A Review of the Impact of Artificial Intelligence on the Labour Market

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Abstract

This research paper reviews the three mechanisms through which artificial intelligence affects the labour market: substitution, creation, and augmentation. Unlike the previous wave of automation, artificial intelligence can perform both manual routine operations and cognitive tasks that require knowledge, thereby expanding its effects on employment. The paper provides evidence that AI can substitute codifiable tasks, create jobs in AI and the digital economy, and increase employee productivity through human-machine cooperation. Nevertheless, these AI effects are not equally distributed. Changes in skills demand due to the introduction of artificial intelligence manifest as increased value placed on skills such as digital literacy, data processing and analysis, problem-solving across disciplines, and lifelong learning, while routine jobs and entry-level positions become more vulnerable. Moreover, changes in employment expectations due to AI affect students and young workers, generating both anxiety and increased motivation for skill development. Previous studies show that AI changes tasks rather than occupations, but differ in their assessments of its employment effects.

Key words

Artificial Intelligence, Labour market, Employment effects, Skill polarization

1. Introduction

Recently, the use of AI has been affecting various aspects of organizational work within the labor market. In addition to influencing the production process, AI technologies have become capable of transforming job duties and even career paths of workers. Compared with earlier automation, which had impacted mostly routine manual labor and standardized production tasks, current AI technologies are capable of performing cognitive and knowledge-based operations, such as text generation, image creation, coding, data analysis, customer service, and decision making. For this reason, the consequences of AI on employment are no longer limited to manufacturing or low-skilled work. Now, this impact is observed in many sectors, including finance, education, healthcare, legal industry, consulting, professional services, and platform-based work.

Consequently, the relation between AI and employment is quite complicated. On the one hand, AI technologies might eliminate jobs that are routine, predictable, and easily codifiable. It means that AI might reduce the demand for labor in some middle-skilled, low-skilled, and entry-level white-collar occupations. On the other hand, AI might create new employment opportunities by enhancing productivity, lowering operational expenses, facilitating innovation and creating new products and services, which can cause the emergence of new forms of labor demand associated with algorithm development, data governance, AI system management, and human-AI collaboration. AI might affect the existing jobs by changing the ways in which people perform the work, for instance, by providing help in processing information, content creation, problem solving, and decision making.

To provide a systematic theoretical foundation, this review draws on Acemoglu and Restrepo's task-based framework [1], which conceptualises production as an allocation of tasks between labour and capital. In this framework, automation enables capital to take over tasks previously performed by labour, generating a displacement effect—corresponding to substitution in this review—that can reduce labour demand and labour's share of value added. This effect may be counterbalanced by the creation of new tasks in which labour retains a comparative advantage, producing what the original model terms the reinstatement effect and what this review classifies as creation. Applying this task-based logic to artificial intelligence, the present review organises the evidence around three analytically distinct but interacting mechanisms: substitution, whereby AI replaces human labour in codifiable tasks; creation, whereby AI-driven innovation generates new tasks, occupations, and industries; and augmentation, whereby AI complements workers and increases their productivity within existing tasks. The net effects of AI on employment and wages therefore depend on the relative strength of these mechanisms, the task composition of industries, the complementarity between AI and workers' skills, firms' adoption strategies, and institutional support for training and labour reallocation. This framework guides the empirical review below and connects technological adoption with subsequent changes in skill demand, wage polarisation, and workers' employment expectations.

This paper is going to consider two mediating mechanisms in the relation between AI and employment: the changes in the skill structure and changes in the employment expectations of workers. On the one hand, the use of AI increases the demand for digital literacy, data analysis skills, interdisciplinary problem solving skills, and continuous learning. On the other hand, it can deepen the wage and employment inequalities among employees with different skill level and adaptability. Additionally, AI affects the employment expectations of workers. Especially those students and young workers who are worried about the future job outlook due to the widespread implementation of AI. Nevertheless, it can motivate them to enhance their skills and change career plans.

In conclusion, the labor market implications of AI should be considered as a dynamic process rather than an outcome of employment destruction or creation. AI affects employment through job reallocation, skill upgrading, task restructuring, and changes in employment expectations. This perspective allows analyzing AI both as a factor that causes employment displacement and as a factor that transforms employment structures and directions.

2. The Three Effects of Artificial Intelligence on the Labour Market

AI does not simply eliminate or create jobs; it reshapes the labour market through three mechanisms: substitution, creation, and augmentation. Taken together, these three effects determine total employment, wage levels, and the employment structure across industries and skill groups.

2.1 Substitution Effect: Technological Unemployment

Based on a task-biased technological progress theoretical perspective, AI is replacing workers with intelligent capital to complete standardised, codified, and routine tasks, creating job displacement and technological unemployment risk [1]. Traditional automation only replaces manual labour on the assembly line, but generative AI extends to routine cognitive work such as copywriting, basic financial accounting, data entry, and primary customer consulting. Middle-skilled positions are also facing a displacement shock. As the marginal cost of using AI is lower than the labour cost for the enterprise, according to the principle of cost minimisation, the enterprise will decrease the employment scale of routine positions, and the labour demand curve will shift to the left. In addition, downward wage rigidity and labour-market frictions in skill transitions make it hard for displaced workers to be re-employed across industries, further resulting in structural technological unemployment. At the same time, the contraction in demand for low-skilled positions lowers their wages, high-skilled labour receives a higher wage premium due to its factor complementarity with AI, and income inequality continues to grow in the labour market. Academic debate over AI-induced unemployment centres on the scale of task substitution: the substitution effect is significant for routine positions in the short run, but as new jobs are created and workers upgrade their skills, the likelihood of large-scale permanent unemployment declines.

2.2 Creation Effect: New Positions and Employment Growth

The creation effect is an employment-compensation mechanism: the development and industrialisation of AI generate new jobs that offset losses in traditional industries [2]. The research selects panel data from 2000 to 2016 from 3500 multinational enterprises with AI patents and conducts empirical analysis. The results show that as the number of AI patents increased by 1%, the firm's average employment scale increased by 2%, and the average AI-related positions recruitment growth rate was over 18.7% in the high-tech industry. On the one hand, the upstream AI industrial chain creates technical positions such as algorithm engineers, data annotators, large-model trainers, and intelligent-system operations and maintenance personnel. On the other hand, digital transformation across industries creates emerging interdisciplinary roles such as AI solutions consultant, data compliance specialist, and business implementation specialist. In the service industry, the share of employment in medium-to-high-end positions has increased by 11.3% over the past 10 years. According to the derived demand theorem, the market demand for AI software, hardware, and digital services expands, thereby increasing demand for high-skilled labour, shifting the labour demand curve to the right. The labour market structure has shifted from labour-intensive to technology-intensive, leading to labour reallocation. However, newly created jobs can only absorb approximately 52% of employment displacement from traditional industries and cannot fully offset employment pressure from the loss of low-skilled positions.

2.3 Augmentation Effect: Labour Productivity Improvement and Skill Empowerment

Under the human-machine collaboration mode, to a large extent, AI is a complementary factor of production that utilises the augmentation effect, through restructuring the positions of task structure, enhancing the marginal product of labour [3]. The research used a sample of over 5,000 employees in the customer service industry. The results show that generative AI auxiliary tools increased work efficiency by 14%. For newly recruited employees and low-skilled practitioners, the increase could be over 34%. AI is responsible for repetitive work such as information retrieval and standardised script writing with high efficiency, freeing employees to focus on high-value-added tasks like interpersonal communication, research, judgment of complex problems, and creative decision-making, decreasing the on-the-job learning cycle, and enabling the large-scale diffusion of knowledge and experience within the organisation. By leveraging AI tools, the employee expands job boundaries, enhancing comprehensive output. The enterprise is willing to pay higher salaries for high-skilled employees who are proficient in using intelligent tools; the original industry's modest expansion of labour demand, and job stability are ensured.

2.4 Interaction of the Three Effects and Estimation of Net Effect

The three effects do not operate independently but operate interactively under dynamic checks and balances [4]. The cited study builds a general equilibrium model of labour-search frictions and identifies two equilibrium outcomes arising from the interaction of the three mechanisms: in the short term, the substitution effect dominates, producing a limited-AI equilibrium and a temporary contraction in total employment; in the long term, as the AI industry matures, the creation and augmentation effects become more significant, intelligent capital shifts from substituting for labour to complementing it, and the labour market converges towards a high-employment equilibrium. The net employment effect of AI depends on the relative strength of three effects, while factors including labour retraining efficiency, industrial attributes and policy guarantee determine the stability level of the transformation of the employment structure.

3. Employment Structural Adjustment: Skill Polarization and Labour Expectations

3.1 Changes in Skill Demand and Wage Polarization

The first effect of AI in terms of employment is the restructuring of tasks rather than a straightforward reduction or expansion of the quantity of jobs. From the point of view of the task-biased technological change, innovations are more likely to substitute tasks that are routine, rule-based, standard and codifiable while increasing the relative importance of non-routine tasks demanding analysis, judgment, communication, and creativity. Autor and Dorn argue that information technology decreased the cost of routine tasks, weakened many middle-skilled occupations and expanded employment at both ends–among low-skilled service employees and high-skilled professionals [5]. This mechanism still applies in the age of AI, but the latter expands its scope, since generative AI is able to process language, code, images and predictions, thus entering white-collar occupations that used to be protected from automation.

Consequently, the polarization of skill demand that AI induces is more sophisticated. On the one hand, firms have a growing need for employees with digital literacy, data analysis skills, prompt design, interdisciplinary solutions and competence in applying AI in their workflow. Employees who can utilize AI in problem identification, checking outputs and making professional judgments are expected to enjoy productivity growth and premium on wages. The World Economic Forum predicts that core skills will change dramatically by 2030, including AI, big data, technological literacy, creative thinking, resilience and lifelong learning [6]. On the other hand, employees whose tasks are routine office tasks, entry-level customer service, content production, data processing and manufacturing are likely to experience a greater threat of substitution. Wage polarization does not imply that all high-educated workers will benefit automatically. Webb and Eloundou et al. observe that some high-income occupations requiring advanced education are also highly exposed to AI [7,8]. It is yet unknown whether the divergence of wages will increase or not, depending on whether AI will complement the workers' core skills or transfer the central tasks to software and capital.

3.2 Workers' Employment Expectations

Besides transforming the nature of existing jobs, AI reshapes the expectations of workers before the displacement or creation of positions takes place. In case of students and young workers, employment expectations are defined not only by the current labour market conditions but also by their opinions on the obsolescence of the majors, reduction of the entry-level occupations and sufficiency of their skills in comparison with competitors. Duan et al. find that AI anxiety decreases the career adaptability and negatively affects the career decision-making of college students [9]. Furthermore, Liang and Zhai found that a greater understanding of the impact of AI may increase the perception of the employment risk among students and employment anxiety is an important mediator of this effect [10]. It means that AI influences the labour market through psychological factors alongside with firms' hiring decisions.

However, employment expectations are not necessarily negative. Workers familiar with AI tools consider technologies as an expansion of their skills instead of threats, while people with career adaptability are more likely to transform their uncertainties into learning motivation. Therefore, universities and firms should not limit themselves to telling workers that AI will not replace them. A more helpful solution would be to inform workers about the tasks which can be substituted, the skills which will be magnified and how training, internships and workplace learning can help workers convert the vague anxiety into specific adjustment.

3.3 Industry and Group Heterogeneity

The impact of AI differs across different industries and social groups. Manufacturing and logistics are more affected by robots and process automation, while administrative support, customer service, translation, basic content production and data entry are more exposed to generative AI. Finance, law, consulting, education and healthcare are highly exposed to AI, but there are still many tasks requiring responsibility, ethical judgment, institutional permissions and face-to-face interaction, which implies coexistence of augmentation and substitution. Felten, Raj and Seamans reveal that the exposure of AI to occupations, industries and regions is extremely heterogeneous [11]. Cazzaniga et al. also differentiate exposure and complementarity, observing that highly educated young workers may transition from high-exposure, low-complementarity jobs to high-exposure, high-complementarity jobs and earn higher wages, while workers without college education are more likely to transition to low-exposure jobs and earn less money [12]. Thus, the critical question is not only what industries will vanish but who will get training, mobility and access to productive utilization of AI.

4. Current Research: Consensus, Methods, Debates and Limitations

4.1 Main Consensus

One of the main conclusions in existing research is that the impact of AI on the labour market should be viewed in terms of tasks rather than occupations. Most of the literature does not argue that AI will replace all types of work. AI transforms the composition of tasks in a certain occupation: codifiable, repetitive and standard tasks are more susceptible to substitution, whereas tasks including analysis, communication, creativity, management and complex judgment become augmented. The framework of substitution, creation, and augmentation provides a useful basis for understanding the threefold nature of AI's impact on the labour market [1]. At the same time, the heterogeneity of the impacts of AI becomes apparent as a general conclusion from existing research. The skills of workers, institutions in the industry, strategies of firm adoption of AI, educational opportunities–all of these factors contribute to different individual outcomes.

4.2 Methodological Reflections

Divergent findings partly arise because empirical strategies identify different objects. Exposure indices map AI capabilities onto occupational tasks or abilities [7,8,11]. They are useful for comparing potential exposure across occupations, industries, and regions, but they do not measure actual adoption and generally cannot determine whether exposure produces substitution or augmentation. Patent-based and dynamic-panel studies instead link innovation to employment over time. Damioli et al. [2], for example, estimate a dynamic firm-level labour-demand model with system GMM, using lagged internal instruments to address persistence and simultaneity. These estimates are more informative than cross-sectional correlations, but their reliability depends on correct dynamic specification, valid instruments, and the absence of higher-order serial correlation; results for AI innovators may also not represent non-innovating firms.

Instrumental-variable (IV) designs seek variation in technology adoption that is unrelated to local labour demand. Acemoglu and Restrepo [13] construct local labour-market exposure to robots using baseline industry composition and instrument it with industry-level robot diffusion in other advanced economies. This strengthens causal interpretation if the first stage is strong and external diffusion affects local employment only through robot adoption. The exclusion restriction can fail if the instrument also captures trade shocks, sector-specific demand, or other technologies. IV therefore identifies a local effect for units whose adoption responds to the instrument, and evidence on industrial robots may not generalise directly to generative AI.

When a discrete adoption date or policy shock is observable, difference-in-differences (DID) compares changes for adopting units with contemporaneous changes for untreated or not-yet-treated units. The staggered workplace rollout studied by Brynjolfsson et al. [3] illustrates this strategy. Causal interpretation requires parallel counterfactual trends, no anticipation, limited spillovers, and no treatment-timed changes in workforce composition. Event-study specifications extend DID by showing pre-trends and dynamic responses, but conventional two-way fixed-effects estimates can be contaminated when adoption is staggered and treatment effects differ across cohorts [14,15]. Accordingly, exposure indices should be interpreted as evidence of potential vulnerability or complementarity, while causal claims about employment and wages are most credible when studies report design-specific diagnostics, use cohort-robust estimators, and obtain consistent results across firm, worker, and local-labour-market data.

4.3 Key Debates: Net Effects, the Boundary between Augmentation and Substitution, and Causal Identification

The first controversy is related to the sign of the net effect of AI on employment and wage dynamics. On the one hand, evidence on industrial robots shows that robots have negative effects on employment and wages in local labour markets, while on the other hand Damioli et al. found positive correlation between employment growth and AI patenting among innovative firms [2,13]. These results mean that technological progress destroys and creates jobs in different cases, although the overall trend of substitution prevails. The second controversy relates to the boundary between augmentation and substitution: in the same highly exposed occupation, AI can be productive for workers providing business judgment, client relations and decision-making, and substitutive for workers performing standardized text production, information search and routines. The last issue is the problem of identification: adoption of AI is usually positively correlated with firm's management quality, capital investment, market competition and initial characteristics of the workforce.

4.4 Methodological Limitations: Data, Endogeneity and Long-Term Dynamics

Methodological limitations remain even in stronger designs. First, many datasets observe task capabilities, patents, or announced adoption rather than actual use, hours, wages, and worker transitions; proprietary samples also limit replication and often underrepresent small firms and developing economies. Second, most studies cover early adopters and short observation windows, so they may miss occupational entry and exit, retraining, wage adjustment, and general-equilibrium spillovers across sectors and regions. Third, evidence is difficult to compare because studies use different units of analysis, exposure measures, and outcomes, and few datasets link firms to individual workers. Future research should combine matched employer-employee panels with direct measures of AI use, harmonised outcome definitions, and transparent identification protocols, while reporting heterogeneous effects by task, skill, age, gender, contract status, industry, and region.

5. Conclusion

In summary, this review shows that artificial intelligence affects the labour market through three connected mechanisms: substitution, creation and augmentation. On the one hand, artificial intelligence may substitute for some routine, codified activities, particularly in repetitive production, administrative support, and cognitive work for beginners. On the other hand, artificial intelligence may create a demand for new kinds of labour in areas such as algorithm development, data management, AI operations, and digital services. Finally, in most occupations, AI acts as an instrument that complements work, helping make workers more productive by speeding up learning and making work easier by substituting for standard operations, enabling workers to concentrate on making judgments and communicating. Hence, the crucial role of AI in the labour market lies in task reorganisation.

Further research should take into account the limitations of current studies. Future studies should connect stronger evidence with practical policy and training design.

Policy responses should address all three mechanisms—substitution, creation, and augmentation—rather than job displacement alone. Recommendations should operate at three levels. First, at the education-system level, universities and vocational institutions should embed AI literacy, data analysis, and career-management modules in curricula, update them annually with employer input, and provide project-based training using workplace AI tools. Second, at the firm level, employers should conduct task-level AI-exposure assessments, provide paid retraining and supervised human–AI practice for affected workers, and monitor completion, redeployment, wage, and retention outcomes. Third, at the social-security level, governments should prioritise low-skilled workers and young jobseekers through individual training accounts, portable skills credentials, targeted job-matching services, and temporary income support during retraining and job transitions.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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