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(Review Article)

A systematic review of Artificial Intelligence and Automation in Employment

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Abstract

AI and automation are reshaping labor markets by displacing repetitive, intermediate-skilled occupations, primarily in manufacturing, logistics, and administration, while expanding highskilled work that includes knowledge-based roles in healthcare, finance, and education. Lowskilled occupations will see declines in demand, while demand for analytical and interactive work is growing - potentially leading to new occupations and hybrid jobs. Routine and repetitive tasks will go away, while knowledge-driven functions will increase. There is still little systematic measurement of AI adoption, mostly based on patents, surveys, words that cooccur, or qualitative approaches. However, newer and more promising approaches include job postings, developer platforms, and task mapping, but they aren't standardized. Although most studies report evidence from high-income countries and firms with higher levels of innovation, this leaves a gap in studies concerning SMEs and lower-income contexts, which are actually more vulnerable to disruption. Most research studies the effects of AI and automation on employment and wages but does not investigate job quality, worker autonomy or wellbeing. Gig platforms and algorithmic governance have increasingly transformed the work experience into one that is more flexible but also precarious. Policymakers have favoured reskilling, continuous learning, and social protection systems, but although many policy options exist there are few evaluations of their effectiveness. There is limited causal evidence of long-term labour market consequences, meanwhile patterns of diffusion of new technologies in different sectors are still not fully understood.

Keywords: Artificial Intelligence; Automation; Employment; Augmentation; Labor Market; Policy

1. Introduction

Artificial Intelligence (AI) and automation are transforming world labor markets, bringing opportunities and challenges alike for workers and policymakers [1, 7]. In contrast to past technological changes, AI does not just execute repetitive but also higher-level cognitive tasks such as pattern recognition, language use, and decision-making [2]. This makes AI generalpurpose technology with very profound implications for employment and inequality [5]. AI's impact on work operates through two mechanisms: automation and augmentation. Automation substitutes machines for human labor, especially in routine-intensive sectors like manufacturing and clerical services [12]. Augmentation complements human skills, enhancing productivity and creating new tasks in knowledge-intensive fields such as healthcare and finance [4, 15]. The balance of these forces determines whether net outcomes involve displacement or job creation [1].

Evidence indicates that automation disproportionately affects low- and mid-skill occupations, whereas augmentation is likely to favor high-skill occupations [14]. This pattern leads to wage polarization and increasing inequality between routine-based and knowledge-based employment [2]. Job quality is also impacted through AI adoption, whereby some employees enjoy flexibility while others face stress and decreased autonomy under algorithmic control [9]. In spite of progress, research is still hampered by persistent constraints. AI adoption is measured mostly using proxies such as patents or surveys that tend to neglect sectoral and regional heterogeneity [5, 6]. The majority of empirical studies are

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based in advanced economies, and SMEs and developing nations are under-represented [8, 24]. Policy interventions such as reskilling and social protection are commonly debated but seldom assessed for their impact [9, 16].

This review integrates the literature on AI-powered automation and work, emphasizing measurement challenges, effects on employment, employment quality outcomes, and policy responses. It also highlights gaps in research and suggests directions for creating inclusive and evidence-based strategies in the evolving world of work.

2. Methodology

This review uses a systematic literature review (SLR) approach to synthesize existing research on Artificial Intelligence, automation, and employment outcomes. This procedure complied with the PRISMA guidelines for transparency and replicability. The SLR process consisted of eight stages: scope definition, search strategy development, database selection, application of inclusion and exclusion criteria, study screening, data extraction, synthesis of findings, and quality assessment.

2.1. Scope of the Review

Overall, the scope was restricted to studies published between 2015 and 2025, in response to the area of acceleration AI adoption. Three thematic dimensions were consulted:

- Measurement of AI adoption (patents, surveys, job postings, developer platforms).
- Effects on the labor market, and employment, wages, inequality, job quality and well-being.
- Policy implications, e.g. learning (re-skilling, lifelong, etc.), social protection and governance.
- Excluded studies paying attention to only technical AI models or algorithm changes, and not Labor implications.

2.2. Search Strategy

A multi-source approach was utilized. Databases searched included Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar. Grey literature was captured from the OECD, ILO, World Bank, and WIPO to alleviate publication bias [9, 16, 8]. Search strings included several elements, using Boolean operators, such as:

- "AI" AND "employment"
- "automation" AND "labor market"
- "AI adoption" AND "measurement"
- "Policy response" AND "jobs"

2.3. Inclusion and Exclusion Criteria

Eligibility criteria were defined as follows

Table 1 Inclusion and Exclusion Criteria

Inclusion	**Exclusion**
Empirical and conceptual studies on AI and employment	Purely technical AI model devel- opment papers
Peer-reviewed articles, working papers, and policy reports	Blogs, news articles, and opinion essays
Studies between 2015–2025	Studies before 2015
Research on wages, inequality, job quality, or policy responses	Studies unrelated to labor mar- kets

2.4. Screening Process

The initial search identified 520 records. After removing 110 duplicates, 410 unique studies were screened by title and abstract. Of these, 230 articles were considered for full-text review, and 120 were examined in detail. Finally, 65 studies met all inclusion criteria and were synthesized.

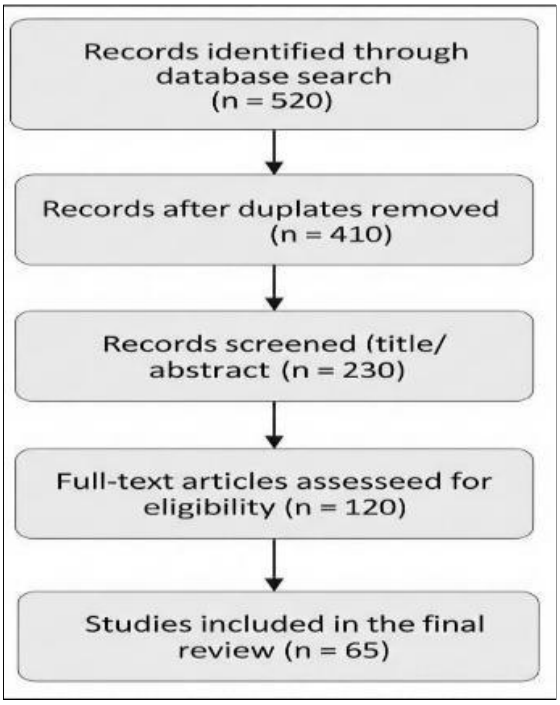

Figure 1 Flow Diiagram of the Screening and Selection Process

2.5. Data Extraction

Utilized a structured template to capture the following information for each study:

- Author(s), date, and geographic context.
- Sectoral coverage (manufacturing, services, gig economy, etc.).
- Types of data (patents, surveys, job postings, administrative datasets).
- Research design (econometric analysis, qualitative case study, mixed method).
- Outcomes examined (employment, wages, job quality, inequality, policy).

2.6. Synthesis Approach

Synthesis was used to organize results into six clusters

- Measurement of AI adoption.
- Employment and wage effects. Job quality and well-being.
- Sectoral and regional impacts.
- Firm-level heterogeneity. Policy responses and governance.
- Contradictions were highlighted, and cross-country comparisons were made when data permitted [2, 4].

2.7. Bias Management and Quality Assessment

Bias was minimized by including both peer-reviewed and grey literature, using explicit selection criteria and evaluating the quality of studies across 4 dimensions: re- liability of the data, methodological rigour, clarity of concept, and transparency. Although studies based on descriptive evidence were noted, they were given less weight in the synthesis.

Limitations

- Three limitations were identified
- The focus on English-language literature might have obscured regional evidence.
- Metrics of AI adoption are still inconsistent, so direct comparisons are challenging [5]. Heterogeneity in sectors and geography limits the generalizability of findings. Despite these limitations, the structured methodology ensures transparency, replicability, and coverage of major developments.

3. Literature review

Research on Artificial Intelligence (AI), automation, and jobs and employment has been expanding rapidly in the past few years across economics, sociology, management, and public policy. Research has shown that AI will probably displace low-skill but routine workers, while augmenting the productivity of high-skill workers. There has been an impressive amount of methods to understand the effects of AI on labour markets, examples include; econometric modelling, vacancy data, policy reports and surveys at the firm-level.

There are four notable themes that occur in the literature. First, the measures of AI adoption vary considerably in form; for example: patents, job postings, indices of task-exposure; and importantly do not explicitly consider existing differences between sectors when assessing their effects. Second, the employment and wage effects display a clear pattern of job polarization in the labour market. In the specific ways that knowledge-intensive workers are being paid premiums to do work, there is also significant evidence that routine occupations at the mid-skill level result in displacement and job losses. Third, there is increasing attention current and future job quality, workers' well-beings - with evidence suggesting both performance improvement and productivity and potential risks to worker health, well-being (stress) and autonomy associated with algorithmic management. Fourth, in looking at sectoral and regional dimensions of job automation and augmentation, the evidence suggests that jobs in manufacturing and clerical occupations are going to be at the highest risk of automation; whereas jobs in healthcare, education and finance can good occupation is AI in particular processes as augmentations.

Finally, studies of firm-level heterogeneity suggest that the firms that are going to benefit most from the adoption of AI are large firms who engage intensely in patenting. Whereas small firms and even medium-sized enterprises are going to be constrained by things like cost and skills - policy responses.

3.1. Summary of Literature

Table summarizes key studies, highlighting their scope, methodology, main findings, and limitations.

Table 2 Summary of Key Literature on AI, Automation, and Employment

Author(s)	Year	Method	Key Findings	Limitations
Acemogluand Restrepo	2018	Econometric modeling	Automation substitutes routine labor, displacing mid-skill jobs.	Limited focus on augmentation and developing regions.
Felten et al.	2021	AI exposure dataset	Linked AI exposure to industries and occupations.	Overrepresents patentintensive sectors.
Autor	2023	Conceptual/ NBER WP	AI could rebuild middleclass jobs via augmentation.	Lacks empirical validation.
OECD	2024	Policy report	Low-skill jobs most vulnerable; reskilling essential.	Limited causal evidence.
World Bank	2025	Policy analysis	Developing economies face higher displacement risks.	Limited SME and firmlevel data.
MIT ShapingWork Project	2023	Vacancy analysis	Increasing demand for AIcomplementary skills.	Focuses only on online job postings.
Brynjolfssonet al.	2014	Case studies and surveys	Early digital adoption showed productivity gains.	Predates modern AI adoption.
ILO	2020	Policy review	Gig platforms expand opportunities but increase precarity.	Narrow focus on platform work.
Brookings Institution	2023	Policy report	AI impacts software jobs, highlights risk of digital inequality.	Country-specific, not global.

National Academies (NASEM)	2024	Consensus study	Governance, ethics, and reskilling essential for inclusive AI adoption.	Lacks detailed empirical evidence.

3.2. Measurement of AI Adoption

Measuring AI adoption accurately is still one of the most intensely discussed challenges. Patentbased metrics have been used extensively, but these measures overstate advanced economies and large firm sectors while overlooking adoption rates in SMEs and informal economy activities [5, 17]. Firm-level surveys and occupational task mapping provide more nuanced insights but do not provide standardized measures across countries [10]. Newer means such as online job advertisements and developer platform activity provide insight into new behaviors but are still not standardized [6]. Consensus on measures of AI adoption are lacking, making cross-country and cross-sectoral analysis difficult and leaving a considerable gap in knowledge in this research area...

3.3. Employment and Wage Effects

Much of the discussion is framed by two complementary forces- automation and augmentation. Automation has an objective of replacing mechanical (although sometimes human-assisted) manual work with a machine, and in this context, refers to displacing workers performing routine-based manual work in roles like clerical, logistics, and manufacturing. Augmentation refers to augmenting people's physical and cognitive abilities, improving productivity, and enabling new types of jobs which are created based on newly enhanced skills to be usable in areas such as healthcare, finance, and professional services. Archival data indicate the labor market is polarizing- low and mid-skill jobs are following routine tasks away, while high-skill workers capture growing premium wages. We see this fulfilled across studies, with some pointing to net job losses, while others point to reallocation and creation with hybrid roles such as being an AI supervisor or an auditor.

3.4. Job Quality and Worker Well-Being

Not only the amount of work, but work quality, is becoming ever more important. Algorithmic management on gig platforms will increase opportunities, but also precarity, surveillance, and potentially stress [16]. Although AI has the potential to improve creativity and reduce monotony and busywork for skilled workers, it also has implications for deskilling and reduced autonomy [19]. The psychosocial implications of AI have received less attention than the quantitative implications for the labor market.

3.5. Sectoral and Regional Perspectives

Sectoral evidence will show stark differences. Manufacturing and transport will be the most exposed to automation, and healthcare and education will push towards augmentation-oriented growth [7]. In advanced economies, reports of productivity increases are common, while developing countries have higher risks of displacement and relatively lower opportunities for reallocation [8, 23]. There are still large knowledge gaps for Sub-Saharan Africa, South Asia, and informal economies [24].

3.6. Firm-Level Heterogeneity

Firm-level dynamics also vary considerably. Large multinational enterprises, for example, are most likely to adopt AI extensively if given the resources to do so [22]. In contrast, SMEs (however, with the majority of the global workforce) are constrained by cost, poor availability of expertise, and a lack of digital infrastructure [8]. Given almost absolute lack of studies on AI employment that focus on informal firms, this is a troubling blind spot.

3.7. Policy Responses and Governance

Policy discussions are shifting their focus to reskilling, learning throughout life, and social protection as ways to address disruption [9, 16]. Digital skills and agile training/retraining are widely recommended [11]. Yet, few studies evaluate the effectivity of the policy, inhibiting evidence-based policy decisions for agencies [7]. Governance issues, like algorithmic openness, fairness, bias, and ethical regulation, have increasingly more potential linkages to labor market outcomes [24].

3.8. Emerging Themes and Gaps

New recent contributions highlight the emergence of new hybrid occupations, the growth of platform work, and issues around algorithmic bias [4]. Some of the major gaps in the research include:

- No standardized measures of AI adoption from multiple sources
- Overrepresentation of advanced economies; underrepresentation of SMEs and developing economies
- Limited research on job quality, autonomy, and well-being
- Overly reliant on correlational evidence instead of causal methods
- Rarely examine reskilling and other social protection interventions
- These gaps need to be addressed in order to provide balanced and globally relevant knowledge.

4. Conclusion

Artificial Intelligence (AI) and automation are shaping the international labor market by reorganizing employment patterns, pay, and job quality. Proofs always reveal that routine and middle-skill jobs are more likely to be displaced, while high-skill industries enjoy augmentation and productivity improvements. This double impact is a cause of wage polarization, generating new prospects for some employees while excluding others. In addition to employment numbers, the literature emphasizes rising emphasis on job quality, autonomy, and workers' well-being as essential facets of technological change. Notwithstanding advances, studies are still hampered by some constraints. AI adoption measurement is not standardized, being based on proxies including patents or surveys that underestimate SMEs and developing economies. Empirical findings are biased towards developed economies, with vulnerable labor markets in low- and middle-income nations remaining under researched. Analysts for the most part still rely on correlational analysis, with little causal distinction between short-run and longrun impacts. Policy measures like reskilling, lifelong learning, and social protection are often put forward but never rigorously tested. Future studies need to bridge these gaps using standardized measures, interdisciplinary techniques, and more extensive geographic area coverage. It is only by such methods that policymakers and researchers can craft efficient policies that balance the risks of automation with opportunities in augmentation, and the benefits of AI-driven change are shared equitably across societies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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