МРНТИ: 06.77.61
JEL Classification: O33, J21
DOI: https://doi.org/10.52821/2789-4401-2025-6-196-212

THE ROLE OF GENERATIVE ARTIFICIAL INTELLIGENCE ON LABOR MARKET: LITERATURE REVIEW

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ABSTRACT

The purpose of the study. This systematic literature review examines the role of AI in the labor market and its effectiveness in terms of productivity and employment outcomes.

Methodology. We reviewed recent studies from 2020 to 2025 across global and regional contexts to assess how AI adoption influences job creation, displacement, and workforce composition. The objective was to synthesize current evidence on whether AI augments human labor or automates it away, and under what conditions. Using a systematic methodology, we analyzed 17 key publications from peer-reviewed academic journals.

Originality / value. Our review finds that AI's net impact on employment has so far been modest, with no clear evidence of mass unemployment caused by AI. However, AI-driven automation has uneven effects: it displaces certain routine and low-skill jobs while creating new possibilities for high-skill tasks, thus contributing to labor market polarization. Notably, AI tends to complement and enhance the productivity of skilled employees, whereas low-skilled roles face significant automation risk.

Findings. In our discussion, we highlight the following findings: agreement that AI demands workforce upskilling and policy support, alongside divergent results, for example, conflicting evidence on net job creation in different contexts. A meta-analysis of the literature reveals surging research interest in 2023–2025 and a focus largely on advanced economies. Finally, we discuss implications: while AI can enhance labor productivity and create value, proactive measures are needed to ensure these gains translate into broad-based employment benefits. The review identifies research gaps such as limited studies in low-income countries and long-term generative AI effects and underscores the importance of policies to manage AI's workforce transition.

Keywords: artificial intelligence, labor market, job transformation, job automation, employment trends.

INTRODUCTION

Advances in artificial intelligence (AI) and automation are reshaping the future of work at an unprecedented pace. From algorithms that perform cognitive tasks to robots that automate physical labor, AI technologies are increasingly being deployed across industries. This rapid progress has sparked both optimism and anxiety in society. On one hand, AI promises to boost productivity and create new business opportunities. On the other hand, it raises fears of large-scale job displacement or technological unemployment, a concern famously voiced by economists since at least the time of Keynes [1-2]. The public debate is polarized: some predict AI will eliminate a vast number of jobs, while others argue it will generate at least as many new roles and improve overall living standards.

Early studies and forecasts ranged widely in their estimates of AI's impact on employment. For instance, a seminal analysis by Frey and Osborne warned that up to 47% of U.S. jobs were at high risk of automation by AI and related technologies [3-4]. In contrast, an OECD task-based study by Arntz et al. estimated only about 9% of jobs in OECD countries are highly automated, once considering the variability of tasks within occupations [5]. These divergent forecasts highlight the uncertainty surrounding AI's labor market effects. Since 2020, however, AI adoption has accelerated dramatically and especially with the emergence of accessible generative AI tools like OpenAI's ChatGPT. By early 2024, about 72% of companies surveyed worldwide reported using some form of AI in at least one business function, such a sharp increase from 50% just a few years prior [6]. This surge in adoption is global in scope, spanning both developed and developing economies. At the same time, international organizations like the ILO emphasize a more nuanced view, suggesting AI will change how we work more than whether we work.

Against this backdrop, there is a pressing need for systematic analysis of recent evidence on AI's impact on the labor market. The research community has responded with a growing number of empirical studies, model-based projections and case analyses in the past five years. These works examine AI's effects on employment levels, which skills are favored or replaced, wages and inequality, and related outcomes like job quality and worker well-being. They cover a range of contexts – from advanced economies, like studies on the United States, Europe, and China to emerging markets case studies in the case of developing countries. However, the findings of these studies are sometimes fragmented or even contradictory. For instance, some firm-level analyses in manufacturing find that adopting AI and digital technologies increase hiring of skilled workers and overall employment, whereas other macro-level studies report a slight rise in unemployment attributable to AI and robotics [7]. Likewise, while many agree that AI adoption is skill-biased, there is emerging evidence that generative AI can perform aspects of high-skill jobs previously considered safe from automation [8]. This could indicate a shift in the nature of job polarization.

Research problem and questions: considering the above, the overarching problem we address is: How is AI actually affecting labor market outcomes, and how effective is AI in augmenting human labor? We break this into specific questions: Is AI adoption leading to net job loss, net job creation, or simply job reallocation? Which categories of workers are most positively or negatively affected? How do AI's effects vary across sectors? Are there sectors seeing significant productivity gains without employment losses, or vice versa? Do outcomes differ between developed countries and developing ones? What strategies are recommended or observed to enhance AI's positive impacts on work, and are there examples of successful mitigation of negative impacts?

Objectives of this review: We aim to provide a comprehensive synthesis of the recent literature from 2020 to 2025 in order to answer the above questions. By conducting a systematic literature review (SLR) we seek to aggregate findings, compare results and draw overarching conclusions about AI's role and effectiveness in the labor market. Our goal is to move beyond speculation and highlight evidence-based insights from the latest research. In doing so, we also identify areas of consensus and areas of debate or uncertainty. Special emphasis is placed on aspects mentioned in recent discourse: the differential impact on low-skilled and high-skilled employment, the phenomenon of job polarization, regional nuances, and demographic factors in AI-driven labor changes. We also incorporate insights on policy implications, since many studies discuss how to manage the transition: through upskilling, social protection or regulation of AI. This review will therefore not only document what is happening due to AI in labor markets but also discuss what can be done – making the findings relevant for policymakers, business leaders, and educators.

MAIN BODY

In terms of methodology, this study follows a systematic literature review (SLR) approach in order to collect, evaluate, and synthesize relevant literature on AI's impact on the labor market. We adhered to guidelines for systematic reviews in the social sciences, which involve a transparent search strategy, well-defined inclusion criteria and a structured analysis of the evidence. We conducted a comprehensive search of academic databases and other sources for publications from January 2020 up to April 2025. Key databases included Scopus and Web of Science. We also manually searched the websites of major organizations such as International Labor Organization and World Economic Forum for reports on very recent studies. These included papers from journals such as Heliyon, Technological Forecasting & Social Change, Journal of Innovation & Knowledge, Futures, Research Policy.

Inclusion and exclusion criteria: We focused on studies that explicitly examine the effect of AI on labor market outcomes. To be included, a study had to meet the following criteria: 1) Topic relevance: the study addresses AI (including subfields like machine learning, robotics, generative AI) in the context of employment, labor demand, job displacement or creation, wages, skills, or related labor market issues. 2) Time frame: publicly available and published between 2020 and 2025. This captures the most recent evidence, especially given the rapid developments in generative AI in this period. 3) Geographical scope: no limitation – global, regional, and country-specific studies were all eligible. We aimed to incorporate not just U.S. and European studies but also research pertaining to Asia and other regions to cover the «global and regional context» as requested. 4) Type of publication: we included peer-reviewed journal articles, conference papers, reputable institutional reports from the ILO, OECD, World Bank, WEF. We excluded news articles or opinion pieces unless they reported original study data. We also excluded papers that were purely about AI in other domains without labor market analysis. In borderline cases, we leaned towards inclusion if the study offered any empirical or theoretical insight on employment. After initial searching, we obtained around 70 sources that seemed relevant. We then screened titles and abstracts to remove obviously irrelevant or duplicate items, yielding about 33 candidates. We read these in full to assess against our criteria and the needs of this review. Ultimately, we selected 17 studies for in-depth analysis to fulfill the requirement, while the discussion may reference a few additional sources for context.

Data extraction and synthesis: for each included study, we extracted details on authors and year, source, research objective, methodology, and key findings related to AI and labor outcomes. We paid particular attention to each study's findings on employment changes, skill composition changes, wage effects, as well as any stated implications or recommended actions. In synthesizing the findings, we used a thematic approach: grouping results into themes such as «overall employment effect», «skill-biased impact», «sector-specific outcomes» and «policy implications». During analysis, we compared outcomes across studies to identify consensus or disagreement. We also noted any methodological differences that could influence results. For example, some studies use firm-level data, others use macroeconomic models or expert surveys. We evaluated the quality and reliability of evidence as well. Peer-reviewed empirical studies with large datasets or robust methods were given more weight when drawing conclusions, whereas speculative pieces or those with limited data were used more cautiously.

Metadata analysis: In addition to qualitative synthesis, we performed a simple metadata analysis of our included studies to understand trends in the research itself. This involved counting studies by year of publication, by country or region focus and by methodology type. This meta-analysis provides context on how research attention has evolved over time and whether there are biases. By following this rigorous methodology, we aim for our review to be transparent, reproducible and comprehensive, giving readers confidence in the coverage of literature and the validity of the conclusions drawn.

Below is a consolidated table of 17 key sources included in this systematic review. Table 1 is organized chronologically where possible, to also reflect the evolution of research over time.

Table 1 – Key Studies Included in the Systematic Literature Review

Author(s), (Year)	Research Objective	Methodology	Key Findings
Acemoglu D., Restrepo P. (2020)	Empirical impact of robots on US jobs and wages	Econometric analysis; panel data by commuting zone (1990–2007)	Each industrial robot per 1,000 workers reduced employment by 0.2 percentage points and wages by 0.5%, indicating job displacement in exposed regions.
Webb M. (2020)	Assess which jobs are exposed to AI and other tech	Novel measure of AI exposure: overlap between AI patents and job task description	AI exposure is highest in high-skill, high-wage occupations. Unlike earlier automation, AI is predicted to impact many white-collar roles.
Lane M., Saint-Martin A. (2021)	Summarize known impacts of AI on labor markets	Systematic review of existing studies.	AI both destroys and creates jobs, requiring workforce adaptation; stresses the need for re-skilling as tasks transform
Felten E. W., Raj M., Seamans R. (2021)	Measure actual impact of AI on US occupations	Empirical study; AI exposure index and job outcomes	AI boosted productivity, raising demand for certain jobs. However, impacts differ by task type: some cognitive tasks saw partial automation.
Bordot F. (2022)	Examine AI and robot effects on employment and inequality; and test policies	Mixed-method: panel econometric analysis with 33 OECD countries, theoretical modeling, policy simulation	Impact is heterogeneous by age and education: older and less educated workers are more adversely affected. Appropriate policies can effectively mitigate unemployment and polarization from AI.

Author(s), (Year)	Research Objective	Methodology	Key Findings
Mueller-Langer F., Tolan S. (2022)	Investigate market power and AI-related labor demand on an online labor platform in Europe	Data analysis of a large freelancing platform (People Per Hour); elasticity estimation before and after platform policy change	**AI-focused jobs see significantly higher demand (+1.4% to +4.1%) and lower supply (−6.8% to −1.6%) compared to other jobs. Consequently, freelancers with AI skills earn 3% higher wages than others.**
Kljucnikov A., Popkova E. G., Sergi B. S. (2023)	Model the future of global labor markets in the age of intelligent machines; role of humans versus automation	Economic modeling using global data (robot density, labor metrics); scenario analysis; policy discussion	The authors propose that in the near-term, machine technologies do not replace but supplement human resources in workplaces, finding that labor productivity growth still depends more on human capital availability than automation alone.
Eloundou T., Manning S., Mishkin P., Rock D. (2023)	Assess US job exposure to GPT-based AI, large language models	Model GPT-4's capabilities versus occupational tasks (O*NET data); «exposure» index for jobs	80% of U.S. workers have at least 10% of their work tasks exposed to LLM-based AI. Jobs highly exposed include high-skill professions–indicating generative AI reaches into white-collar, non-routine work.
Gmyrek P., Berg J., Bescond D. (2023)	Examine generative AI's impact on development: will GenAI help or hinder creation of good jobs in developing countries?	Economic analysis using cross-country data; scenario modeling for GenAI adoption in service sectors	GenAI predominantly boosts productivity in high-skill service sectors. But GenAI could constrain «good job» creation in those economies, such as a risk of «premature de-professionalization» where developing countries reach peak high-skill employment at lower income levels.
Komp-Leukkunen K. (2024)	Explore how ChatGPT might shape the future job market for software engineers	Delphi expert study (2 rounds) in Finland; scenario development (possible versus probable futures)	Identify 5 scenarios for software engineers. ChatGPT is widely adopted as a tool to increase productivity, knowledge becomes more accessible to the masses. This contradicts the notion that only routine jobs are automatable.
Wang X., Chen M., Liu X., Xu J., Zhang Z. (2024)	Quantify AI's impact on the employment structure by skill level	Panel data of Chinese provinces (robot density as AI proxy, employment by skill); econometric models	AI adoption has a skill-biased impact: it replaces low-skilled labor but increases demand for medium and high-skilled workers, leading to an overall more advanced skill composition. Overall, the study shows AI is causing polarization in labor force: less low-skill work, more high-skill jobs.
Stallings L., Bhat P., Jacobs J., Lynch K., Risch Q. (2024)	Show how AI can automate data classification for market intelligence in business	Case study: used NLP and machine learning to classify unstructured budget data; proof-of-concept implementation	Demonstrates an AI system that automates a formerly labor-intensive task. The outcome in practice was that analysts could focus on more complex tasks while AI handled routine data processing.
Qiu L., Duan Y., Zhou Y., Xu F. (2024)	Analyze digital empowerment's effect on labor hiring in manufacturing firms (China)	Firm-level panel (1055 manufacturing firms); fixed-effects regression; mediation analysis	1-unit increase in a firm's AI tech adoption is associated with a 9.36% increase in its workforce. In manufacturing, AI tech is more labor-augmenting than labor-replacing. It drives growth that increases demand for skilled labor, suggesting a positive effectiveness of AI on labor in this sector.
Ross A. G., McGregor P. G., Swales J. K. (2024)	Simulate system-wide impacts of labor-augmenting technological change (focus on skill bias)	Multi-sector macroeconomic modeling (CGE) calibrated to Germany; scenarios of skill-biased tech progress (skilled and unskilled labor efficiency)	Long-run: pervasive labor-augmenting tech, like AI, increases GDP and total employment in the long run. Technological progress leads to higher output and enough new job creation to offset losses. In the short and medium run: there can be transitional unemployment and wage suppression, especially if tech adoption is rapid. Policy intervention may be needed to assist displaced workers.
Xu G. (2024).	Examine how the adoption of AI affects labor demand in small and micro enterprises, including overall employment and skill composition.	Firm-level panel data (2013-2021) on Chinese small and micro enterprises. Econometric modelling with firm fixed effects (FE); regression analysis with controls.	AI adoption does not lead to mass job losses in SMEs. Strong heterogeneous effects in private and high-tech firms. AI contributes to structural shifts in employment, increasing demand for higher-skilled roles. The main mechanism is substitution of routine and low-skilled tasks, while more complex tasks are complemented by AI

Author(s), (Year)	Research Objective	Methodology	Key Findings
Jacobs J. (2024)	Investigate if AI-driven labor market polarization translates into socio-political polarization	Merged dataset: US survey and occupation-level AI exposure; OLS with fixed effects	Two groups: «AI losers» in occupations highly susceptible to automation and «AI winners» in occupations highly complemented by AI. The study highlights an indirect «effectiveness» issue: even if AI boosts productivity, its uneven benefits might fuel polarization and require policy responses to maintain social cohesion.
Qu G., Jing H. (2025)	Explore how AI adoption affects corporate tax avoidance via labor costs	Firm-level analysis (Chinese A-share companies); text analysis to measure AI adoption; regression models	Finds that AI adoption leads to higher high-skilled labor and tech costs for firms, which in turn incentivizes greater tax avoidance strategies. In essence, as companies invest in AI (experts, software) to maintain profits, firms engage in more aggressive tax planning.
Note – compiled by authors based on sources [8-24].			

The above table includes a mix of empirical studies from econometric analyses to surveys, theoretical works and reports. Key findings are abbreviated and focus on labor market outcomes.

The literature reviewed provides a multifaceted picture of how artificial intelligence is affecting labor markets. In this section, we discuss the findings comparatively, highlighting areas of agreement and divergence among studies. Throughout, we critically analyze why certain studies might reach different conclusions and identify research gaps or ambiguities that remain:

Firstly, net employment effect: no mass unemployment so far, but localized displacement exists. One striking consensus is that, at the aggregate level, AI has not yet led to a dramatic reduction in total employment. Several sources conclude that fears of technology-induced mass unemployment have not materialized in recent years. For example, the OECD's review finds no evidence of overall employment contraction due to automation; instead, labor markets have continued to add jobs, albeit with changing task compositions [25]. The ILO similarly asserts that widespread job displacement is not imminent, with an estimate that only about 2% of jobs globally are at high risk of being fully automated by AI in the near term [16]. These broad findings align with historical experience that new technologies tend to create new jobs even as they displace others, leading to reallocation rather than persistent unemployment. However, this does not mean that AI has had no disruptive effects. Wang and co-authors report a clear decline in low-skill employment in China attributable to AI and robotics [18]. International organizations also indicate that routine clerical, sales and service occupations in Kazakhstan and the wider Central Asia region face moderate to high automation exposure due to digitalization and AI-enabled technologies [26]. Mueller-Langer and co-authors document that on online freelance platforms, tasks requiring less specialized skill see less demand, while AI-skilled freelancers command a premium [13]. Moreover, Ross A. and co-authors reconcile these findings by modeling short-term displacement and long-term adjustment effects [21]. It means that AI-driven productivity improvements can reduce labor demand temporarily. On the other hand, it eventually creates new job opportunities through increased output and demand. In addition, Bordot F. in a macroeconomic simulation, finds that effective policy intervention can moderate transitional unemployment effects [12]. The net effect being small does not mean individual sectors aren't heavily impacted.

Manufacturing versus services show different trends. In manufacturing, especially in countries like China, studies find AI and digital tech adoption often coincides with more employment [20]. This somewhat counterintuitive result is explained by output expansion: digital technologies improve productivity and quality, enabling firms to grow and hire more rather than less. It suggests a scenario of augmentation and scale effect outweighing automation effect in that context. Conversely, in many service sectors we see signs of actual staff reduction. For example, banks adopting AI chatbots or automating back-office processes often streamline their workforce. The WEF employer survey data indicates significant expected job losses in administrative roles due to automation, which are predominantly service-sector jobs. The World Bank's analysis raises this point: many developing countries have not yet industrialized or built large service sectors and AI could undercut the offshoring model that helped countries create white-collar jobs. Thus, while global net unemployment may remain low, developing regions could experience a net negative impact on «good jobs» growth [27-28]. Which may effectively be a lost opportunity even if not outright layoffs. This is a more subtle effect: AI potentially constraining job creation rather than causing direct unemployment, a nuance highlighted by that study. So, the literature suggests that AI has been more effective as a tool for productivity than a destroyer of jobs – overall employment has been resilient. Yet, pockets of displacement exist and are concentrated among routine work and industries.

Secondly, skill-biased technological change and polarization: a prominent theme is that AI acts as a skill-biased technological change (SBTC). It is disproportionately benefiting skilled workers and replacing or diminishing opportunities for lower-skilled workers. Virtually all empirical studies support this to some extent. In the case of high-skill complementation AI, especially advanced algorithms and machine learning, often serves as a complement to high-skilled labor. For example, Felten E. and co-authors found occupations with greater AI exposure saw wage and employment gains, implying these workers used AI to enhance their productivity or scope of work [11]. Similarly, Mueller-Langer and co-authors show that those with AI skills earn a premium on freelance platforms [13]. Such evidence that skilled tech workers are in higher demand thanks to AI. In companies, the adoption of AI tends to create more demand for data scientists, AI specialists, and managers who can implement AI. Other studies directly measure that companies undertaking digital transformation increased their hiring of highly educated and trained workers [20]. The effect is so consistent that in their data no net job loss occurred, which means they simply swapped out or added more skilled roles. Furthermore, Ross A.'s CGE model scenario where tech augments skilled labor shows positive effects spilling over even to unskilled employment in the long run [21]. Because more skilled labor productivity can drive growth that eventually raises overall labor demand, including complementary lower-skill services. Low-skill substitution: on the flip side, multiple studies underscore that lower-skilled, routine jobs are most at risk from AI and automation. Evidence from China shows that AI-driven automation replaces low-skill workers, while middle and high-skill employment expands [18].This is classic labor market polarization, by hollowing out of the bottom and growth at the top. Bordot's cross-country analysis confirms that automation's impact is heterogeneous by education level, with lower-educated workers more likely to experience unemployment from AI. Likewise, Manyika's automation potential index used in Jacobs J. essentially labels many blue-collar and some service roles [23]. As «AI losers» – janitors, drivers, assembly line workers, but also telemarketers and bookkeepers – which aligns with this pattern.

The joint outcome of these two tendencies is job polarization, such as growth in high-skill, high-pay employment and stagnation, or decline in low-skill, low-pay employment, often with the middle hollowed out. Indeed, researchers effectively identified two socio-economic groups emerging from AI-driven polarization: one largely high-skill «winners» and one lower-skill «losers» with not just economic but also ideological differences. Author's findings are an important reminder that labor market polarization can lead to social and political polarization, an externality of AI's uneven impact. If one segment of workers consistently sees their jobs threatened or downgraded while another prospers, societal tensions can rise. However, the prevailing evidence is that AI's immediate effect is skill-biased in favor of those with higher education and digital skills. This raises important considerations: the «winners» typically are younger, highly educated, tech-savvy, often male workers in urban areas, whereas the «losers» tend to be older, less educated, performing routine tasks and this often correlates with lower income and sometimes specific demographics. Overall, there's a risk that AI exacerbates gender inequality. For example, if AI cuts many secretarial positions (mostly held by women), while creating more AI engineer jobs (largely occupied by men), the gender employment gap could widen.

Thirdly, industry and sectoral specifics: different industries experience AI differently, both in extent and outcome. As noted, evidence from China and some developed countries suggests that automation in manufacturing can coincide with expansion, especially if the automation is partial and augments worker capability [20]. Manufacturing shows AI can be a productivity boon without necessarily destroying the sector's jobs, but it does change the job profiles dramatically. There are fewer low-skill assembly jobs and more maintenance or programming jobs. Within services, some segments are highly exposed to AI – notably finance, information technology, law, accounting, consulting. In fact, companies in these fields are adopting AI to improve efficiency and output, which could increase their competitiveness and possibly market size. Healthcare and education:

these large sectors have not been discussed much in the provided literature, likely because AI's role there is still emerging. These are typically labor-intensive sectors that historically resist automation to some degree due to the human element. However, AI could streamline administrative tasks or provide decision support, potentially freeing up workers to focus on improving service quality. That could be an «effectiveness» gain without job loss. The net impact in these sectors is still to be seen, but given their importance, they represent a gap in current research. This means that we need more studies on how AI affects service quality, workload, and job demand in fields like healthcare, education, and public sector.

In the case of gig and platform economy Mueller-Langer and co-authors provided a window into freelance platforms, noting a shortage of AI-skilled workers relative to demand [13]. This indicates that on such platforms, AI is not eliminating gigs, rather, it's creating premium gigs. It is for those who can do AI-related projects. Public sector and policy jobs: not directly covered in our sources, but AI can also automate some government functions, like chatbots for citizen inquiries, processing applications. The effect could be to improve service with potentially fewer clerks needed. An open question is how government employment will adapt – likely slower than private sector and with more emphasis on retraining.

Fourthly, policy responses and adaptation strategies: a major concern in literature is ensuring that the workforce can adapt to AI-driven changes. The effectiveness of AI in the labor market is not predetermined. It depends on complementary policies and actions. As AI automates tasks, the workforce must learn new skills to move into the tasks and jobs that are in demand. Studies like Komp-Leukkunen suggest even in high-skill fields, curricula need to incorporate AI tools to prepare future workers [17]. Bordot's policy simulations found that with the right policies, technological unemployment can be effectively addressed [12]. It means that we can prevent long-term joblessness by interventions like shorter work weeks or universal basic income, allowing more sharing of work. Essentially, policies should ensure the gains from AI are shared through wages, social programs and that those who lose jobs are not left behind. Education System Alignment: on a longer horizon, schools and universities must adapt curricula to prepare the future workforce. STEM education, digital literacy and unique human skills, like creativity, critical thinking, emotional intelligence, should be emphasized. If routine jobs vanish, we need an education that doesn't prepare people for routine work but for adaptive careers. The Gender parity report specifically calls out encouraging more girls and women into STEM and AI fields to avoid exacerbating gender gaps [29]. Policies that stimulate job creation in complementary areas are crucial. For instance, AI will likely create jobs in the tech sector through supporting entrepreneurship and startups in AI can create employment. Additionally, investing in sectors that are labor-intensive and not easily automated could absorb workers from shrinking sectors. In the context of monitoring and research, as AI evolves quickly, the sudden emergence of ChatGPT in 2022–2023 took many by surprise in terms of its capabilities, continuous analysis is needed to update policy. The uncertainty around generative AI's impact is a prime example, because policymakers are only beginning to grasp implications.

Fifthly, ambiguities and research gaps: despite the rich literature, several open questions and areas of mixed evidence emerge from our review. Many 2023–2024 studies are trying to gauge the early impact of generative AI (like GPT) [15, 17, 30]. While these show impressive productivity gains and high exposure of white-collar work, it remains uncertain how firms will integrate these tools long-term. Will they reduce hiring of entry-level analysts? Or will lower costs generate new services and thus more jobs? The macro-outcome will depend on business decisions and possibly regulation. This area needs long-term studies, such as tracking companies that adopt GPT tools versus those that don't over a few years to see differences in headcount and output. Will AI depress wages for certain roles due to automation or increase wages due to productivity? Wages might rise for in-demand skilled roles and stagnate or fall for roles that become commoditized or where humans compete with AI. For instance, if AI can do 50% of a paralegal's tasks, an employer might value the human less. Entrepreneurship and job creation: are new businesses emerging thanks to AI, like how the internet created entirely new sectors? Early anecdotal evidence may show that some entrepreneurs use AI to create products faster, or individuals become freelancers offering AI-assisted services. The net job creation from these new ventures isn't yet clear. No consensus yet, as we're in early stages. For years, there was talk of a «productivity paradox» where AI and IT advancement did not immediately reflect in productivity statistics. Some recent signs show productivity upticks in firms using AI. If AI leads to a productivity boom, that could lower prices and potentially stimulate demand enough to create jobs. If not and productivity gains accrue mainly to profits, the distribution of benefits could be skewed.

In the case of developing world focus we identified that some regions have little direct research yet. How will low-income countries with large young populations and fewer high-skill jobs be affected? They may not lose many jobs to AI because they haven't industrialized fully. So far, evidence like Liu Y. is speculative but plausible [28]. There's a research gap in examining AI's impact on employment in low-income settings. For instance, could AI in agriculture reduce farm labor in countries where agriculture employs many? Or could it increase yields and farm incomes? There is not much literature there yet. Beyond employment and wages, worker well-being under AI is a concern. Do workers feel greater stress due to AI monitoring or performance pressure? Sociological and psychological impacts are under-studied. Jacobs J. linking to political attitudes is one approach to capturing broader impacts [23]. More qualitative research on how workers experience AI in their daily tasks would complement the quantitative studies. There's a gap in evidence on which policies are working. For example, retraining programs: what is their success rate for tech-displaced workers? Places like France experimented with 35-hour work weeks, but not specifically due to AI. As some propose ideas like universal basic income to handle potential AI-driven job scarcity, small pilots have been run but have no consensus.

The review also surfaces some contradictory findings that warrant explanation. Does AI increase or not change total labor demand? For example, Qiu L. and co-authors say increase (firm-level in manufacturing), while Xu G. says overall not obvious effect, whereas Bordot F. says slight increase in unemployment [12, 20, 21]. A firm adopting AI might hire more, but economy-wide, if many firms adopt, some old firms might close. On a macroscale, Bordot F. found an average unemployment effect across many countries, which was small but positive. It means that not all sectors had that expansion effect or it was offset by declines elsewhere. These differences highlight that AI's impact can be positive in microcosm but still disruptive in macro if not all sectors benefit equally. High-skill job risk: most say high-skill benefit, but Komp-Leukkunen K. and Eloundou T. and co-authors show us that even high-skill tasks are automated [15, 17]. This is not necessarily a contradiction, so it means AI's frontier is moving upward into high-skill territory. High-skill workers may still benefit overall because they leverage AI as a complement. But if AI gets good enough to truly perform expert work, like making medical diagnoses as well as a doctor, then even high-skill roles could face redundancy. We haven't seen that on scale yet; AI is still error-prone and needs human oversight in complex tasks. But it's a looming question: does the SBTC pattern hold if AI becomes very advanced, or do we get a new paradigm? None of the studies show that yet, but the ChatGPT phenomenon, as Komp's experts noted, shows even creative, non-routine tasks aren't immune [17]. Some argue AI could allow for less work. So far, there is no evidence of reduced working hours due to AI specifically. If anything, people tend to continue working full weeks and the productivity gains go into more output or profits. This is a societal choice in a sense. Consequently the 19th and 20th century tech led to shorter work weeks over long periods, but recent decades saw stagnant or even increasing work hours for many. Finally, critical voices and caution, a few sources challenge overly rosy views. Frey C. and Osborne M.'s high-risk estimate, while probably overstated, served to jolt policymakers into action early on [3]. These underline that while AI hasn't crushed employment, it has altered the social contract in ways we are just beginning to grasp.

Research gaps identified – we need more data on long-term impacts, especially of generative AI. More studies in developing economies and on informal labor and interdisciplinary research combining economics with sociology, psychology, and political science to fully understand AI's ramifications. To gain insight into the state of research on AI and labor markets, we conducted a simple metadata analysis of the collected studies. We examined trends in publication year, geographic focus, and methodologies of the sources in our review. This provides context on how scholarly and policy attention has evolved and whether there are biases or gaps in literature.

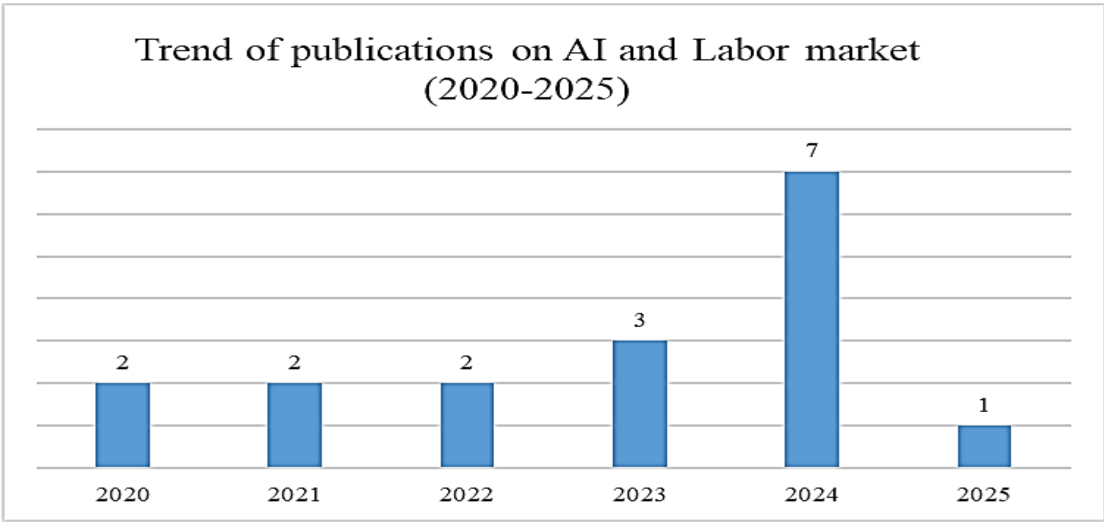

Figure 1 – Trend in number of selected publications on AI's labor market impact (2020–2025).
Note – compiled by authors based on sources [8-24].

Research on AI's labor market effects has grown rapidly in recent years, especially after 2022. Figure 1 above illustrates the number of key publications per year among our sources. There is a clear uptick starting 2022 and a peak in 2023–2024. In 2020–2021, relatively fewer high-profile studies were published. These years have likely had ongoing research but perhaps not yet a critical mass of data on AI deployment. By 2022, as AI adoption became more tangible and urgent, publications increased. 2023 saw a surge of reports and papers, coinciding with the breakthrough of generative AI into public awareness. Indeed, multiple reports from WEF and World Bank, moreover academic papers in 2023 focused on the implications of large language models. The slight dip projected in 2025 likely reflects that many 2025 studies are still forthcoming. The general trend indicates growing scholarly attention, with 2024 producing the highest volume of studies in our sample. Because many works were accepted and published online in late 2023 or early 2024. This trend is expected to continue upward given the fast-moving developments in AI. In summary, there's been an explosion of research interest in the past two to three years, mapping onto AI's technological leaps and rising policy concerns.

The data indicate that 48% of our reviewed studies were published in 2023–2024 alone, whereas earlier years had fewer studies. This likely reflects both the increasing real-world impact of AI and the maturation of research methods to study it. And it also suggests a potential lag in policy: many findings are very recent, meaning policymakers are dealing with new evidence in real-time. The flurry of publications in late 2023 on generative AI shows how quickly literature is responding to technological advances.

Geographic focus of studies. We categorized each study by its primary geographic focus. Figure 2 presents that nearly half of the studies concentrate on advanced economies (primarily the USA and Europe), while about 16% focus on China. A significant portion (28%) are global or multi-country analyses. Only a small share (8%) explicitly focuses on other emerging economies.

In the case of gap, there is relatively sparse literature focusing on Africa, Latin America, or even regions like the Middle East. This suggests that more research is needed in diverse regional contexts, as the impact and policy implications of AI might differ significantly in those settings. The current evidence base is dominated by high-income country experiences and a few large emerging economies, notably China.

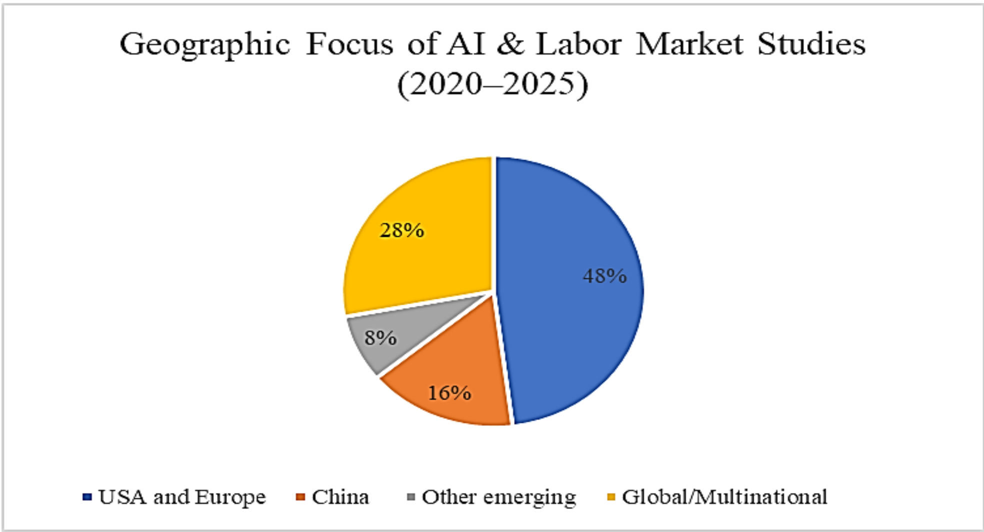

Figure 2 – Geographic focus of reviewed studies selected publications on AI's labor market impact.
Note – compiled by authors based on sources [8-24].

The studies in our review employ a range of methodologies: approximately half are quantitative empirical studies (econometric analyses), around one-quarter are policy or scenario analyses by organizations (drawing on surveys or literature synthesis). According to Figure 3, the rest include theoretical models, expert elicitation (Delphi), and case studies. Specifically, we observed many econometric papers leveraging existing data (labor force surveys, firm data, O*NET job features) to statistically infer AI's impact. Models and simulations help explore long-term scenarios and policy effects that empirical data can't fully capture [12, 21]. The presence of multiple literature reviews and reports indicates an effort to aggregate knowledge and provide guidance.

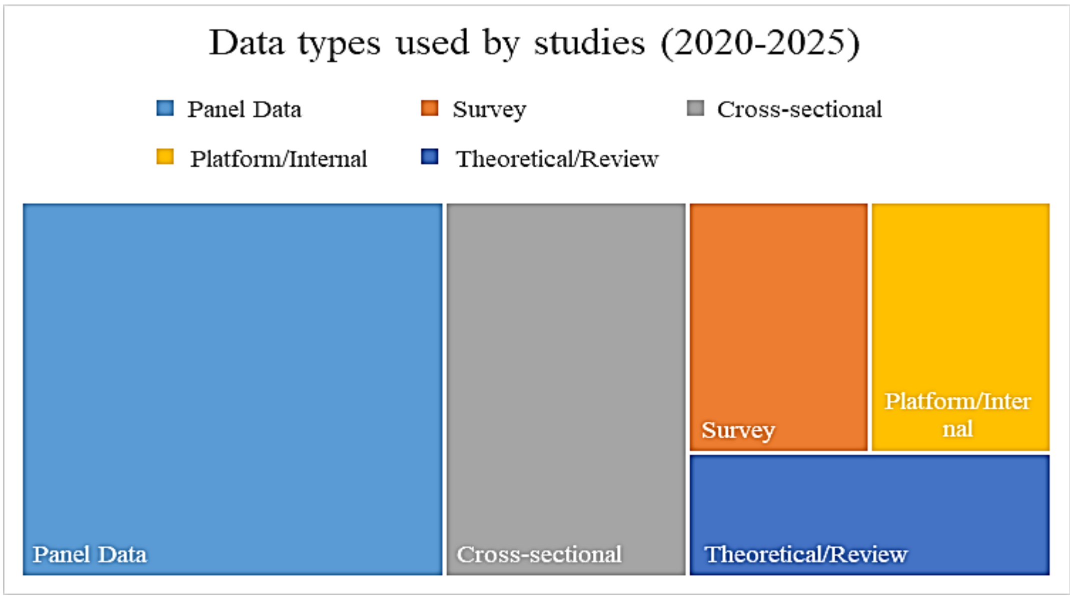

Figure 3 – Data focus of reviewed studies.
Note – compiled by authors based on sources [8-24].

One trend is the increasing use of novel data and interdisciplinary methods in the last year or two. For example, natural language processing is used to quantify AI exposure of occupations and to measure firm adoption via text analysis [15, 24]. Surveys of experts and companies (Delphi) complement data-driven approaches to capture forward-looking insights. We also see social science merging with computer science. The metadata analysis highlights that while the research base is expanding, it is concentrated in certain regions and methods. Most empirical evidence comes from a few economies and focuses on short and medium-term effects. There is room for more longitudinal studies and studies in diverse cultural-economic contexts. Additionally, few studies directly evaluate policy interventions, which is a gap that needs filling as more experiments in managing AI transitions occur. In conclusion, the metadata suggests literature is in a dynamic, fast-growth phase, driven largely by concerns in advanced economies, with methodological innovation underway. This context is important for interpreting our review findings: they are the best evidence to date, but ongoing and future research may further refine understanding of AI's role in labor markets.

Limitations. This systematic review has several limitations that must be acknowledged, reflecting constraints in scope and methodology. Many studies focus on specific regions or countries, such as the United States of America, Europe, or China, limiting generalizability to a global context. The evidence base is skewed toward advanced economies and emerging markets with available data, leaving out low-income countries and diverse cultural contexts. Most empirical studies capture short-term effects of AI adoption, providing a snapshot rather than long-term trends. Longitudinal data are scarce, and the rapidly evolving nature of AI means findings can become quickly outdated as new technologies emerge. There is substantial heterogeneity in research methods and definitions of «AI» making comparisons difficult. The reviewed works include case studies, surveys, cross-sectional firm analyses and conceptual papers. This variation in methods and measures of labor outcomes leads to inconsistent results and challenges in synthesizing conclusions across studies. Many studies have a narrow scope in terms of outcomes measured. For instance, focusing only on employment count or productivity, but not on job quality, wages or worker well-being. Indirect effects are less commonly quantified, which constrains a holistic assessment of AI's labor market effectiveness. The pace of AI innovation outstrips the pace of research. By the time findings are published, the technology may have advanced or diffused further. This lag makes it hard to capture the dynamic, evolving impact of AI – a limitation inherent in studying a fast-moving target. Consequently, today's conclusions may need continual revision as AI capabilities and adoption patterns change. These limitations suggest caution in interpreting the results. The patterns identified are contingent on current data and contexts, and future developments could alter these trajectories. Acknowledging these weaknesses provides transparency and underscores the need for further research to address them.

RESEARCH FINDINGS (CONCLUSION)

This systematic literature review examined the effectiveness of artificial intelligence on labor market outcomes. Overall, the evidence indicates mixed effects on employment. AI adoption has in some cases led to job displacement or redundancy, particularly for routine and manual roles susceptible to automation. At the same time, many studies report job creation, task augmentation and productivity gains as firms integrate AI, especially for high-skill and technical occupations. In essence, AI is functioning as a skill-biased technology: it tends to increase demand for skilled labor while automating certain lower-skill tasks. This has contributed to shifts in the skill composition of workforces rather than uniform employment losses across the board. Furthermore, the impact of AI varies considerably by sector. In knowledge-intensive service sectors like healthcare and education, AI systems often complement human workers. In contrast, in sectors such as production and logistics (which involve repetitive processes), we see more automation of functions, leading to restructuring and retraining of personnel to perform more complex tasks. These sectoral variations underscore that AI's effect on labor is context-dependent rather than monolithic.

The findings suggest that artificial intelligence is not an «employment apocalypse» but a catalyst of transformation in the world of work. Its net impact on jobs and productivity depends on how organizations and societies respond. On the one hand, automation based on artificial intelligence can contribute to economic growth and the emergence of new professions that did not exist before, by increasing efficiency and productivity. Without active adaptation, AI can exacerbate skills deficits and inequalities. So, workers with outdated skills risk exclusion while those with in-demand skills reap the benefits. In the short term, careful management is required to ensure AI augments human capabilities instead of simply replacing them. The review findings imply that policy choices and business strategies will significantly mediate AI's ultimate impact on the labor market.

For instance, if companies choose to use AI to complement their workers through upskilling and job redesign rather than purely cut labor costs, the outcome can be more positive in terms of employment and job quality.

Governments should facilitate workforce transition and skills development in the age of AI, such as investing in education and continuous training programs to prepare workers for AI-complementary roles, also strengthening labor market institutions to support those displaced. Policy frameworks must also address inequities and ethical issues introduced by AI. For example, updating regulations on AI-driven hiring to prevent bias and ensuring that the gains from AI productivity are broadly shared. Firms implementing AI should adopt a responsible innovation strategy. Rather than viewing AI purely as a tool to cut costs, businesses are encouraged to use AI to augment human labor – automating repetitive tasks to free employees for more creative, complex work. This requires redesigning job roles and workflows to maximize human-AI collaboration. Organizations should also invest in retraining their workforce, equipping employees with the skills to work effectively alongside AI systems. Interdisciplinary research is crucial to understanding how AI interacts with organizational practices and worker behavior. There is also an implication that researchers must keep pace with AI's rapid evolution: studying current generative AI tools and their adoption in workplaces will be essential to provide up-to-date insights.

Building on the gaps identified in this review, future studies should aim to address the limitations and open questions. Conduct long-term studies tracking the evolution of AI impacts overtime at both firm and worker levels. Such research would help capture lagged effects and adjustment processes that short-term studies miss. Comparative studies across developed and developing countries would shed light on how AI's labor market effects differ by economic context. Likewise, examining sectors beyond the current focus can uncover unique challenges and opportunities of AI in those domains, informing more inclusive global insights. Investigate the effectiveness of various policy measures and business interventions in managing AI's impact. Similarly, assessing the impact of government incentives for AI adoption that require worker upskilling could provide valuable evidence. By rigorously testing which strategies best mitigate negative effects of AI on employment, researchers can provide guidance on evidence-based practices for policymakers and managers. As AI capabilities continue to advance, research should explore emerging new job categories and entrepreneurial opportunities created in the wake of these technologies. This includes studying how AI spurs complementary innovations and how educational curricula and training programs can anticipate these future skill requirements.

In conclusion, artificial intelligence is reshaping labor markets in complex ways rather than simply eliminating work. Its effectiveness in augmenting human labor versus displacing it hinges on a variety of factors, including skill preparedness, organizational strategy and supportive policy frameworks. The key findings highlight a balance of positive and negative effects; by leveraging its significant potential for productivity and job enhancement, tempered by concerns over displacement and inequality. Stakeholders who recognize and act on this nuanced reality can better harness AI's benefits while safeguarding the workforce. The dialogue between evidence and action must continue, guiding us toward labor market outcomes where artificial intelligence serves as a tool for human progress and widespread economic well-being.

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ГЕНЕРАТИВТІ ЖАСАНДЫ ИНТЕЛЛЕКТТІҢ ЕҢБЕК НАРЫҒЫНДАҒЫ РӨЛІ: ӘДЕБИЕТТЕРГЕ ШОЛУ

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АҢДАТПА

Зерттеу мақсаты. Бұл жүйелі әдебиеттерге шолу жасанды интеллекттің еңбек нарығындағы рөлін және оның өнімділігі мен жұмыспен қамту нәтижелері бойынша тиімділігін зерттеуге бағытталады.

Әдіснамасы. Біз жасанды интелектті енгізу жұмыс орындарын құруға, халықтың қоныс аударуына және жұмыс күшінің құрамына қалай әсер ететінін бағалау үшін жаһандық және аймақтық контексттерде

2020 жылдан 2025 жылға дейінгі соңғы зерттеулерді қарастырдық. Мұндағы көздегеніміз жасанды интеллект адам еңбегін арттырады ма, әлде оны автоматтандырады ма және нақты қандай жағдайларда екендігі туралы деректерді синтездеу болды. Жүйелі әдістемені қолдана отырып, рецензияланған академиялық журналдардың 17 негізгі жарияланымдарын талдадық.

Зерттеудің бірегейлігі/құндылығы. Біздің шолуымыз жасанды интеллекттің жұмыспен қамтуға таза әсері осы уақытқа дейін қарапайым деңгейле болғанын және жасанды интеллект тудырған жаппай жұмыссыздықтың нақты дәлелі жоқ екеніне айғақтар ұсындық. Жалпы сипатта, жасанды интеллектке негізделген автоматтандыру біркелкі емес әсер етеді: ол белгілі бір күнделікті және біліктілігі төмен жұмыстарды ығыстырып, сонымен қатар жоғары білікті жұмыс үшін жаңа мүмкіндіктер ашады. Осылайша еңбек нарығының поляризациясына ықпал етеді. Яғни, жасанды интеллект білікті жұмысшылардың өнімділігін толықтыруға және арттыруға бейімділімен сипатталса, енді бір ретте біліктілігі төмен лауазымдарда автоматтандыру қаупі жоғары екендігі тағы бар.

Зерттеу нәтижелері. Талқылау бөлімінде біз конвергентті нәтижелерді жинақтап атап өтеміз. Әдебиеттерді мета-талдау әдісі негізінде 2023-2025 жылдардағы зерттеулерге деген қызығушылықтың артып келе жатқанын және негізінен экономикасы дамыған елдерге бағытталғанын көрсетеді. Бұған қоса, біз оның салдарын да талқылап өттік. Жасанды интеллект еңбек өнімділігін арттырып, құндылықтардың жаңа легін құрғанымен, бұл жетістіктердің кең ауқымды жұмыспен қамту жеңілдіктеріне айналуын қамтамасыз ету үшін елеулі деңгейлердегі белсенді шаралар қажет. Шолу нәтижесінде табыс деңгейі төмен елдердегі шектеулі зерттеулер мәселесі мен жасанды интеллекттің ұзақ мерзімді генеративті әсерлері сияқты зерттеулердегі гэптерді анықтадық. Сондай-ақ, жасанды интеллекттің жұмыс күшіне әсеріндегі оңтайлы басқару саясатының маңыздылығын көрсеттік.

Түйін сөздер: жасанды интеллект, еңбек нарығы, жұмыс трансформациясы, еңбекті автоматтандыру, еңбек нарығының тенденциялары.

РОЛЬ ГЕНЕРАТИВНОГО ИСКУССТВЕННОГО ИНТЕЛЛЕКТА НА РЫНКЕ ТРУДА: ОБЗОР ЛИТЕРАТУРЫ

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АННОТАЦИЯ

Цель исследования. В этом систематическом обзоре литературы рассматривается роль искусственного интеллекта на рынке труда и его эффективность с точки зрения производительности и результатов трудоустройства.

Методология. Мы проанализировали последние исследования, проведенные в период с 2020 по 2025 год в глобальном и региональном контекстах, чтобы оценить, как внедрение искусственного интеллекта влияет на создание рабочих мест, перемещение персонала и состав рабочей силы. Цель состояла в том, чтобы обобщить современные данные о том, улучшает ли искусственный интеллект человеческий труд или автоматизирует его, и при каких условиях. Используя систематическую методологию, мы проанализировали 17 ключевых публикаций из рецензируемых научных журналов.

Оригинальность / ценность исследования. Наш обзор показывает, что чистое влияние ИИ на занятость до сих пор было скромным, и явных свидетельств массовой безработицы, вызванной ИИ, не было. Однако автоматизация, основанная на ИИ, имеет неравномерный эффект: она вытесняет некоторые рутинные и низкоквалифицированные рабочие места, в то же время создавая новые возможности для высококвалифицированной работы, что способствует поляризации рынка труда. Примечательно, что ИИ, как правило, дополняет и повышает производительность квалифицированных

работников, в то время как низкоквалифицированные рабочие места подвергаются более высокому риску автоматизации.

Результаты исследования. В ходе нашего обсуждения мы выделяем сходящее. Широко распространенное мнение о том, что искусственный интеллект требует повышения квалификации рабочей силы и политической поддержки, наряду с расходящимися результатами, такими как противоречивые данные о создании новых рабочих мест в разных контекстах. Метаанализ литературы свидетельствует о растущем интересе к исследованиям в 2023-2025 годах и сосредоточении внимания в основном на странах с развитой экономикой. Наконец, мы обсуждаем последствия: хотя искусственный интеллект может повышать производительность труда и создавать ценность, необходимы активные меры для обеспечения того, чтобы эти достижения трансформировались в широкие преимущества при трудоустройстве. В обзоре выявлены пробелы в исследованиях, такие как ограниченное количество исследований в странах с низким уровнем дохода и долгосрочных генеративных эффектов ИИ, а также подчеркивается важность политики для управления переходом рабочей силы с использованием ИИ.

Ключевые слова: искусственный интеллект, рынок труда, трансформация рабочих мест, автоматизация рабочих мест, тенденции занятости.

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МРНТИ: 06.01.29
JEL Classification: O33
DOI: https://doi.org/10.52821/2789-4401-2025-6-212-227

ҚАЗАҚСТАНДАҒЫ ЖАСАНДЫ ИНТЕЛЛЕКТТІҢ ДАМУЫ: САЛАЛЫҚ ШОЛУ, 2019-2023

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АҢДАТПА

Зерттеу мақсаты. Қазақстандағы жасанды интеллекттің дамуын талдау, оның экономикалық процестерге әсерін анықтау, сондай-ақ, әртүрлі салаларда жасанды интеллект технологияларын тиімді пайдалану бойынша ұсыныстар әзірлеу.

Әдіснамасы. Зерттеу әдістері ретінде цифрлық экономикада жасанды интеллектті қолданудың теориялық тәсілдерін талдау, деректерді статистикалық зерттеу, әртүрлі салаларда жасанды интеллектті енгізу тәжірибелерін трендтік, салыстырмалы және SWOT-талдау қолданылды. Мақаланы жазу