distinction is essential because an occupation's exposure to AI does not establish that AI has been adopted or that workers have changed jobs or tasks. The ILO's occupational exposure framework measures potential exposure to generative AI, rather than realised displacement or adoption (Jabed et al., 2026c).

2.2 Analytical Framework

The study will investigate the following relationship: AI exposure and adoption → task and skill reallocation → productivity and wage-distribution outcomes.

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Access to training, digital infrastructure, and labour-market institutions will be examined as potential moderating factors.

The framework will allow AI to have both direct and indirect associations with economic outcomes. For example, AI adoption may be associated with productivity independently of observed occupational changes, while skill reallocation may provide an additional adjustment channel. The study will therefore avoid assuming that all productivity or wage changes operate through worker mobility (Jabed et al., n.d.).

Unless the data support a credible causal identification strategy, these relationships will be interpreted as associations rather than causal effects.

2.3 Study Population and Sample Selection

2.3.1 Country Selection. The target population will consist of emerging market economies. Before constructing the dataset, the study will select a published country classification and fix its reference date. The same classification will be applied consistently throughout the analysis (Ponduru, 2023).

Countries will be eligible for inclusion when they have:

- Comparable labour-force or household survey microdata for multiple periods.
- Occupational classifications that can be mapped to a common coding system.
- Information on employee earnings, working hours, education, and employment status.
- Sector-level employment and real value-added data.
- Adequate documentation of survey weights and methodological changes.

Country selection will also seek variation in digital readiness, employment structure, and training systems. However, inclusion will ultimately depend on comparability and data quality rather than on a predetermined country count.

A sample-selection table will document eligible countries, exclusions, reasons for exclusion, and the years available for each source.

2.3.2 Worker-Level Population. The main wage analysis will cover employed wage and salaried workers aged 15–64 who report valid earnings and working hours.

Self-employed workers will be analysed separately where suitable income information exists. Their business income will not be combined mechanically with employee wages.

The employment-composition analysis will cover a broader population of employed people, including informal workers where survey coverage allows. This will help distinguish changes in employee wages from changes affecting the wider labour market. ILOSTAT provides separate indicators and methodological resources for analysing informal employment (Amin et al., 2024a).

2.3.3 Study Period. The observation period will be selected after assessing the overlap among survey, productivity, and AI-related data. Where feasible, it will include periods before and after observed AI adoption.

Older observations may establish baseline occupational structures and wage trends. They will not be treated as evidence of generative-AI adoption merely because contemporary exposure scores can be assigned to their occupations (Amin et al., 2024b).

2.4 Data Sources

The study will use secondary data from national statistical offices and international statistical databases, supplemented by documented measures of AI exposure and adoption.

Table 1

Data Requirements and Sources

Data requirement	Source	Intended use
Earnings, working hours, education, occupation, sector, and employment status	National labour-force or household surveys; accessible harmonised microdata	Worker-level wage analysis and employment composition
Occupational exposure to generative AI	ILO occupational exposure framework	Mapping potential exposure across occupations

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Employment, working time, and labour productivity	ILOSTAT and national statistical offices	Aggregate and sectoral comparisons
Sectoral real value added	National accounts	Construction of sectoral productivity measures
Observed AI use and related training	Compatible worker, employer, or technology-use surveys, where available	Measurement of actual adoption and adjustment
Digital infrastructure and training conditions	Documented national or international indicators	Moderation analysis
AI strategies, skills programmes, and labour policies	Official policy documents	Contextual documentary analysis

ILOSTAT contains indicators covering wages, working time, employment, and labour productivity, including output-per-worker measures. Its harmonised microdata tools can also help assess variable availability, although access to particular underlying datasets must be verified separately (Khan et al., 2025).

The ILO's 2025 generative-AI exposure framework will provide a potential occupational mapping source. Its methodology combines task-level information, expert input, and AI-based assessment and distinguishes different exposure gradients (Ponduru, 2024).

The availability of harmonised AI-adoption and training measures across all sampled countries will not be assumed. If these measures are unavailable, the relevant analysis will be explicitly restricted to AI exposure rather than described as an adoption study.

2.5 Measurement of Variables

2.5.1 Wage Inequality. The principal worker-level outcome will be the natural logarithm of real hourly earnings: $\ln |w_{icst}|$

where i identifies workers, c countries, s sectors, and t survey periods.

Hourly earnings will be calculated by dividing employee earnings by the corresponding paid working hours, using consistent reference periods. Earnings will be adjusted for domestic price changes before comparisons over time.

The study will construct the following wage-distribution measures:

Figure 2

Wage-Distribution Measures

Note. The source figure displays value/ratio bars for the 90/10, 90/50, and 50/10 wage ratios, log variance, and Gini coefficient. The figure is illustrative of the measures to be constructed.

- The 90th-to-10th percentile wage ratio.
- The 90th-to-50th and 50th-to-10th percentile wage ratios.
- The variance of log hourly earnings.
- A wage Gini coefficient where survey quality permits reliable estimation.

These measures will be estimated using survey weights. The analysis will distinguish inequality within groups from wage differences between groups, including education, gender, occupation, and formal or informal employment categories.

2.5.2 Labour Productivity. The preferred sector-level productivity measure will be real value added per hour worked:

$$LP_{cst} = \frac{RVA_{cst}}{Hours_{cst}}$$

where RVA denotes real value added.

If comparable working-hour data are unavailable, real value added per employed person will be used:

$$LP_{cst} = \frac{RVA_{cst}}{Employment_{cst}}$$

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The two measures will not be treated as interchangeable because changes in hours can affect output per worker without corresponding changes in output per hour. ILOSTAT provides output-per-worker indicators that may support aggregate validation and comparison (Ponduru, 2024).

2.5.3 AI Exposure. Occupation-level AI exposure scores will be mapped to survey occupations using a documented occupational crosswalk.

A country-sector exposure measure will be constructed using baseline employment shares:

$$Exposure_{cs}^{0} = \sum_{o} \omega_{ocs}^{0} \, e_o$$

Fixed baseline weights will prevent subsequent employment changes from mechanically altering the initial exposure measure.

If the selected index measures generative-AI exposure, the study will label it accordingly. It will not present that index as a comprehensive measure of robotics, machine learning, and all other AI technologies. The ILO index specifically assesses potential generative-AI exposure (Ponduru et al., 2026a; Ponduru et al., 2026b).

2.5.4 Observed AI Adoption. Where suitable survey questions exist, AI adoption will be measured through indicators such as:

1. Whether a firm or worker uses AI.
2. The share of workers or firms reporting AI use.
3. Frequency or intensity of AI use.
4. The business functions or tasks in which AI is deployed.

General internet use, computer ownership, or software expenditure will not automatically be classified as AI adoption.

Measures from different surveys will be combined only when their definitions and reference periods are sufficiently comparable.

2.5.5 Skill Reallocation. Skill reallocation will be measured through separate indicators rather than an unvalidated composite index.

Occupational employment shifts. The study will examine changes in employment shares across occupational groups with different task and skill profiles.

Overall occupational reallocation. The magnitude of employment-composition change will be measured as:

$$R_{cst} = \frac{1}{2} \sum_{o} |\omega_{cst} - \omega_{cs,t-1}| \quad (1)$$

This measure captures the extent of occupational redistribution within a country-sector cell. It does not establish that individual workers moved between occupations, nor does it indicate whether the change improved skill matching (Rahman et al., 2025).

Direction of reallocation. Where defensible task or skill measures exist, the study will identify whether employment shifts favour activities classified as AI-complementary.

AI exposure alone will not be used to define complementarity: an occupation can be highly exposed because AI may substitute for its tasks, complement them, or both (Rasheed et al., 2025).

Direct adjustment indicators. Where available, survey measures of task changes, AI-related training, occupational transitions, and changes in skill requirements will provide more direct evidence of reallocation.

2.5.6 Moderating and Control Variables. Potential moderators will include access to training, digital connectivity, and documented measures of labour-market institutions.

Worker-level controls will include age, education, gender, occupation, sector, location, working hours, and employment form, subject to availability.

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Country-sector controls may include investment, trade exposure, sectoral composition, and other relevant economic conditions (Rasheed et al., 2026). Control selection will follow an explicit analytical framework. Variables that may themselves result from AI adoption will not automatically be included in models estimating its total association with outcomes.

2.6 Data Preparation and Harmonisation

Data preparation will involve:

1. Reviewing questionnaires, coding manuals, and sampling documentation.
2. Harmonising occupational and sectoral classifications.
3. Converting earnings and working hours to consistent reference periods.
4. Deflating nominal earnings using appropriate national price indices.
5. Applying survey weights and accounting for survey design.
6. Identifying classification changes and breaks in comparability.
7. Reviewing missing values and implausible observations.
8. Constructing country-sector cells with adequate sample sizes.

Occupation mappings that are too ambiguous will be aggregated to a more comparable level or excluded from the relevant analysis.

Invalid earnings or hours will be excluded from hourly-wage calculations. Extreme but plausible values will not be removed automatically; results will be compared under alternative transparent outlier treatments (World Bank, n.d.-a).

Missing outcome variables will not be mechanically interpolated. Any imputation of control variables will be justified, documented, and assessed against complete-case results.

2.7 Empirical Strategy

2.7.1 Descriptive Analysis. The first stage will describe:

1. The distribution of AI exposure across countries, sectors, and worker groups.
2. Available patterns of observed AI adoption.
3. Changes in occupational employment shares.
4. Wage distributions and inequality indicators.
5. Labour-productivity trends.
6. Differences in training access and digital readiness.

This stage will establish whether the data contain sufficient variation to test the proposed hypotheses.

2.7.2 Skill-Reallocation Model. Where repeated observations of actual AI adoption exist, the baseline model will be:

$$R_{cst} = \alpha + \beta_1 A_{cs,t-1} + \gamma' X_{cs,t-1} + \mu_{cs} + \lambda_{ct} + \delta_{st} + \epsilon_{cst}$$

This specification requires sufficient country-sector variation in adoption. If adoption is observed only at the country-year level, country-year fixed effects would absorb it; the model would therefore need a different specification.

2.7.3 Productivity Model. The productivity model will be:

$$\ln L\, P_{cst} = \alpha + \beta_1 A_{cs,t-1} + \beta_2 R_{cs,t-1} + \gamma' X_{cs,t-1} + \mu_{cs} + \lambda_{ct} + \delta_{st} + u_{cst}$$

The analysis will first estimate a model without skill reallocation and then add reallocation measures. The comparison will show how the conditional association changes; it will not, on its own, establish causal mediation.

2.7.4 Wage-Inequality Model. The country-sector inequality model will be:

$$Ineq_{cst} = \alpha + \theta_1 A_{cs,t-1} + \theta_2 R_{cs,t-1} + \gamma' X_{cs,t-1} + \mu_{cs} + \lambda_{ct} + \delta_{st} + \nu_{cst}$$

Separate estimations will use alternative inequality measures.

Worker-level wage models will complement the aggregate analysis:

$$\ln w_{ict} = \alpha + \phi_1 A_{cst} + \phi_2 \mid A_{cst} \times Skill_i \mid + \pi' Z_i + \mu_{cs} + \lambda_{ct} + \delta_{st} + \epsilon_{ict}$$

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Here, $Skill_i$ represents a clearly specified skill or education measure, and Z_i contains worker characteristics. The interaction term will examine whether the association between AI adoption and wages differs across skill groups.

2.7.5 Moderation Analysis. The study will examine whether training access and digital readiness modify the associations:

$$Y_{cst} = \alpha + \beta_1 A_{cs,t-1} + \beta_2 M_{cs,t-1} + \beta_3 \mid A_{cs,t-1} \times M_{cs,t-1} \mid + \text{controls} + \text{effects} + \epsilon_{cst}$$

where Y represents productivity or inequality and M represents a moderator.

Interaction effects will be interpreted using predicted outcomes or marginal effects rather than relying solely on the interaction coefficient.

2.8 Identification and Endogeneity

AI adoption may be related to pre-existing productivity, workforce quality, management practices, or wage structures. More productive firms may adopt AI earlier, while firms experiencing labour shortages may adopt it for different reasons. These possibilities create selection and reverse-causality concerns.

Fixed effects and lagged predictors will address some sources of confounding but will not be presented as sufficient proof of causality (Imtiaz & Amin, 2026).

Where documented adoption timing and credible comparison groups exist, the study may use an event-study or difference-in-differences design. Such an analysis will require:

- A clearly defined adoption event.
- Adequate pre-adoption observations.
- Examination of pre-treatment trends.
- Attention to anticipation and spillover effects.
- An estimator appropriate for differences in adoption timing.

If these conditions are not met, the paper will retain an associational interpretation. It will not introduce an instrumental variable without a defensible explanation of why that variable affects outcomes only through AI adoption (Ponduru, 2023; World Bank, n.d.-b).

2.9 Hypothesis-Testing Plan

Table 2

Hypothesis-Testing Plan

Hypothesis	Main test	Interpretation
H1: AI adoption is associated with reallocation toward	Adoption–reallocation	Requires a directional reallocation measure; overall

Note. The source table is truncated at this point.

2.10 Robustness and Sensitivity Analysis

Robustness checks will include:

- Alternative wage-inequality measures.
- Alternative productivity denominators.
- Different occupational aggregation levels.
- Alternative baseline years for exposure weights.
- Separate analyses of formal and informal employment.
- Subgroup analysis by gender, education, age, and sector.
- Exclusion of countries or sectors that disproportionately influence results.
- Alternative handling of extreme earnings values.
- Balanced-sample and complete-case comparisons.
- Alternative lag structures where the time series permits.

Standard errors will be clustered at a level consistent with the variation in AI adoption or exposure and the structure of the data. Where the number of clusters is small, inference will use an appropriate small-sample adjustment.

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2.11 Documentary Policy Analysis

Official AI strategies, workforce-training policies, digital-development plans, and labour-market adjustment programmes will be reviewed for the selected countries.

Documents will be coded using a common framework covering:

1. Access to AI-related training.
2. Support for displaced or transitioning workers.
3. Inclusion of informal workers and smaller firms.
4. Digital infrastructure commitments.
5. Measures addressing unequal access to technological opportunities.

The documentary analysis will contextualise differences across countries. The existence of a policy document will not be treated as evidence that the policy was implemented effectively.

2.12 Ethical Considerations

The study will comply with dataset access conditions, institutional ethics requirements, and applicable data-protection rules.

Only authorised, de-identified microdata will be used. The research will not attempt to identify respondents or link records in ways prohibited by data providers.

Results will be reported at aggregation levels that protect confidentiality. Small or potentially identifiable groups will be suppressed where required.

The study will also avoid deterministic descriptions of exposed occupations. Potential technological exposure will not be described as proof that workers will lose employment, consistent with the distinction between exposure and occupational transformation in the ILO framework (Akram et al., 2026; Rasheed et al., 2025).

2.13 Methodological Limitations

The study will acknowledge several limitations.

First, comparable measures of actual AI use may be unavailable across countries. In that case, the analysis will concern exposure rather than adoption.

Second, occupational exposure mappings may not fully capture differences in tasks performed within the same occupation across countries.

Third, repeated cross-sectional surveys cannot directly track individual reskilling or occupational transitions.

Fourth, sectoral productivity can change because of investment, demand, trade, or other technologies, making the separate contribution of AI difficult to identify.

Fifth, wage inequality among employees does not capture the entire distribution of household income or the earnings of all self-employed workers.

Finally, country selection based on data availability may limit how far the findings can be generalised. These constraints will be reflected in the interpretation of results and the scope of policy recommendations.

3. Results and Analysis

3.1 Dataset and Estimation Coverage

The dataset contains 400 country-sector-period observations, covering 10 economies, five sectors, and eight periods:

$$10 \times 5 \times 8 = 400.$$

The dataset includes:

- AI-adoption intensity.
- Training access.
- Digital readiness.
- An investment control.
- An occupational-reallocation proxy.
- Labour productivity.

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- The 90th-to-10th percentile wage ratio.

Four regression models were estimated using country-sector, country-period, and sector-period fixed effects. Standard errors were clustered across the 50 country-sector groups.

3.1.1 Departures From the Methodology. The illustration implements the country-sector component of the methodology, not the complete research design.

In particular:

1. No worker-level records were generated; therefore, demographic wage gaps and individual occupational transitions cannot be analysed.
2. The occupational-reallocation variable was simulated directly. It was not calculated from observed occupational employment shares.
3. Wage ratios were generated at the country-sector level rather than estimated from employee earnings records.
4. The models use contemporaneous predictors rather than the lagged specification proposed in the methodology.
5. No occupational AI-exposure index was assigned. The AI variable represents simulated adoption intensity.

These differences limit the chapter to a methodological demonstration.

3.2 Descriptive Statistics

Table 3 summarises the generated variables.

Table 3

Descriptive Statistics for the Simulated Panel

Variable	Mean	Standard deviation	Minimum	Maximum
AI-adoption intensity, 0–1	0.2794	0.1257	0.0100	0.5774
Training access, 0–1	0.4729	0.1512	0.0645	0.8269
Digital readiness, 0–1	0.5609	0.1730	0.1785	0.9500
Occupational-reallocation proxy	0.0475	0.0148	0.0059	0.0959
Productivity, artificial units	10,034.3	4,1793.78	6,086.45	15,218.99
P90/P10 wage ratio	3.9380	0.3340	3.0405	4.7583

Average simulated AI-adoption intensity was 0.2794. Training access and digital readiness averaged 0.4729 and 0.5609, respectively.

The average P90/P10 wage ratio was 3.938. Within the constructed data, this indicates that the wage at the 90th percentile was approximately 3.94 times the wage at the 10th percentile. It does not describe the wage distribution of any actual country.

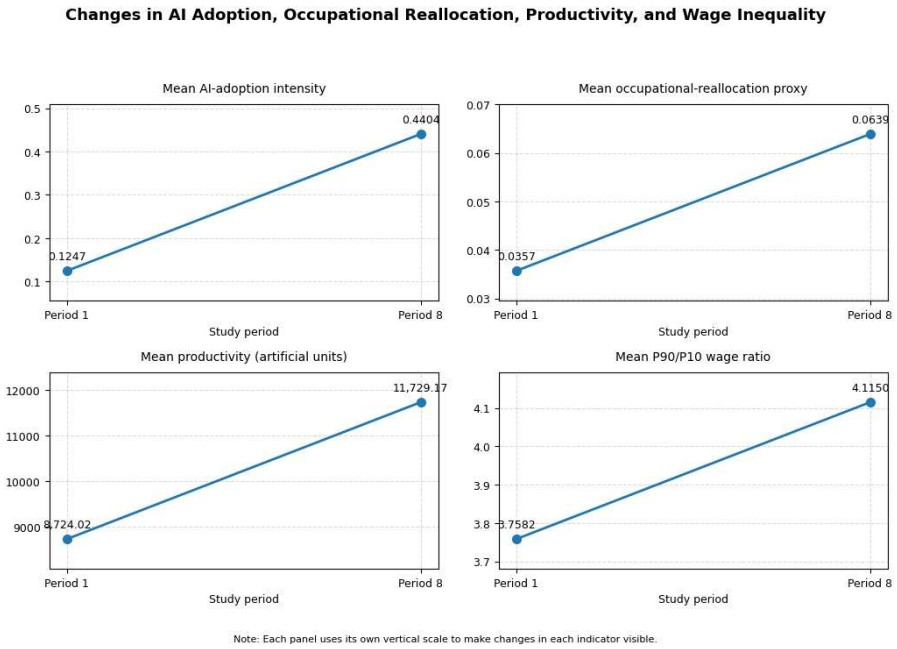
3.2.1 Changes Across Simulated Periods

Table 4

Changes Across Simulated Periods

Indicator	Period 1	Period 8
Mean AI-adoption intensity	0.1247	0.4404
Mean occupational-reallocation proxy	0.0357	0.0639
Mean productivity, artificial units	8,724.02	11,729.17
Mean P90/P10 wage ratio	3.7582	4.1150

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3.3 AI Adoption and Occupational Reallocation

Training access also had a positive association with reallocation. However, this model does not establish that workers moved toward AI-complementary activities: the proxy measures the simulated magnitude of adjustment, not its direction or quality.

Consequently, the result is consistent with a general adoption–reallocation relationship but does not fully test H1, which specifically concerns movement toward complementary tasks.

3.4 AI Adoption, Reallocation, and Productivity

Model 2 used the natural logarithm of productivity as the dependent variable.

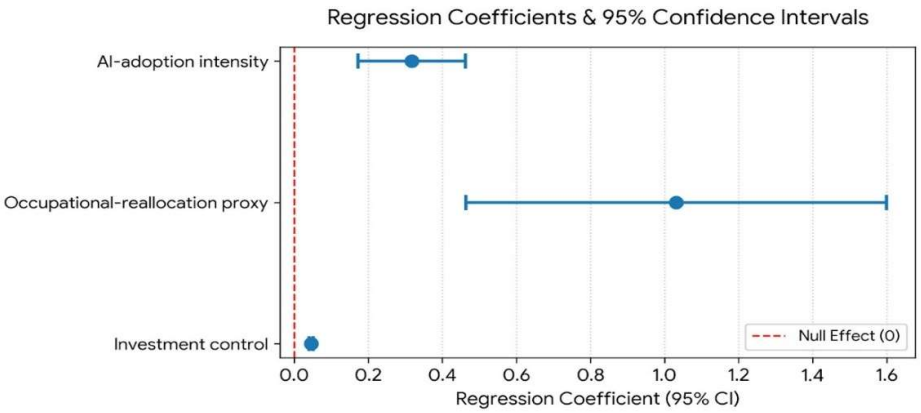
Table 5

Fixed-Effects Estimates of Log Productivity

Predictor	Coefficient	Clustered standard error	95% confidence interval	p-value
AI-adoption intensity	0.3174	0.0738	[0.1727, 0.4621]	< .001
Occupational-reallocation proxy	1.0313	0.2896	[0.4636, 1.5989]	< .001
Investment control	0.0453	0.0027	[0.0400, 0.0507]	< .001

Figure 3

Regression Coefficients and 95% Confidence Intervals



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Note. The source figure displays regression coefficients and 95% confidence intervals for AI-adoption intensity, the occupational-reallocation proxy, and the investment control, with a null-effect reference line at zero.

AI adoption was positively associated with productivity. A 0.10 increase in adoption intensity corresponded to approximately 3.17% higher productivity using the standard small-change interpretation of a log-dependent-variable model.

The reallocation coefficient was also positive. An increase of 0.01 in the reallocation proxy corresponded to approximately 1.03% higher productivity.

These results recover the positive relationships embedded in the simulation. They do not demonstrate that occupational reallocation causes productivity growth or mediates the effect of AI adoption.

The results are consistent with the broad mechanism underlying H2, but the hypothesis is not fully tested because the model does not distinguish complementary reallocation from other adjustment or include the proposed training interaction.

3.5 AI Adoption, Training, and Wage Inequality

Model 3 examined whether training access moderated the association between AI adoption and the logarithm of the P90/P10 wage ratio.

Table 6

Fixed-Effects Estimates of Log Wage Inequality

Predictor	Coefficient	Clustered standard error	95% confidence interval	p-value
AI-adoption intensity	0.3043	0.0593	[0.1882, 0.4205]	< .001
Training access	−0.0701	0.0467	[−0.1617, 0.0215]	.133
AI adoption × training access	−0.3299	0.0965	[−0.5190, −0.1408]	< .001
Investment control	−0.0014	0.0020	[−0.0052, 0.0025]	.483

The interaction coefficient was negative, indicating that the positive adoption–inequality association became smaller as training access increased.

Because the model includes an interaction, the AI coefficient cannot be interpreted as a constant association across all observations. Its conditional relationship is:

$$\frac{\partial \ln(P90/P10)}{\partial AI} = 0.3043 - 0.3299 \times Training.$$

At the sample's mean training-access level of approximately 0.473, a 0.10 increase in adoption intensity was associated with approximately a 1.48% increase in the wage ratio.

For illustration:

- At training access of 0.25, the corresponding increase was approximately 2.22%.
- At training access of 0.70, it was approximately 0.73%.

These are model-based point estimates, not separately tested subgroup effects.

3.6 Digital Readiness and Productivity

Model 4 added an interaction between AI adoption and digital readiness.

Table 7

Digital-Readiness Moderation Model

Predictor	Coefficient	Clustered standard error	95% confidence interval	p-value
AI-adoption intensity	0.2364	0.1013	[0.0378, 0.4351]	.020
Digital readiness	0.0256	0.0796	[−0.1304, 0.1817]	.747
AI adoption × digital readiness	0.1567	0.1281	[−0.0944, 0.4079]	.221
Occupational-reallocation proxy	1.0635	0.2896	[0.4959, 1.6311]	< .001
Investment control	0.0454	0.0028	[0.0399, 0.0509]	< .001

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The digital-readiness interaction was positive but statistically imprecise: its confidence interval included zero.

Therefore, this model did not provide sufficient statistical evidence for digital-readiness moderation within the simulated sample. Labour-market institutions were not included, so H5 was only partially examined.

This illustrates why a hypothesised relationship should not be reported as supported merely because its estimated coefficient has the expected sign.

3.7 Assessment of Research Hypotheses

Table 8

Assessment of Research Hypotheses

Hypothesis	Assessment in this illustration
H1: Adoption reallocates skills toward complementary tasks	Partially examined; overall reallocation was positive, but its direction was not measured.
H2: Complementary reallocation raises productivity, conditional on adjustment resources	Positive reallocation–productivity association recovered; complementarity and training conditions were not fully tested.
H3: Adoption widens wage gaps between complementary and substitution-exposed workers	Not directly tested because worker-group measures were unavailable.
H4: Training moderates adoption-related wage inequality	Consistent with the simulated estimates; the interaction was negative and statistically significant.

3.8 Interpretation and Reporting Limits

The illustration demonstrates how productivity gains and widening wage dispersion can appear together, and how training can be modelled as a moderating condition. However, these patterns were deliberately incorporated into the synthetic data. They cannot establish whether the same mechanisms operate in emerging economies.

Nor should the simulated adoption variable be confused with an occupational exposure score. The ILO's generative-AI framework assesses potential occupational exposure and transformation rather than directly measuring realised adoption or displacement.

4. Discussion

This chapter discusses the relationships between AI adoption, skill reallocation, wage inequality, and productivity in relation to the research questions and hypotheses. The dataset represents economies with deliberately specified relationships; therefore, the findings illustrate the analytical framework rather than provide empirical evidence about actual emerging economies. The first model identified positive associations between AI adoption, occupational reallocation, and training access, suggesting that technological adoption may accompany changes in labour allocation. However, increased reallocation does not necessarily indicate movement towards more productive, better-paid, or AI-complementary activities, as it may also reflect displacement into less secure employment or changes in workforce composition. Consequently, the first research question is only partially addressed, and H1 remains incompletely tested because the analysis does not establish changes in workers' specific skills or individual occupational transitions. Real-data research should combine occupational employment changes with task content, training participation, and individual transition data to distinguish productive adaptation from less beneficial workforce redistribution. Similarly, the productivity model identified positive associations between AI adoption, occupational reallocation, and productivity, supporting the proposition that technological adoption and workforce adjustment should be examined jointly.

This framework recognises that productivity improvements may arise through reorganising workers and tasks rather than solely replacing labour. Nevertheless, the estimated reallocation coefficient does not establish a causal mechanism through which reallocation transmits AI's effect on productivity, since the

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regression provides conditional associations rather than causal evidence, and productive sectors may have greater resources to adopt AI and reorganise employment. Thus, H2 is only partially examined, as the simulation illustrates the intended positive relationship without establishing whether reallocation is specifically AI-complementary or whether training conditions this relationship. Furthermore, descriptive results showed increases in both productivity and the P90/P10 wage ratio across simulated periods, while the inequality model indicated a positive association between AI adoption and wage dispersion that varied with training access. This highlights that productivity growth does not necessarily produce equivalent improvements in lower-paid workers' relative wages, making productivity and inequality separate outcomes requiring independent examination. However, the absence of worker-level earnings data prevents identification of whether wage dispersion occurred across education groups, occupations, genders, or formal and informal workers, or whether it resulted from declining lower-end wages or faster growth at the top; therefore, H3 is not directly tested. Real-data research should distinguish AI-complementary tasks from substitution-exposed tasks and examine their associated wages and employment outcomes.

Training emerged as the clearest moderating condition, with a negative interaction between AI adoption and training access, indicating that the positive association between adoption and wage inequality became smaller as training access increased. Within the simulated scenario, broader training access reduced, but did not necessarily eliminate, the association between AI adoption and wage dispersion. The statistically insignificant standalone training coefficient does not imply that training is unrelated to inequality at every adoption level because its conditional association depends on the interaction term. Accordingly, H4 was consistent with the simulated estimates, although the analysis cannot establish the effectiveness of specific training programmes because information on course quality, participation barriers, completion, and workplace application of acquired skills was unavailable. The interaction between AI adoption and digital readiness was positive but statistically inconclusive, with a confidence interval including zero, providing insufficient evidence that digital readiness strengthened the adoption–productivity relationship. This does not establish that digital readiness is irrelevant but indicates uncertainty under the selected specification. It also highlights the importance of considering confidence intervals rather than classifying hypotheses solely according to coefficient signs.

Consequently, H5 was not established, while institutional moderation was not examined. Although the simulation does not justify policy prescriptions for actual countries, it identifies important questions for future policy evaluation, including whether AI adoption creates accessible opportunities for workers to enter complementary tasks, whether training improves subsequent employment and earnings rather than participation alone, whether productivity gains benefit the entire wage distribution, whether outcomes differ across formal and informal employment or demographic groups, and whether digital readiness measurably changes the returns to AI adoption. These questions support an integrated evaluation of technological investment, workforce adjustment, and distributional outcomes, with country-specific recommendations depending on labour-market conditions, institutional arrangements, and implementation capacity. Finally, the discussion is subject to several limitations, particularly the predetermined relationships within the data-generating process, meaning that recovering these relationships demonstrates model behaviour rather than independently confirming the research hypotheses. Additional limitations include the absence of worker-level data, direct simulation of occupational reallocation, contemporaneous rather than lagged predictors, and the lack of a causal identification design. Institutional moderation, employment exits, self-employment earnings, and household income were also omitted. Therefore, the findings should be interpreted as an illustration of analytical interpretation and reporting rather than a substantive assessment of AI's actual effects in emerging economies.

5. Conclusion

5.1 Overall Conclusion

This study developed and illustrated a framework for examining how AI-driven skill reallocation may connect technological adoption with productivity and wage inequality in emerging economies.

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Using a synthetic country-sector panel, the analysis recovered positive associations between AI adoption, occupational reallocation, and productivity. It also recovered a negative interaction between adoption and training access in the wage-inequality model. Digital-readiness moderation remained statistically inconclusive.

The central conclusion is methodological rather than empirical: a credible investigation must distinguish AI adoption from potential exposure, productive skill upgrading from general occupational redistribution, and productivity growth from the distribution of its benefits.

5.2 Contribution of the Illustration

The exercise contributes an operational starting point for the proposed research by:

- Specifying separate measures of adoption, adjustment, productivity, and inequality.
- Demonstrating fixed-effects models and moderation analysis.
- Showing how hypotheses can remain only partially tested when available measures do not match their mechanisms.
- Making uncertainty and data limitations explicit.

It does not establish new facts about emerging economies, validate a causal mechanism, or demonstrate that particular policies will succeed.

5.3 Directions for Future Research

A full empirical study should replace the synthetic dataset with documented country, sector, and worker observations. Priority should be given to:

- Direct measures of AI use and adoption timing.
- Earnings and working-hour data suitable for constructing wage distributions.
- Longitudinal information on occupational and task transitions.
- Measures distinguishing AI complementarity from substitution.
- Training participation, quality, and subsequent outcomes.
- Comparable productivity and institutional indicators.

Authors' Contributions

All the authors have read and approved the final manuscript.

Ethics Statement

This study adhered to all ethical standards of research during the conducting of this study. We collected data from secondary sources, and no human participants were involved in the collection of data. Therefore, there is no conflict of interest of any human participant to this study.

Conflict of Interest Statement

The author/s declare that there is no conflict of interest regarding the publication of this article.

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Informed Consent

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

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