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THE ECONOMIC IMPLICATIONS OF ARTIFICIAL INTELLIGENCE FOR EMPLOYMENT AND LABOUR PRODUCTIVITY: A DESCRIPTIVE EVIDENCE SYNTHESIS (2020–2025)

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Abstract

This study examines the economic implications of artificial intelligence (AI) for employment and labour productivity using published evidence from 2020–2025. It synthesizes enterprise AI-adoption statistics, occupational-exposure assessments, and empirical workplace studies to distinguish technological diffusion, potential labour-market transformation, and reported productivity outcomes. The reviewed evidence indicates expanding business adoption of AI and productivity improvements in selected customer-support and professional-writing tasks. However, occupational exposure does not necessarily translate into actual job displacement, and productivity gains observed in specific workplace settings cannot be directly generalized to national labour productivity. Potential labour-market adjustment pressures vary across income groups and genders, while some evidence suggests that less experienced workers may benefit disproportionately from AI assistance. Overall, the findings indicate that task transformation and worker augmentation provide a more balanced interpretation of AI's employment implications than the assumption of uniform labour replacement. Key policy priorities include improving digital infrastructure, strengthening relevant workforce skills, supporting workers during occupational transitions, and protecting workers' interests. As a descriptive evidence synthesis rather than an original causal analysis, this study highlights the need for more harmonized AI-adoption data and further research into employment, wages, and long-term productivity outcomes.

Keywords: Artificial Intelligence, Employment, Labour Productivity, Generative AI, Occupational Exposure, Evidence Synthesis.

1. Introduction

Artificial intelligence (AI) has become an important subject of economic research because of its potential to reshape production, employment, and labour productivity. Unlike technologies that primarily automate explicitly programmed activities, AI systems can support tasks involving language, prediction, information processing, and problem-solving. These capabilities create opportunities to improve workplace efficiency while raising concerns about job displacement, changing skill requirements, and the distribution of economic gains. The central economic question is therefore not simply whether AI can perform human tasks, but how its integration into production changes the demand for labour and the productivity of workers.

The period from 2020 to 2025 provides a useful window for examining these developments. Workplace evidence from this period includes the deployment of AI-based assistance in customer support during 2020–2021, experimental research on generative AI in professional writing in 2023 and updated global assessments of occupational exposure in 2025. Together, these developments make it possible to examine both observed productivity effects in specific settings and the potential implications of AI for employment across countries. However, these forms of evidence answer different questions: workplace studies measure outcomes following particular interventions, whereas occupational-exposure assessments estimate which tasks or jobs could be affected by the technology (Acemoglu, 2025; Ali et al., 2026; Asif et al., 2026; Shaikh & Asif, 2026).

AI may influence employment through both labour-substitution and labour-complementarity mechanisms. The substitution mechanism arises when firms use AI to perform tasks previously undertaken by employees, potentially reducing labour requirements for particular activities. The complementarity mechanism operates when AI helps workers complete tasks more effectively, improves access to information, or supports better decisions. Productivity improvements may also reduce production costs and encourage output expansion, creating an additional source of labour demand (Acemoglu & Johnson, 2024). Consequently, the employment effects of AI depend on the balance between task displacement, worker augmentation, and broader adjustments in production rather than on technological capability alone (Ali et al., 2026; Acemoglu & Restrepo, 2024).

Recent empirical evidence demonstrates that AI can generate substantial productivity improvements in particular workplace settings. Brynjolfsson et al. (2025) examine the introduction of a generative AI assistant using data from 5,172 customer-support agents and find that access to the tool increased productivity, measured by issues resolved per hour, by approximately 15%. The benefits were greater for less experienced and lower-skilled agents, suggesting that AI assistance can help disseminate effective working practices and accelerate learning (Brynjolfsson et al., 2025; Cazzaniga et al., 2024; Shaikh & Asif, 2026). Nevertheless, the authors emphasize that their findings concern a particular firm and do not establish the aggregate employment or wage effects of generative AI.

Experimental research provides complementary evidence. Noy and Zhang (2023) study 453 college-educated professionals completing occupation-specific writing tasks and find that access to ChatGPT reduced average task-completion time by 40% while increasing output quality by 18%. These findings indicate that AI can improve performance in selected professional activities and reduce productivity differences between workers. However, improvements in the speed and quality of individual tasks should not be interpreted as equivalent increases in economy-wide labour productivity (Bhowmik et al., 2025; Comunale & Manera, 2024). Their aggregate significance depends on the range of tasks affected, the extent of adoption, and the way organizations integrate AI into their production processes.

The implications for employment are similarly uneven. The International Labour Organization's (ILO, 2025) assessment estimates that approximately one in four workers globally is employed in an occupation with some exposure to generative AI, while 3.3% of global employment falls within the highest exposure category (Eloundou et al., 2023). Clerical occupations remain particularly exposed, although advances in generative AI also affect specialized activities within professional and technical occupations. Importantly, occupational exposure does not demonstrate that jobs have already disappeared or will necessarily be eliminated. Because occupations generally combine multiple tasks, including those requiring human input, the assessment identifies job transformation as a more likely outcome than the complete replacement of most occupations (Filippucci et al., 2024a).

A global perspective is essential because the opportunities and adjustment costs associated with AI differ across economies. The ILO estimates that the share of employment with some generative AI exposure reaches 34% in high-income countries, compared with 11% in low-income countries. These differences reflect variation in occupational structures and should not be treated as direct measures of actual AI adoption. The International Monetary Fund (Cazzaniga et al., 2024) further emphasizes that countries' ability to benefit from AI depends on their preparedness, including digital infrastructure, workforce capabilities, and institutional frameworks (Filippucci et al., 2024b; Wooldridge, 2010). Thus, lower occupational exposure does not

necessarily imply greater economic advantage; it may coexist with more limited access to the productivity benefits of AI.

The effects of AI may also differ across worker groups. Although some workplace studies show relatively large productivity improvements among less experienced workers, the broader distributional consequences depend on whether AI substitutes for or complements their tasks. The IMF (Cazzaniga et al., 2024) identifies the possibility of increasing labour-income inequality when AI strongly complements high-income workers, while higher returns to capital may contribute to wealth inequality (World Bank, n.d.). At the same time, sufficiently large productivity gains could raise incomes more broadly. These competing possibilities highlight the importance of examining employment and labour productivity together rather than assuming that technological progress produces uniform benefits for all workers (Rahman et al., 2025; OECD, 2025b).

Existing research provides valuable evidence on AI-assisted task performance, occupational exposure, and the potential macroeconomic implications of artificial intelligence. However, these strands of evidence differ in their units of analysis, research designs, and interpretation. Experimental and firm-level studies examine productivity outcomes in specific tasks or workplaces, whereas global occupational-exposure assessments estimate the potential for AI to affect work activities rather than measure actual job displacement (OECD, 2025a). Enterprise adoption statistics provide a further perspective by indicating the extent to which organizations report using AI. These distinctions make it important to interpret the available evidence in a way that avoids conflating technological adoption, potential exposure, observed employment outcomes, and productivity changes.

Against this background, this paper synthesizes published global evidence from 2020–2025 to examine the economic implications of artificial intelligence for employment and labour productivity. It addresses three research questions:

1. What does the available evidence indicate about the relationship between AI and employment-related outcomes?
2. What productivity changes have been reported in AI-assisted workplace activities, and under what conditions have these improvements been observed?
3. How do the reported implications of AI vary across economies, industries, occupational groups, and worker categories?

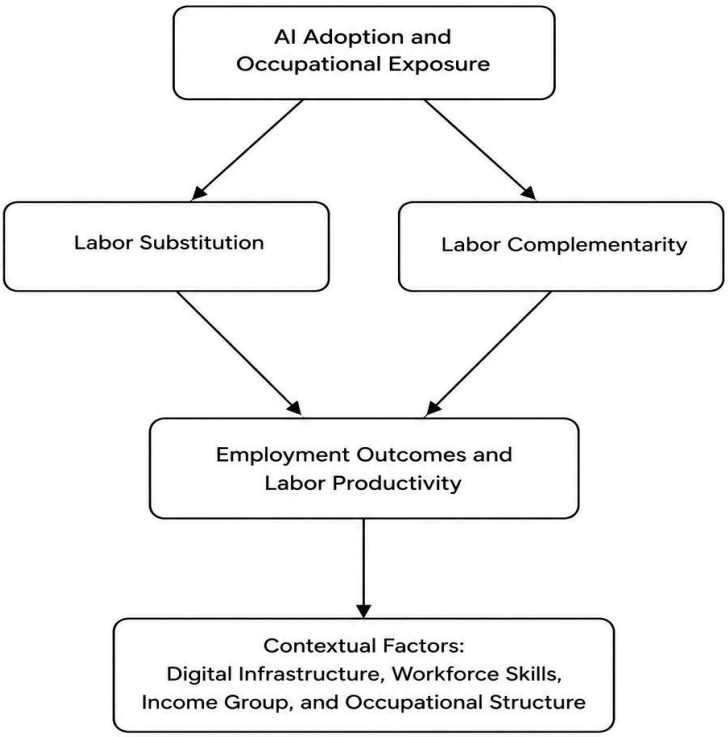
The study adopts a descriptive evidence-synthesis approach. It compares reported findings across different evidence categories while considering differences in geographical coverage, measurement definitions, study settings, and observation periods. It does not estimate an original country-level econometric model or claim to identify a single causal effect of AI on employment or labour productivity (Asif & Khan, 2026; Shaikh, 2026).

The paper makes three contributions. First, it brings employment-related evidence and labour-productivity findings together while distinguishing potential task displacement from worker augmentation and observed labour-market outcomes. Second, it considers the global distribution of AI-related opportunities and adjustment pressures, including differences in occupational structures, digital preparedness, and workforce capabilities. Third, it evaluates evidence published or relevant to the 2020–2025 period while highlighting the limits of comparing findings drawn from different populations, methods, and levels of analysis. This approach provides a structured basis for understanding the economic implications of AI without assuming that findings from individual tasks or firms necessarily apply to entire economies.

2. Conceptual Framework: AI, Employment and Labour Productivity (2020–2025)

Figure 1

Conceptual Framework: AI, Employment and Labour Productivity (2020–2025)



The policy relevance of this analysis lies in identifying how productivity improvements can be supported while limiting adverse labour-market adjustments. The International Monetary Fund (Cazzaniga et al., 2024) emphasizes the importance of supporting labour reallocation and protecting workers adversely affected by technological change, alongside strengthening digital infrastructure and workforce skills in emerging and developing economies. The International Labour Organization (Gmyrek et al., 2025) also highlights the importance of social dialogue and targeted policy responses in managing occupational transformation (OECD, 2024). These perspectives suggest that the economic benefits of AI depend not only on technological development but also on the institutions, workforce capabilities, and complementary investments that shape its implementation.

The remainder of the paper is organized as follows. Section 3 describes the evidence base and methodological approach used to synthesize published findings on AI adoption, employment, and labour productivity. Section 4 presents the results of the descriptive evidence synthesis. Section 5 discusses the findings, cross-country differences, and policy implications. Section 6 concludes the paper and identifies directions for future research.

3. Research Methodology

3.1 Research Design

This study adopts a descriptive evidence-synthesis approach to examine the economic implications of artificial intelligence (AI) for employment and labour productivity during 2020–2025. Rather than conducting an original country-level econometric analysis, the study examines and compares findings from published statistical reports and empirical workplace studies to identify patterns in AI adoption, occupational exposure, and productivity outcomes. The analysis is organized around three dimensions (OECD, 2024; Noy & Zhang, 2023). First, enterprise-level statistics are used to describe trends in business AI adoption. Second, occupational-exposure estimates are examined to assess how the potential for AI-related task transformation differs across economic and demographic groups. Third, empirical workplace studies are analysed to understand how AI assistance affects worker performance in specific tasks and settings.

The findings are interpreted comparatively, taking into account differences in the scope, measurement, and units of analysis across the available evidence. Enterprise AI adoption, occupational exposure, and task-level productivity are treated as distinct measures and are not combined into a single quantitative estimate. This approach supports a structured interpretation of the available evidence while recognizing that the findings do not establish a causal relationship between AI adoption and aggregate employment or labour productivity.

Accordingly, the study focuses on describing and interpreting existing evidence rather than estimating original regression coefficients or claiming causal effects at the national or global level.

3.2 Study Period and Unit of Analysis

This study examines evidence relevant to the period 2020–2025. The period was selected to assess recent developments in AI adoption, occupational exposure, and labour productivity. However, the temporal coverage varies across the evidence sources included in the analysis, and complete annual data are not available for every indicator throughout the six-year period.

The units of analysis differ according to the type of evidence examined. OECD statistics describe enterprise-level AI adoption, occupational-exposure estimates describe the potential for AI-related task transformation across worker groups and economies, and workplace studies examine productivity outcomes in specific tasks and settings (Khan et al., 2025). These units are analysed separately because they measure different aspects of AI's economic implications.

For each evidence source, the analysis considers its reporting period, population or geographic coverage, unit of analysis, and outcome measures. Differences in data availability, definitions, and measurement methods are taken into account when interpreting findings. The study does not construct a harmonized country-year panel or estimate original country-level regression models (Hasan et al., 2025).

Where evidence is concentrated in OECD member countries or other relatively high-income economies, the findings are interpreted according to the actual coverage of the relevant source rather than assumed to be globally representative. The overall 2020–2025 period therefore defines the scope of the study, not a complete annual dataset covering every indicator and country.

3.3 Data Sources and Evidence Selection

This study uses secondary evidence from published international statistical reports, official databases, and empirical workplace studies to examine the economic implications of artificial intelligence for employment and labour productivity during 2020–2025. The selected evidence is organized into three main components: enterprise AI adoption, occupational exposure to AI, and workplace productivity outcomes.

Table 1

Data Sources and Their Analytical Roles

Evidence component	Source type	Intended use
Business AI adoption	OECD enterprise AI statistics and relevant national business surveys	Describe trends in business AI adoption within the reported coverage
Occupational exposure	Published international reports and occupational-exposure assessments	Examine the potential for AI-related task transformation across economies and worker groups
Employment-related implications	Published empirical studies and official labour-market reports	Identify reported employment patterns and potential labour-market implications
Workplace productivity	Empirical studies of AI-assisted work and worker performance	Examine productivity-related outcomes in specific tasks and workplace settings
Geographic and methodological coverage	Source documentation and study descriptions	Assess comparability, study populations, reporting periods, and measurement limitations

OECD publications provide information on enterprise AI adoption, while international occupational assessments and empirical workplace studies contribute evidence on potential task transformation and observed productivity outcomes. Official statistical databases may provide additional context for interpreting labour-market and productivity trends. However, these sources are used according to their actual coverage and analytical purpose rather than combined into a single country-year dataset.

Evidence is considered relevant when it directly addresses at least one of the study's central dimensions: business AI adoption, occupational exposure, employment-related implications, or workplace productivity. Preference is given to sources that clearly describe their study population or geographic coverage, reporting period, measurement approach, and principal outcomes (Green & Lamby, 2025).

For each included source, the analysis records the source type, publication year, period covered by the evidence, geographic or population coverage, unit of analysis, key findings, and relevant limitations. Where available, information about survey definitions and changes in measurement is also considered to support accurate interpretation.

The evidence is compared descriptively, with attention to differences in study design, population, geographic coverage, and outcome definitions. Enterprise AI adoption, occupational exposure, and task-level productivity are treated as distinct measures. Occupational exposure is not interpreted as observed job displacement, and productivity improvements in individual workplace studies are not assumed to represent equivalent increases in national labour productivity (Imtiaz, 2026; Khan et al., 2026; Gummadavelli et al., 2026).

Because the study synthesizes existing evidence rather than constructing an original country-level panel, country inclusion criteria, regression-variable availability, and panel sample-size calculations are not applicable. Instead, the geographic scope and limitations of each source are documented, and conclusions are restricted to what the available evidence supports.

3.4 Measurement of Variables

3.4.1 Employment. Employment-related outcomes are examined using the employment-to-population ratio where consistently defined data are reported by the selected sources. This indicator represents the proportion of the relevant population that is employed and provides a descriptive measure of labour-market participation in employment.

The employment-to-population ratio is expressed as:

$$EMP_{it} = \left(\frac{Employed\ persons_{it}}{Corresponding\ population_{it}}\right) \times 100$$

Here, $i$denotes the country and $t$denotes the year. The interpretation of this indicator depends on the age coverage and statistical definitions used in the original source. Where supplementary indicators, such as unemployment, labour-force participation, or employment growth, are reported, they are discussed separately because they represent different dimensions of labour-market conditions (Gmyrek et al., 2025).

The analysis distinguishes observed employment outcomes from estimates of occupational exposure to AI. Occupational exposure indicates the potential for AI to affect tasks within an occupation; it does not, by itself, demonstrate that jobs have been eliminated or that unemployment has increased.

3.4.2 Labour Productivity. Labour productivity is examined using measures reported in the selected sources, including GDP per person employed where comparable data are available. This indicator represents economic output per employed person and should not be interpreted as output per hour worked.

Labour productivity per employed person can be expressed as:

$$LP_{it} = \frac{GDP_{it}^{PPP}}{Employment_{it}}$$

Where GDP is expressed in purchasing-power-parity (PPP) terms, the resulting indicator supports comparisons across countries when the underlying definitions, price basis, and reference years are sufficiently comparable.

$$PROD_{it} = \ln(LP_{it})$$

This expression defines a possible transformed indicator; it does not imply that a regression model has been estimated. The discussion considers reported productivity changes in their original contexts, including task-level experiments and workplace studies. Improvements in task completion time or output are not

automatically treated as equivalent to increases in national labour productivity. Differences in working hours, workforce composition, industry structure, and study design are considered when interpreting the findings.

3.4.3 Artificial Intelligence Adoption. AI adoption is examined using reported measures of enterprise AI use where these are available in the selected sources. Enterprise adoption can be expressed as:

$$AI_{it} = \left(\frac{\text{Enterprises using } AI_{it}}{\text{Enterprises} \in \text{the relevant survey population}_{it}} \right) \times 100$$

Here, AI_{it} represents the percentage of enterprises reporting AI use in the relevant country and period, where the source provides comparable country-year information. Survey coverage, enterprise-size thresholds, sector composition, and question wording are considered when interpreting reported adoption rates.

For example, an adoption rate of 15% means that 15% of enterprises in the specified survey population reported using AI. It does not mean that 15% of workers use AI or that AI generates 15% of total economic output.

Missing observations are treated as unavailable rather than as zero adoption. Occupational-exposure estimates are also kept separate from adoption measures because potential exposure to AI and actual organizational use of AI represent different concepts (Filippucci et al., 2025).

3.4.4 Contextual Economic Indicators. In addition to the three principal dimensions, contextual economic indicators are considered where the selected sources provide relevant evidence. These indicators help explain why the relationship between AI adoption, employment, and productivity may differ across countries, industries, and workplaces (Gomes et al., 2025). They are used to organize and interpret the evidence rather than as control variables in an estimated regression model.

Table 2

Analytical Indicators and Their Interpretation

Indicator	Proposed measurement or evidence	Purpose in the analysis
Employment	Employment-to-population ratio and other reported employment outcomes	Describes observed labour-market conditions
Labour productivity	GDP per person employed, where comparable data are available	Examines broader output-per-worker patterns
AI adoption	Percentage of enterprises reporting AI use	Describes organizational adoption of AI
Investment	Gross fixed capital formation as a percentage of GDP, where reported	Provides context on capital investment
Trade openness	Exports and imports relative to GDP, where reported	Provides context on international economic integration
Digital infrastructure	Reported connectivity or digital-access indicators	Describes conditions that may support AI adoption
Human capital	Reported education, skills, or workforce-capability indicators	Provides context on workers' capacity to use AI

The contextual indicators are not assumed to be available for every country or year. Their inclusion in the table identifies dimensions relevant to interpreting the evidence; it does not imply that a complete dataset has been assembled or that these variables have been included in a statistical model.

3.4.5 Comparability Across Evidence Categories. The analysis distinguishes enterprise-level AI adoption, employment outcomes, labour-productivity indicators, and contextual economic measures. Each indicator is interpreted according to its original unit of analysis, population coverage, reporting period, and measurement definition.

Where sources differ in their methods or coverage, these differences are considered when comparing their findings. Numerical estimates from different evidence categories are not directly combined unless their definitions and measurement bases support a meaningful comparison.

3.5 Evidence Synthesis and Comparative Analysis

The selected evidence will be organized into four analytical categories: AI adoption, employment-related outcomes, labour productivity, and contextual economic conditions. Rather than estimating econometric models, the study synthesizes reported statistics and empirical findings to examine how AI adoption may be associated with changes in employment and productivity across different economic and workplace settings.

3.5.1 Employment Evidence. Employment-related findings will be examined using the indicators and outcomes reported in the selected sources, including employment levels, employment growth, unemployment, labour-force participation, and changes in occupational responsibilities, where available. The analysis will distinguish observed labour-market outcomes from estimates of occupational exposure to AI (Gmyrek et al., 2023).

Differences in country coverage, observation periods, population definitions, and research methods will be considered when comparing findings. An association between AI adoption and an employment outcome will not be interpreted as evidence that AI alone caused the observed change. Other economic, technological, and institutional factors may also contribute to labour-market outcomes.

3.5.2 Labour-Productivity Evidence. Productivity-related findings will be organized according to the outcome measured and the setting in which the evidence was collected. These outcomes may include task completion time, the quantity of work completed, output per worker, and broader labour-productivity indicators. The analysis will distinguish experimental or workplace-level productivity improvements from changes in aggregate economic productivity. Findings from individual tasks or specific organizations will not automatically be generalized to national economies. Where studies report different productivity measures, the results will be described separately unless their definitions and measurement bases support direct comparison (Green & Lamby, 2025).

3.5.3 Comparison Across Evidence Sources. Evidence will be compared across countries, industries, occupational groups, and workplace settings where the selected sources permit meaningful comparisons. The synthesis will consider whether reported findings are consistent, differ across contexts, or remain uncertain.

Enterprise AI-adoption rates, occupational-exposure estimates, employment outcomes, and productivity measures will not be treated as interchangeable indicators (Gmyrek et al., 2025). The analysis will describe patterns and possible relationships supported by the available evidence without calculating a common regression coefficient or claiming a single causal effect of AI across countries.

The conclusions will reflect the coverage and limitations of the selected sources. Where evidence is insufficient, inconsistent, or not directly comparable, this uncertainty will be stated explicitly.

3.6 Interpretation of Evidence and Uncertainty. The findings will be interpreted according to the type of evidence, the population examined, the observation period, and the methods used in the original source. Quantitative estimates will be reported with their original units and relevant contextual information wherever available (Gmyrek et al., 2024).

The analysis will distinguish descriptive patterns, empirical associations, and causal claims. Descriptive changes in AI adoption, employment, or productivity will not be presented as proof that AI caused those changes. Similarly, statistical associations reported by individual studies will be interpreted in light of their research designs and stated limitations.

Where source studies provide confidence intervals, standard errors, or other uncertainty measures, these will be considered when interpreting the reported findings. Such measures will not be calculated independently unless the necessary data and an appropriate analytical procedure are available.

The economic importance of a finding will be assessed separately from its statistical significance. Particular attention will be given to the size and practical meaning of reported changes, the conditions under which the findings were obtained, and the extent to which they may apply to other countries, industries, or worker groups.

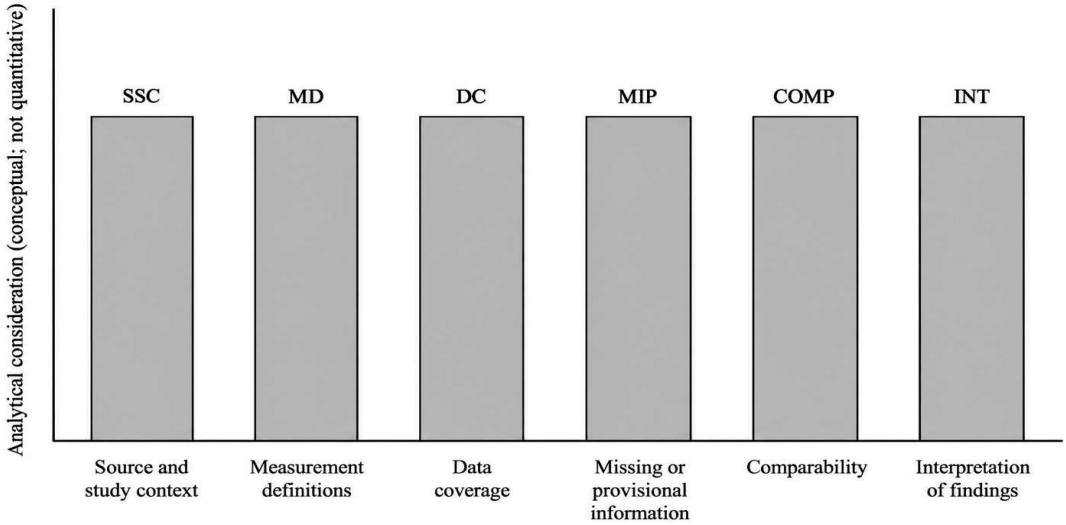
3.7 Evidence Organization and Quality Assurance

The selected sources will be examined for their relevance to the research objectives, the clarity of their measurement definitions, and the suitability of their findings for comparison. For each source, the analysis

will consider the publication period, geographical or workplace coverage, unit of analysis, principal indicators, and main findings.

Figure 2

Quality and Comparability Considerations in AI Evidence Synthesis



Main considerations used to assess and compare evidence on AI, employment, and labour productivity.

The analysis will not assume that complete annual AI-adoption data are available for every country throughout 2020–2025. Differences in data availability and reporting periods will be acknowledged when describing trends. The resulting synthesis will prioritize transparent interpretation of the reported evidence rather than implying that a harmonized country-year dataset has been constructed or statistically estimated.

3.8 Descriptive Analysis

The descriptive analysis will summarize the evidence reported in the selected sources on AI adoption, employment-related outcomes, and labour productivity during 2020–2025. Quantitative findings will be organized according to their measurement definitions, geographical coverage, observation periods, and units of analysis.

Where comparable numerical data are available, the analysis will consider reported averages, medians, ranges, standard deviations, and the number of observations, as provided by the original sources or calculated from sufficiently comparable data (Gmyrek et al., 2023). These statistics will not be calculated across incompatible indicators or populations.

The descriptive analysis will examine the following dimensions:

1. Trends in reported enterprise AI adoption across the available countries and years.
2. Reported changes in employment and labour productivity over the study period.
3. Differences in data coverage and measurement definitions across economies.
4. Differences between country-level, enterprise-level, occupational-level, and task-level findings.
5. Relationships among AI adoption, employment, and productivity reported in the selected studies.

Cross-country averages will be interpreted in light of their country composition and weighting method where this information is available. An average based on a changing set of countries will not be treated as representing a fixed population over time. Similarly, reported correlations will be interpreted as descriptive associations rather than evidence of causation.

Because the selected sources may use different definitions and samples, the analysis will not assume that all indicators can be combined into a single dataset. Any numerical comparison will be made only when the underlying measures are sufficiently comparable.

3.9 Comparative Analysis and Evidence Heterogeneity

The study will examine whether reported relationships between AI adoption, employment, and labour productivity differ across countries, industries, occupational groups, and workplace settings. Comparisons will

depend on the information available in the selected sources and will not be presented as newly estimated statistical effects.

The comparative analysis will consider the following dimensions:

1. **Employment outcomes:** Differences in reported employment, unemployment, labour-force participation, and changes in occupational responsibilities.
2. **Productivity outcomes:** Differences between task-level performance improvements, workplace productivity findings, and aggregate labour-productivity indicators.
3. **Country and economic context:** Differences associated with reported income levels, digital infrastructure, workforce skills, and economic structure, where comparable evidence is available.
4. **Time-period differences:** Changes in reported AI adoption and economic outcomes across the available years, taking account of differences in source coverage.
5. **Measurement sensitivity:** Whether conclusions appear to depend on differences in definitions, survey populations, study designs, or reported indicators.
6. **Pandemic-period context:** Whether findings from the early part of the study period require separate interpretation because of unusual labour-market and economic conditions.

Table 3

Comparative Dimensions for Evidence Synthesis

Dimension	Evidence examined	Purpose
Employment	Reported labour-market outcomes and occupational changes	Identify patterns in employment-related findings
Productivity	Task-level, workplace-level, and aggregate measures	Distinguish productivity outcomes measured at different levels
Economic context	Income levels, investment, and economic structure where reported	Interpret differences across economies
Digital readiness	Connectivity, digital infrastructure, and workforce skills where reported	Examine contextual differences in AI adoption
Time period	Reported findings across 2020–2025	Identify temporal patterns while accounting for coverage differences
Measurement	Definitions, samples, and methods used by the original sources	Assess the comparability and limitations of findings

The dimensions in Table 3 provide a framework for organizing and comparing existing evidence. They do not imply that interaction models, leave-one-country-out estimations, alternative regression specifications, or other econometric robustness tests have been conducted. Where the evidence is insufficient to support a comparison, the relevant limitation will be reported rather than addressed through unsupported numerical estimation.

3.10 Interpretation and Identification Limitations

The study will distinguish descriptive patterns, empirical associations, and causal effects when interpreting the economic implications of AI. The available evidence may indicate that AI adoption coincides with changes in employment or productivity, but such patterns do not necessarily establish that AI caused those changes.

Several limitations are relevant to interpretation. First, reverse causality may arise when more productive firms or economies are more likely to adopt AI. Second, other factors, including investment, institutional changes, digital infrastructure, workforce skills, and broader economic conditions, may influence both AI adoption and labour-market outcomes. Third, differences in survey definitions, source coverage, and measurement methods may affect the comparability of reported estimates.

The use of existing studies and aggregate statistics also limits the ability to isolate the contribution of AI from other technological and economic developments. Findings from individual firms, specific occupations, or task-based experiments may not directly represent outcomes at the national level.

Accordingly, this study will interpret reported associations in the context of each source's research design and stated limitations. It will not claim that country fixed effects, year effects, instrumental variables,

or difference-in-differences procedures address these concerns, because the revised study does not estimate an original econometric model.

The term "economic effects" in the paper title refers broadly to the potential and reported economic implications of AI. Conclusions about causal effects will be made only when supported by appropriately designed studies included in the evidence synthesis.

3.11 Ethical Considerations and Reproducibility

This study relies on secondary evidence from published research and publicly available aggregate statistics. It does not involve direct recruitment of human participants or the collection of personally identifiable information. Any applicable institutional requirements concerning ethics review or exemption will be checked in accordance with the relevant institutional policies. Transparency and reproducibility will be supported by documenting the sources used, publication details, data-access dates where applicable, indicator definitions, and the procedures used to organize and compare the evidence. Where numerical values are extracted or calculations are performed, the relevant source, unit of measurement, and calculation procedure will be documented.

The study will distinguish information reported by original sources from the authors' interpretation of that information. No regression coefficients, statistical significance levels, diagnostic results, or other original estimation results will be reported unless the corresponding analysis has actually been conducted.

3.12 Methodological Limitations

This study has several methodological limitations. First, the 2020–2025 observation window may not capture the long-term consequences of AI adoption for employment and labour productivity. Second, AI-adoption statistics may not be available for every country and year, and differences in survey coverage, enterprise-size thresholds, and measurement definitions may restrict direct comparisons.

Third, the evidence includes different units of analysis, ranging from national economic indicators to enterprise surveys, occupational-exposure estimates, and task-level workplace studies. These forms of evidence provide complementary perspectives but cannot automatically be combined into a single quantitative measure of AI's economic implications.

Fourth, reported associations between AI adoption and economic outcomes may be influenced by other factors, including investment, economic structure, workforce skills, and broader technological change. A descriptive evidence synthesis cannot independently eliminate these alternative explanations or establish causal effects.

Finally, country-level indicators cannot identify the precise effects experienced by individual workers, including job displacement, occupational transitions, changes in job quality, or productivity gains from AI assistance. Workplace and task-level findings can provide additional context, but their implications for national employment and productivity must be interpreted cautiously.

These limitations will guide the interpretation of the findings. If comparable numerical evidence is unavailable for a particular country, period, or indicator, the study will describe the available evidence and its limitations rather than combine incompatible measures or imply that missing data have been statistically estimated.

4. Results: Descriptive Findings from Published Evidence

4.1 Scope and Interpretation of the Results

This chapter presents descriptive findings on artificial intelligence adoption, occupational exposure, and workplace productivity relevant to the study period of 2020–2025. It draws on official OECD and International Labour Organization (ILO) statistics and published empirical research.

Three types of evidence are reported separately. Enterprise-adoption statistics describe the extent to which surveyed businesses use AI. Occupational-exposure estimates identify employment potentially affected by generative AI. Workplace studies measure productivity outcomes following access to AI tools in particular settings. These indicators do not measure the same phenomenon and are therefore not combined into a single estimate of AI's economic effect.

The chapter does not report original country-panel estimates. Consequently, its findings establish descriptive patterns and summarize published workplace evidence rather than identify a global causal effect

on employment or labour productivity.

4.2 Changes in Enterprise AI Adoption

OECD statistics indicate a substantial increase in enterprise AI adoption between 2023 and 2025. The share of firms reporting AI use rose from 8.7% in 2023 to 14.2% in 2024 and 20.2% in 2025. These figures indicate that enterprise AI adoption more than doubled over the two-year period, reflecting the expanding use of AI technologies among businesses in OECD countries for which data are available.

Table 4

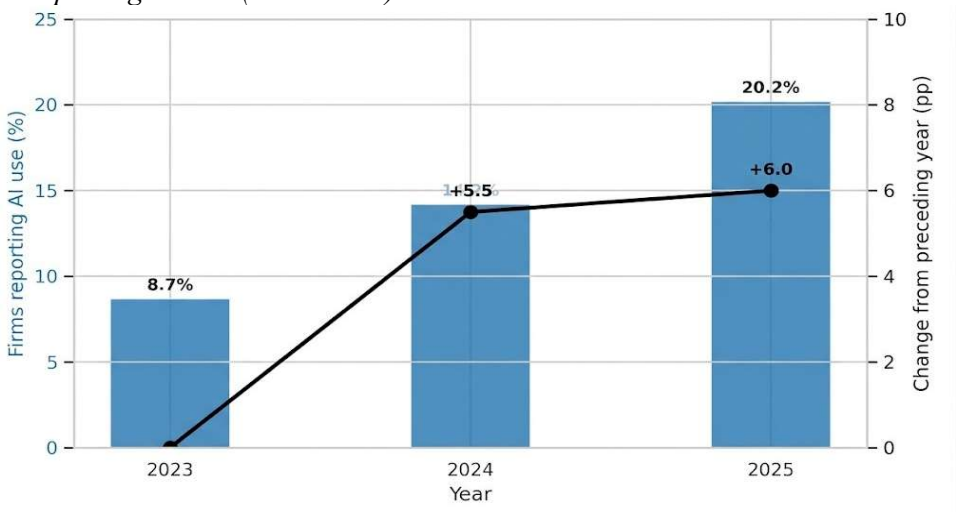
OECD-Reported Enterprise AI Adoption, 2023–2025

Year	Firms reporting AI use (%)	Change from preceding year (percentage points)
2023	8.7	—
2024	14.2	5.5
2025	20.2	6.0

Source: OECD, ICT Access and Usage by Businesses database and published OECD statistics. Percentage-point changes are calculated from the reported adoption rates. The figures cover OECD countries for which data are available and should not be interpreted as worldwide enterprise adoption rates.

Figure 3

Growth of Firms Reporting AI Use (2023–2025)



Between 2023 and 2025, the reported share of firms using AI increased by 11.5 percentage points, from 8.7% to 20.2%. This represents more than a doubling of the reported adoption rate over the period. The figures provide descriptive evidence of the rapid diffusion of AI among enterprises within the coverage of the OECD statistics.

However, increased adoption does not, by itself, establish that AI caused changes in employment or labour productivity. The adoption indicator records whether firms report using AI; it does not directly measure the intensity of use, the number of employees affected, or the economic value generated. Furthermore, differences in national coverage, survey definitions, and reporting periods should be considered when comparing adoption rates across countries.

4.3 Global Occupational Exposure to Generative AI

The International Labour Organization (ILO) assessment published in 2025 identifies substantial potential exposure of global employment to generative artificial intelligence (AI). According to the reported estimates, approximately 24% of global employment falls within occupations with some degree of exposure to generative AI, while 3.3% falls within the highest exposure category. The estimates indicate that the potential effects of generative AI extend across the global workforce, although the degree of exposure varies across occupations and economies.

Table 5
Selected Global Employment-Exposure Indicators, 2025

Indicator	Share of corresponding employment (%)
Global employment with some generative AI exposure	Approximately 24
Global employment in the highest exposure category	3.3
Employment in high-income countries with some exposure	34
Employment in low-income countries with some exposure	11

Source: International Labour Organization (ILO), 2025 assessment of generative AI and occupational exposure. Exposure represents the potential for AI to affect occupational tasks, not observed job losses.

The difference between the reported exposure shares for high-income and low-income countries is 23 percentage points. This difference suggests that workers in high-income economies are more concentrated in occupations whose tasks may be affected by generative AI. However, occupational exposure should not be interpreted as a direct measure of AI adoption or the actual economic benefits and costs experienced by workers.

The estimates also do not imply that 24% of global jobs will disappear. Occupations generally consist of multiple tasks, and exposure to AI does not necessarily mean that all tasks within an occupation can be automated. The ILO assessment therefore highlights the importance of distinguishing potential occupational transformation from complete job replacement.

Overall, these findings indicate substantial potential for labour-market adjustment associated with generative AI. However, the reported exposure shares do not establish the number of jobs already displaced, the net effect on employment, or the magnitude of changes in wages and labour productivity. Such outcomes require separate empirical evidence.

4.4 Gender Differences in Occupational Exposure

The ILO estimates also indicate differences in potential generative AI exposure between female and male employment. Globally, 4.7% of female employment falls within the highest exposure category, compared with 2.4% of male employment. In high-income countries, the corresponding shares are 9.6% for female employment and 3.5% for male employment.

Table 6
Highest-Category Generative AI Exposure by Gender, 2025

Employment group	Female employment (%)	Male employment (%)	Female–male difference (percentage points)
Global	4.7	2.4	2.3
High-income countries	9.6	3.5	6.1

Source: ILO estimates and associated reporting. Female-male differences are calculated from the reported shares.

The reported figures show that female employment has a higher share in the highest generative AI exposure category than male employment, both globally and in high-income countries. The female-male difference is 2.3 percentage points globally and 6.1 percentage points in high-income countries. These patterns suggest that the potential effects of generative AI may be unevenly distributed across gender groups.

Differences in occupational composition, including the representation of women in clerical occupations, may contribute to this pattern. Nevertheless, the exposure estimates alone cannot establish that women experience higher rates of unemployment, layoffs, wage reductions, or other adverse labour-market outcomes as a result of AI.

Accordingly, the findings should be interpreted as evidence of differences in potential occupational exposure rather than proof of unequal realized economic effects. Assessing actual gender-specific outcomes would require additional labour-market data on employment transitions, wages, working hours, and AI adoption across occupations.

4.5 Productivity Evidence from Customer Support

Brynjolfsson et al. (2025) examine the introduction of a generative AI assistant among 5,172 customer-support agents. Their published research reports an average productivity increase of approximately 15%,

measured by the number of customer issues resolved per hour.

Table 7

Published Productivity Findings from Customer Support

Component	Reported finding
Study	Brynjolfsson et al. (2025)
Publication year	2025
Workers studied	5,172 customer-support agents
Productivity measure	Customer issues resolved per hour
Average productivity increase	Approximately 15%
Distribution of gains	Larger improvements among less experienced and lower-skilled workers

Source: Published study by Brynjolfsson et al. (2025).

The reported findings indicate that AI assistance can improve worker productivity in a specific customer-support setting. The larger gains observed among less experienced and lower-skilled workers suggest that AI tools may help employees perform tasks more effectively by providing guidance and supporting the application of effective working practices.

However, these results should be interpreted within the context of the study. An approximately 15% increase in issues resolved per hour does not establish an equivalent increase in firm-wide or national labour productivity. The findings also do not independently determine whether AI adoption increases total employment, reduces hiring, changes staffing requirements, or affects wages. These outcomes depend on additional organizational and labour-market factors that are not established by the reported productivity measure.

Accordingly, this study provides evidence of realized productivity improvements in a particular workplace context. Its findings are relevant to understanding the potential benefits of AI-assisted work, but they should not be generalized to all occupations, industries, or national economies without further evidence.

4.6 Experimental Evidence from Professional Writing

Noy and Zhang (2023) investigate the effects of ChatGPT on professional writing tasks in an experiment involving 453 college-educated professionals. Their findings indicate that access to ChatGPT reduced average task-completion time by 40% and increased assessed output quality by 18%.

Table 8

Published Experimental Findings from Professional Writing

Component	Reported finding
Study	Noy and Zhang (2023)
Publication year	2023
Participants	453 college-educated professionals
Activity	Occupation-specific professional writing tasks
Average task-completion time	Reduced by 40%
Average output quality	Increased by 18%

Source: Published experimental study by Noy and Zhang (2023).

The findings indicate that ChatGPT improved both the speed and assessed quality of performance on the writing tasks included in the experiment. These results provide evidence that generative AI can assist workers in completing certain professional activities more efficiently. However, the magnitude of the reported improvements applies to the experimental tasks and conditions rather than to all forms of professional work.

A 40% reduction in task-completion time should not be interpreted as a 40% increase in national labour productivity. Economy-wide productivity also depends on the types of tasks performed, the share of work affected by AI, the extent of adoption, and how organizations incorporate the technology into their production processes. Similarly, an improvement in assessed writing quality does not automatically translate into an equivalent increase in economic output.

The customer-support and professional-writing findings are therefore reported separately rather than averaged into a single productivity estimate. The studies examine different activities, use different outcome measures, and operate in distinct research settings. Considered together, they provide evidence of potential

productivity gains from AI assistance while illustrating why results from individual workplace studies cannot be directly generalized to the wider economy.

4.7 Integrated Interpretation of Employment and Productivity Findings

The descriptive evidence presented in this chapter highlights three main findings regarding the economic implications of artificial intelligence (AI) for employment and labour productivity during the 2020–2025 period.

First, the OECD-reported figures indicate a substantial increase in enterprise AI adoption between 2023 and 2025. The reported share of firms using AI rose from 8.7% in 2023 to 20.2% in 2025. This pattern indicates the expanding use of AI among enterprises within the coverage of the reported statistics. However, adoption rates alone do not establish the effects of AI on employment or productivity.

Second, the ILO occupational-exposure estimates indicate that the potential effects of generative AI vary across economies and worker groups. Exposure shares differ between high-income and low-income countries and between female and male employment. These differences highlight the uneven distribution of potential occupational adjustment. Nevertheless, exposure estimates do not measure actual job displacement, changes in unemployment, or realized wage effects.

Third, the workplace studies reviewed in this chapter report measurable productivity improvements in specific settings. The customer-support study reports an average increase of approximately 15% in issues resolved per hour, while the professional-writing experiment reports a 40% reduction in task-completion time and an 18% improvement in assessed output quality. These findings suggest that AI assistance can improve performance on selected tasks, although the magnitude and distribution of the benefits may depend on the task, workplace, and characteristics of the workers involved.

Taken together, the evidence illustrates two related but distinct dimensions of AI's economic implications: potential changes in the composition of labour demand and observed improvements in performance on selected workplace tasks. Expanding adoption creates opportunities for AI-assisted work, while occupational-exposure estimates identify activities and worker groups that may experience technological change. However, the available findings do not establish whether these developments have increased or reduced total employment or aggregate labour productivity across the global economy.

The results should therefore be interpreted as descriptive evidence rather than as estimates of a single causal effect of AI. Differences in data coverage, measurement, research design, and analytical level prevent the adoption statistics, occupational-exposure estimates, and workplace productivity findings from being combined into one overall effect. Further research using comparable longitudinal data is needed to assess how AI adoption relates to employment, wages, and productivity across countries and industries.

4.8 Evidence Gaps and Implications for Further Research

The available evidence does not support the construction of a complete annual global results table covering AI adoption, employment, and labour productivity for every year from 2020 to 2025. The enterprise-adoption figures presented in this section cover 2023–2025, the ILO occupational-exposure estimates describe potential exposure in 2025, and the workplace productivity studies examine specific interventions and task settings. These differences in temporal coverage, measurement, and analytical units limit direct comparisons across the evidence categories.

The findings also highlight several areas requiring further research. First, more consistent and comparable data are needed to track enterprise AI adoption across countries and over time. Second, longitudinal labour-market data are needed to determine how AI adoption relates to changes in employment, wages, working hours, and occupational transitions. Third, further research should investigate whether productivity improvements observed in specific workplace settings translate into sustained gains in firm-level and national labour productivity. Finally, studies covering different countries, industries, and worker groups could help clarify how digital infrastructure, workforce skills, and occupational composition shape the economic implications of AI.

Given these limitations, the present study remains a descriptive synthesis of published evidence rather than an original econometric investigation. It reports published statistics and workplace findings without estimating new country-panel coefficients or claiming causal effects on global employment or labour

productivity. The identified evidence gaps therefore provide directions for future empirical research rather than a requirement to estimate additional models within the present study.

5. Discussion

5.1 Interpretation of the Main Findings

The evidence presented in this study highlights a distinction between the expanding adoption of artificial intelligence, its potential influence on employment, and its demonstrated effects on workplace productivity. OECD-reported enterprise AI use increased from 8.7% in 2023 to 20.2% in 2025, indicating a substantial expansion within the coverage of those statistics. However, increasing adoption does not independently establish improvements in aggregate productivity or changes in total employment. It demonstrates that more businesses are reporting AI use, while the economic consequences depend on how the technology is integrated into production and work organization.

The occupational-exposure evidence presents a similarly qualified picture. The ILO estimates that approximately one-quarter of global employment has some exposure to generative AI, but exposure should not be interpreted as an equivalent proportion of jobs at risk of immediate elimination. Occupations comprise multiple tasks, and AI may automate some activities while leaving others dependent on human judgment, interaction, and responsibility. The findings therefore support an interpretation centred on occupational transformation rather than uniform job replacement.

By contrast, the customer-support and professional-writing studies provide evidence of realized productivity improvements in particular settings. These studies demonstrate that AI can improve worker performance, but they do not establish the magnitude of economy-wide productivity gains. The central implication is that the potential benefits of AI are supported by workplace evidence, while their aggregate employment consequences remain unresolved.

5.2 AI, Worker Augmentation, and Labour Productivity

The productivity findings are consistent with a worker-augmentation mechanism. In the customer-support study, access to an AI assistant increased issues resolved per hour by approximately 15%, with greater benefits among less experienced and lower-skilled agents. This pattern suggests that AI can make effective working practices more accessible and help workers perform tasks that would otherwise require greater experience.

The writing experiment provides complementary evidence. Participants with access to ChatGPT completed tasks more quickly and produced higher-quality outputs. These results suggest that AI assistance can reduce the time required for selected information-processing activities without necessarily sacrificing quality.

Nevertheless, the relationship between task-level performance and aggregate labour productivity requires careful interpretation. A productivity improvement in one activity will contribute to overall output only to the extent that the activity is economically important and the technology is adopted effectively. Acemoglu's (2025) macroeconomic analysis emphasizes the importance of the share of tasks affected and the cost savings achieved in those tasks when evaluating broader economic gains. Consequently, the workplace estimates in this study should be treated as evidence of specific capabilities rather than universal productivity parameters.

5.3 Employment Transformation Rather Than a Single Employment Effect

The results do not support a simple conclusion that AI either increases or decreases employment everywhere. AI can substitute for particular tasks, complement workers in others, and change the skills required within an occupation. These mechanisms can operate simultaneously, making the net employment outcome dependent on production decisions and the characteristics of the work involved.

This distinction is particularly important when interpreting the ILO exposure estimates. Higher exposure indicates greater potential for task change, but it does not establish whether employers will reduce headcounts, redesign jobs, or expand output. The customer-support productivity findings also cannot determine aggregate employment outcomes, because improved worker performance does not reveal how firms subsequently adjust hiring and staffing.

The study therefore suggests that employment analysis should move beyond total job counts. Relevant

outcomes include changes in occupational responsibilities, recruitment requirements, workforce composition, and opportunities for workers to move between activities. However, these outcomes have not been directly measured in the present descriptive synthesis and remain priorities for further empirical investigation.

5.4 Cross-Country Differences and Economic Preparedness

The difference in occupational exposure between high-income and low-income economies highlights the importance of economic structure. The ILO reports that 34% of employment in high-income countries has some generative AI exposure, compared with 11% in low-income countries. These figures indicate that potentially affected activities are distributed unevenly across the global economy.

Lower exposure should not automatically be interpreted as greater economic resilience or a more favourable development outcome. Countries with limited technological access may experience fewer immediate disruptions while also capturing fewer productivity benefits. The IMF (Cazzaniga et al., 2024) identifies digital infrastructure, workforce capabilities, and institutional preparedness as important conditions for realizing the benefits of AI.

A global interpretation must therefore distinguish exposure from readiness. The former concerns the tasks AI could affect; the latter concerns the capacity to adopt the technology and manage its consequences. The descriptive evidence does not directly estimate how these factors interact, but it indicates why a uniform global employment, or productivity effect would be an inadequate representation of the available findings.

5.5 Distributional Implications for Workers

The gender differences in occupational exposure demonstrate that potential adjustment pressures are not evenly distributed. Globally, the highest exposure category accounts for 4.7% of female employment and 2.4% of male employment. The gap is larger in high-income countries, where the corresponding shares are 9.6% and 3.5%.

These differences reflect occupational composition, including women's representation in clerical activities. They identify groups that may face more substantial task transformation, but they do not demonstrate corresponding differences in actual unemployment or income losses.

At the same time, the customer-support evidence shows that less experienced workers can receive relatively large productivity benefits from AI assistance. This finding complicates the assumption that AI necessarily benefits only the most highly skilled workers. Distributional outcomes depend on whether AI complements workers' activities, replaces them, or changes the value of their existing expertise. The IMF (Cazzaniga et al., 2024) similarly emphasizes that complementarity and returns to capital can influence the distribution of economic gains.

5.6 Policy Implications

The evidence supports a policy approach that combines the promotion of productive AI use with measures to assist workers experiencing adjustment. The IMF (Cazzaniga et al., 2024) emphasizes strengthening digital infrastructure and skills while supporting labour reallocation and protecting adversely affected workers. The ILO (Gmyrek et al., 2025) highlights social dialogue and targeted responses. On this basis, the evidence points to the following priorities:

1. Developing training that helps workers use AI in the tasks relevant to their occupations.
2. Supporting workers whose responsibilities change substantially, rather than limiting assistance to those who have already lost employment.
3. Improving access to the infrastructure and organizational capabilities needed for productive adoption.
4. Monitoring differences across occupations, genders, and economies.
5. Strengthening statistical systems to distinguish adoption, exposure, and realized labour-market outcomes.

These are policy implications drawn from the evidence, not interventions whose effectiveness has been tested by this study. Their implementation should reflect country-specific labour markets and institutional conditions.

5.7 Limitations and Directions for Future Research

The principal limitation of this study is that the evidence combines different units of analysis. OECD statistics describe enterprise AI adoption, ILO estimates describe potential occupational exposure, and

workplace studies examine the effects of specific AI interventions. These sources provide complementary insights, but their differences in measurement, coverage, and research design prevent them from being combined into a single global estimate of AI's economic effects.

The study also does not provide a harmonized annual country-level dataset covering the full 2020–2025 period. Consequently, it cannot estimate the independent relationship between AI adoption and national employment or labour productivity while accounting for other economic factors. As a descriptive evidence synthesis, the study identifies reported patterns and summarizes published findings rather than estimating original econometric models or establishing causal effects.

Future research should connect comparable measures of AI adoption with observed changes in employment, wages, working hours, occupational transitions, and labour productivity. Firm-level and worker-level data could help clarify whether productivity gains arise from improved task performance, changes in workforce composition, or labour substitution. Longer observation periods would also help distinguish short-term adjustments from more persistent economic effects.

Further research should additionally examine how digital infrastructure, workforce skills, occupational composition, and institutional conditions influence the relationship between AI adoption and economic outcomes across countries. These extensions would help address the gap between demonstrated productivity improvements in selected workplace settings and the still-uncertain aggregate employment consequences of AI.

6. Conclusion

This study examined published global evidence on the relationship between artificial intelligence, employment, and labour productivity during 2020–2025. Its central conclusion is that AI can improve performance in specific workplace activities, while its broader employment consequences remain uneven and insufficiently established. The available evidence supports neither the claim that AI inevitably causes widespread unemployment nor the assumption that its productivity benefits automatically translate into greater employment.

The evidence indicates three important developments. First, OECD-reported enterprise AI adoption increased substantially between 2023 and 2025, demonstrating expanding business use within the coverage of those statistics. Second, the ILO's global assessment identifies considerable occupational exposure to generative AI, with differences across income groups and genders. This exposure represents the potential for task transformation rather than a measured rate of job displacement. Third, customer-support and professional-writing studies demonstrate improvements in worker performance following access to AI assistance. These findings establish productivity benefits in particular settings, but they cannot be interpreted as equivalent increases in national or global labour productivity.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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