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Review

AI-driven transformation of labor market structures: employment restructuring, skill polarization, and adaptation pathways

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Abstract: This paper examines how artificial intelligence reshapes labor markets through task reconfiguration, skill reorganization, and income differentiation. Using sociotechnical systems theory and skill-biased technological change, it analyzes AI's impact across tasks, occupations, skills, and earnings. Findings show that AI primarily restructures tasks within occupations rather than eliminating entire jobs. Standardized, digitized tasks face high automation risk, while cognitive tasks benefit from human-AI collaboration. New technical roles emerge, but skill mismatches and entry barriers limit employment gains, and compensation effects depend on workers' adaptability. AI increasingly demands hybrid skills-digital, analytical, and collaborative-deepening inequality among worker groups. Cross-nationally, developed countries face higher task exposure due to knowledge-intensive economies, while developing nations struggle with infrastructure and skill constraints. Ultimately, AI's labor market effects are heterogeneous and depend on technology-skill-institutional dynamics.

Keywords: artificial intelligence; labor market; social technology system theory; employment structure; adjustment path

1. Introduction

1.1. Research background

Artificial intelligence (AI) is reshaping the labor market's operational logic. The rapid iteration of machine learning, natural language processing, and generative artificial intelligence is driving AI into various knowledge labor fields such as text generation, program development, financial analysis, education and healthcare, and professional services, beyond traditional manufacturing automation and basic data processing scenarios. The mode of AI involvement in the labor process has changed significantly, with some tasks now capable of being completed independently by AI or through human-machine collaboration, and workers' actual work content has also shifted[1].

According to the International Labor Organization 2025 report, approximately one quarter of the global workforce is employed in occupations with some degree of exposure to generative AI. Employment in the highest-exposure category accounts for 3.3% of global employment. Exposure var ies substantially across countries: 34% of employment in high-income countries falls into occupations with some degree of AI exposure, compared with only 11% in low-income countries. These figures come from the report's global occupational exposure index, indicating that generative AI has extensively intervened in occupational activities and that the technological shock shows significant national and regional differences[2].

The impact of AI on the labor market cannot be equated simply with a decline in the total number of jobs. Early automation research focused on the

substitution of technology for labor, assuming that tasks with clear rules and fixed processes were more likely to be taken over by machines, while tasks requiring complex judgment, creative output, and social interaction had stronger attributes of labor complementarity[3]. With the development of the task analysis paradigm, the academic community began to decompose occupations into multiple sub-tasks, examining the real effects of technological change at the task level. Technology can both take over some human labor tasks and create new production tasks and labor demands[4]. After AI enters the labor scene, tasks within the same occupation will simultaneously undergo automation, and labor capabilities will be enhanced; the occupation itself may not necessarily disappear entirely. Generative AI further expands this transformation, with cognitive tasks such as text processing, code generation, information assessment, and content production being affected by technological shock, and many knowledge-intensive occupations involved in the technological reconfiguration process[5]. International Labor Organization research also confirms that the impact of generative AI on most occupations is reflected more in task reconfiguration and occupational transformation than in the complete replacement of entire occupations.

The technological shock has gradually shifted from the macro level of occupations to the micro level of tasks, and task-level reconfiguration further transmits to skill demands, employment forms, and workers' income distribution, constituting the underlying logic of labor market transformation in the era of artificial intelligence.

1.2. Current academic debates

Whether artificial intelligence is reducing employment opportunities or reconfiguring the employment landscape remains the core controversy in this field. Existing research on this topic falls into three representative analytical perspectives.

The first is the substitution perspective. This perspective holds that artificial intelligence mainly serves as a task-replacement mechanism, with AI systems taking over tasks previously performed by workers, thereby reducing the demand for corresponding human resources in enterprises. At the macro level of the labor market, the large-scale application of artificial intelligence will significantly alter the traditional labor input structure and inhibit overall employment. Technological automation will gradually replace routine labor content, resulting in a clear employment substitution effect[6]. From the perspective of occupational attributes, different occupations differ significantly in their adaptability to technological change. The degree to which a profession's tasks can be encoded and the extent of process standardization directly determine the risk of being replaced by artificial intelligence. Some occupations are inherently more susceptible to technological substitution[7]. From the perspective of specific employment scenarios, the impact of artificial intelligence substitution is clearly structural and spatially heterogeneous. Many process-based and standardized basic occupations fall into the high-exposure domain of AI, making them primary targets of technological substitution. Employment vulnerability across regions and industries shows significant differentiation characteristics[8]. From the perspective of long-term employment evolution trends, AI-driven technological transformation will continue to reshape traditional employment patterns. Through regular task substitution, it rewrites the labor form of traditional positions, promoting continuous iterative adjustments in the future employment landscape and causing the continuous contraction of traditional repetitive labor positions[9].

The core consensus of the substitution perspective is that artificial intelligence effectively substitutes for human labor through task automation,

compressing traditional labor demand across multiple dimensions such as macro scale, micro positions, and industry regions. Overall, the existing research based on the substitution perspective has fully verified the employment substitution effect of artificial intelligence and clarified the basic characteristics of high-risk substitution occupations, but it focuses mainly on the static results of job substitution and risk identification, lacking more detailed and systematic exploration of the dynamic process of artificial intelligence task substitution, boundary conditions, and differentiated impact mechanisms.

The second is the enhancement perspective. This perspective does not emphasize the replacement of humans by machines but highlights artificial intelligence's amplifying effect on workers' capabilities. Artificial intelligence takes on low-complexity, repetitive tasks, freeing workers' energy and enabling them to devote more to high-value aspects such as analysis, communication, coordination, and problem-solving. In human-machine collaborative work scenarios, artificial intelligence can break through the limitations of traditional work boundaries, optimize employees' work processes, enhance their engagement and overall work performance, and achieve mutual empowerment between technology and humans[10]. Systematic reviews show that the rational application of artificial intelligence can effectively optimize workers' work experience, improve job fit, and enhance workers' career well-being, forming a positive working ecosystem of human-machine complementarity[11]. The human-machine collaboration model, supported by technological empowerment, can simplify basic work processes, reduce workers' workload, and enable them to focus on core creative work, continuously optimizing output quality[12]. From the perspective of organizational transformation, industrial transformation driven by artificial intelligence is not merely job replacement; it relies on technological upgrading to promote innovation in organizational management models and human capital development, fully releasing workers' core value by optimizing the structure of human resource allocation[13].

At the same time, the popularization of artificial intelligence has reshaped the ability-demand system of the future workplace, forcing workers to build a new type of work skill system adapted to the era of intelligence and leveraging digital tools to achieve the iterative upgrade of personal work capabilities[14]. The capacity gains brought about by technological empowerment are universal. Artificial intelligence can effectively help workers enhance their output, improve decision-making quality, and significantly increase overall labor productivity[15]. At the enterprise practice level, the deep application of artificial intelligence has promoted on-the-job training, skill upgrading, and job reconfiguration, enabling workers to update skills and build capacity through continuous learning and further strengthening the compatibility of human-machine collaboration at work[16]. Thus, the core consensus of the enhanced perspective is that the core value of artificial intelligence lies in human-machine complementarity, capacity empowerment, and efficiency improvement. Technology helps workers focus on high-value creative work.

Overall, this perspective fully reveals the positive gains of artificial intelligence on the capabilities, work performance, and human capital development of workers, but it focuses more on the positive effects of technological empowerment and has not yet formed a comprehensive and systematic discussion on the heterogeneity of empowerment for workers with different skill levels and in different industries, as well as the potential issues of ability dependence and thinking weakening that may arise in the process of human-machine collaboration.

The third perspective is the creation perspective. This perspective focuses on the new labor demands brought about by technology. The implementation of

artificial intelligence will create new tasks, work content, and even entirely new career categories that did not exist before, creating new job positions. In the context of the digital economy, the expansion of the artificial intelligence industry itself will drive demand for labor in upstream and downstream sectors, expanding employment and reshaping the original employment structure, giving rise to a batch of emerging positions relying on intelligent technology[17]. Some studies directly analyze the employment effect of artificial intelligence within the binary framework of substitution and creation, arguing that while technology displaces some traditional labor, it also generates new labor scenarios through production model innovation, and the potential for new employment cannot be ignored[18]. From the perspective of task change logic, the application of artificial intelligence will change the task boundaries of production activities, generating a large number of previously non-existent human-machine collaboration tasks, and the expansion of tasks has become an important source of employment creation[19].

The employment creation brought about by technological iteration is not simply an increase in the number of positions, but also reflects the update and reconfiguration of the work content within the original occupation, and workers need to undertake new work content related to the operation, debugging, and optimization of AI tools, expanding the boundaries of labor activities[20]. At the same time, AI-driven job creation is constrained by the institutional environment, market conditions, and public policies. The technology itself only provides the possibility of employment generation, and whether it can be transformed into a real increase in employment depends on external supporting conditions[21]. Thus, the creation perspective breaks away from the fixed judgment that "technology inevitably squeezes employment", emphasizing that artificial intelligence has the inherent potential to generate new tasks and new occupations. Different from the previous two perspectives, which mainly discuss the already apparent real impacts, this perspective's analysis often takes into account both real observations and trend predictions, and has not yet reached a unified empirical conclusion on the scale, distribution, and labor adaptation thresholds of new positions, especially lacking in-depth examinations of the quality and labor rights of new positions.

In summary, existing research based on the three perspectives of substitution, enhancement, and creation has explained the differentiated impacts of artificial intelligence on the labor market, providing diverse theoretical support for understanding AI's employment effects. However, these three perspectives are fragmented and independent, have not formed a unified analytical framework, and cannot explain the heterogeneous coexistence of substitution, enhancement, and creation effects in reality. No single perspective can fully explain the complex effects of artificial intelligence on employment structure, skill systems, and labor forms. Because existing research is fragmented and largely one-dimensional, this paper proposes the core research question: How can we systematically explain the heterogeneity mechanism of artificial intelligence's impact on the labor market and clarify the linkage logic of task reconfiguration, skill differentiation, and market adaptation?

Based on these issues, this paper combines the theory of social-technical systems, the task perspective, and the theory of skill-biased technological change to analyze the impact of artificial intelligence entering the labor process on the structure of the labor market. The article first analyzes the impact of artificial intelligence on the employment structure, focusing on job substitution, job task reorganization, and new employment opportunities; then it analyzes the changes in skill demands brought about by artificial intelligence, paying attention to AI-related technical skills, complementary skills, and the skill differentiation among different workers; finally, it analyzes the adjustment methods of the labor market from the perspectives of workers, enterprises, education systems, and

the government, discussing issues such as skill update, job adjustment, talent cultivation, and employment support. The article mainly analyzes employment reconfiguration, skill differentiation, and adjustment paths, paying attention to how artificial intelligence changes labor tasks, employment opportunities, and skill demands, as well as how different entities respond to changes in the labor market structure.

2. Theoretical explanation of the structural changes in the labor market driven by artificial intelligence

The reshaping of the labor market by artificial intelligence is not a simple act of technological substitution, but rather a systematic transformation that spreads through multiple layers and involves multiple factors. Technology does not directly determine employment outcomes. Through an integrated analysis framework combining social technology system theory, the perspective of task change, and the theory of skill-biased technological change, it can be seen that artificial intelligence first embeds itself in a social technology system composed of workers, organizations, institutions, and technology, triggering the overall reconfiguration of the system; then it reshapes the task structure in the workplace, generating threefold effects of task substitution, task enhancement, and task creation; ultimately, it forces the iterative evolution of labor skills requirements, leading to comprehensive adjustments in the employment structure, income distribution, and the labor market. Accordingly, this paper follows the progressive logic of "system reconfiguration-task transformation-skill differentiation" and gradually disassembles the internal mechanism by which artificial intelligence drives changes in the labor market. **Figure 1** shows the complete transmission logic of the changes in the labor market structure driven by artificial intelligence.

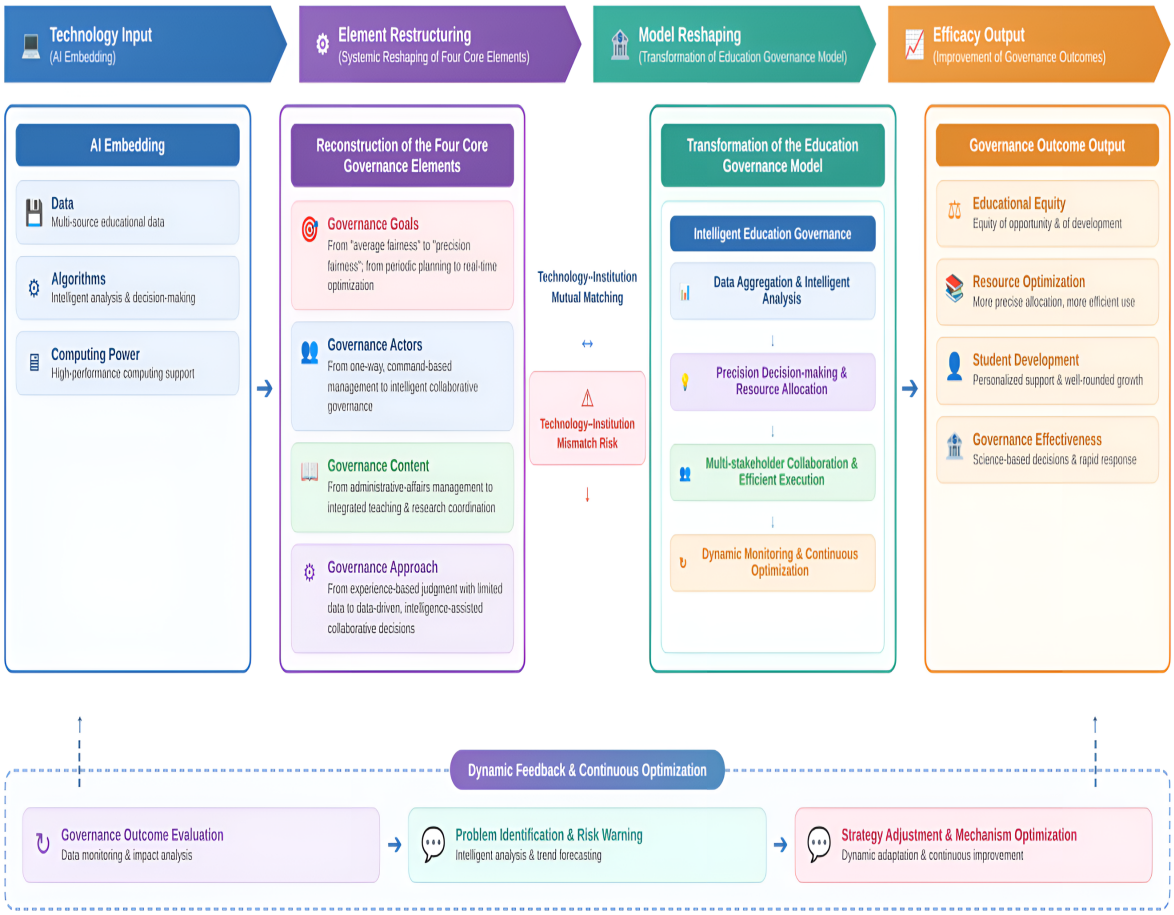


Figure 1: Logical Analysis Diagram of the Structural Changes in the Labor Market Driven by Artificial Intelligence

2.1. Social technology system theory: the collaborative evolution of artificial intelligence and labor systems

Social-technical systems theory serves as the fundamental macro-level basis for interpreting AI's employment effects. Its core viewpoint is that technology has never operated independently; every technological application is embedded in a complex system of workers, organizational structures, institutional rules, and technical tools. The technology system and the social system are interdependent and evolve collaboratively, ultimately jointly determining the employment market outcomes. This explains why AI does not directly produce a single employment substitution or creation result[22]. Without considering organizational models, personnel capabilities, and institutional environments, relying solely on technical performance cannot predict labor market changes.

This theory breaks the linear perception of "technology determining employment" and emphasizes that AI's impact on the labor market is essentially a process of overall reconfiguration of the socio-technical system. AI is not an isolated technical variable embedded in the production scenario; instead, it integrates deeply into the entire process of enterprise production, services, and management, forming a new interactive matching relationship with workers' capabilities, job responsibilities, organizational divisions, and management systems. After enterprises introduce AI technology, not only will information processing and data calculation technology tools change, but the entire set of labor production and organizational operation systems will also be transformed: the job responsibilities of existing employees, team collaboration models, work process norms, and management authority and responsibility boundaries will all be adjusted accordingly.

Specifically, after AI takes over standardized and process-oriented basic tasks, the focus of workers shifts from mechanical execution to result review, complex decision-making, interpersonal communication, and innovation optimization; enterprises, in order to adapt to AI technology applications, will reassign job authorities, restructure the division of labor system, and optimize management systems, achieving the adaptation and matching of the technology system and the labor social system. Different enterprises and industries differ in laborers' capabilities, organizational structures, and institutional environments. Even when the same AI technology is applied, the resulting job adjustments and employment changes will be completely different.

In conclusion, social-technical systems theory provides a systematic analytical perspective for the research in this article, showing that AI-driven labor market changes result from the combined effects of technological iteration, laborer adaptation, organizational adjustment, and institutional optimization, rather than a simple technological substitution effect. It provides macro-theoretical support for the subsequent analysis of enterprise job restructuring, laborer adaptation transformation, and institutional system adjustment.

2.2. Employment structure reconfiguration from the perspective of tasks

Social-technical systems theory explains the systematic characteristics of AI-driven labor system transformation, but it has not yet clearly defined the specific carriers and core paths through which artificial intelligence alters the labor process. The task-based analytical perspective fills this gap and serves as a key bridge connecting macro-systemic changes with micro-level employment variations. This perspective discards the traditional notion of "overall occupation replacement" and regards specific tasks as the basic micro-unit of technological impact on employment. The core logic is: AI does not directly replace or eliminate complete occupations; instead, it reconfigures task content, task allocation, and task combination methods, generating three effects: task

substitution, task enhancement, and task creation, ultimately achieving the gradual reconfiguration of the employment structure[23].

This perspective can reasonably explain why occupations with high AI exposure have not entirely disappeared. In occupations such as program development, financial analysis, administrative management, and educational services that are vulnerable to AI impact, tasks such as code generation, text writing, data statistics, and information organization, which are standardized and repetitive, can be efficiently replaced by AI, but non-standardized and highly complex tasks such as goal planning, risk assessment, complex decision-making, emotional interaction, and innovative design still rely heavily on workers. The core change after the implementation of AI is the reconfiguration of task allocation and the division of labor between humans and machines, rather than the complete disappearance of job positions.

Further examination reveals that reconfiguration at the task level will continuously optimize task structure and skill combinations within occupations. On one hand, AI replaces low-end repetitive tasks, liberating the productivity of workers and enabling them to focus on high-value and high-creativity work, achieving complementary human-machine capabilities and amplifying labor productivity[24]; on the other hand, the implementation of AI technology will give rise to new work scenarios and job tasks, including AI tool operation, data verification and review, intelligent system debugging, and AI application solution optimization, forming new growth points in labor demand.

Unlike traditional research that focuses on "job addition or reduction, or unemployment status" in a single dimension, the task perspective shifts the research core from "changes in the number of jobs" to "all-round changes in job content, labor division, and employment quality", accurately depicting the real form of employment reconfiguration in the era of artificial intelligence. It includes both the reduction of traditional tasks and the upgrading of existing job content and the emergence of new jobs, providing a basis for the subsequent dissection of specific forms of employment structure change.

2.3. Skill-biased technological change and skill demand differentiation

The iterative reconfiguration of task structure will further be transmitted to the labor market. Based on the theory of skill-biased technological change, it can clearly explain why task changes would trigger differentiation in laborers' skill demands and employment outcomes across groups. The core implication of the theory of skill-biased technological change is that technological progress does not universally empower all laborers; instead, it is significantly skill-biased, altering the marginal output and market demand of laborers at different skill levels and reshaping the skill structure and income distribution of the labor market. The bias of technological change is not fixed and is regulated by multiple factors such as labor supply, market environment, and the institutional system[25].

Artificial intelligence, as a disruptive technology, further strengthens and complicates the skill-biased characteristics of technology, promoting the dual iterative change in laborers' skill demands. On one hand, core fields such as the development of artificial intelligence algorithms, model training, algorithm optimization, and the implementation of intelligent systems have a rigid demand for highly specialized professional skills, continuously expanding the market premium for highly skilled laborers; on the other hand, for the vast majority of ordinary laborers, technological iteration does not require all to transform into technical research and development talents, but rather requires adapting to new task scenarios, mastering comprehensive adaptation skills such as AI tool application, information discrimination, data integration, human-machine collaboration, problem optimization, etc., to achieve deep coupling with the AI

task system.

This skill-biased change directly causes the differentiation of labor market groups: highly skilled laborers with solid digital literacy, complex cognitive abilities, and innovative decision-making capabilities can leverage AI tools to enhance work efficiency and fully enjoy the technological dividends; while low-skilled laborers who have long engaged in standardized and repetitive tasks, with a single skill structure and weak update and iteration capabilities, their original core skills are replaced by AI, the adaptability of their positions continues to decline, and they face greater employment adjustment pressure and unemployment risks[26].

Therefore, the skill change triggered by artificial intelligence is not a simple skill upgrade, but a differentiated reconfiguration of the adaptability and technology dividend acquisition capabilities of different skill groups. Based on this theory, this paper distinguishes low-, medium-, and high-skilled laborer groups, sorts out the typical tasks, AI intervention models, and skill demand iterative characteristics of different groups, as shown in **Table 1**, clearly presenting the differentiated change logic of the laborer skill structure driven by artificial intelligence.

Table 1 Changes in Tasks and Skill Requirements for Different Skill Levels of Workers under the Influence of Artificial Intelligence

Worker Type	Typical Work Tasks	AI Intervention Mode	Changes in Skill Demands
Lowskilled Workers	Repetitive data entry, basic operations, simple sorting, standardized services	Mainly task substitution; part of work is completed by AI and automated systems	Demand for repetitive skills declines, while digital foundational competencies and job adaptability become more critical
Mediumskilled Workers	Standardized analysis, basic documentation, routine data processing, business operations	Coexistence of task substitution and assistance; AI undertakes partial standardized tasks	Growing demand for AI tool proficiency, information judgment, data processing, and humanAI collaboration capabilities
Highskilled Workers	Algorithm R&D, model optimization, complex decisionmaking, scheme design	AI serves as an auxiliary tool to perform basic computations, with humans leading innovation and decisionmaking	Rising demand for highlevel professional competencies including algorithm R&D, complex cognition and model tuning

In conclusion, the three theories form a complete progressive analytical framework: The social-technical system theory constructs a macro analytical framework, clearly indicating that the employment effect of AI is the result of a multi-factor system reconfiguration; The task perspective focuses on the micro functional carriers, revealing the core path by which AI changes the employment structure through task reconfiguration; The skill-biased technological change theory explains the skill differentiation and group differences triggered by task changes. The three theories progress layer by layer and support each other, comprehensively explaining the complete transmission mechanism of "the embedding of artificial intelligence technology-the reconfiguration of the social-technical system-the iterative task structure-the restructuring of the employment structure-the differentiation of skill demands-the overall adjustment of the labor market", providing rigorous and systematic theoretical support for the subsequent research in the entire text.

3. The real manifestations and differentiated characteristics of the structural changes in the labor market driven by artificial intelligence

The application of artificial intelligence is transforming enterprises' production methods and labor processes. While improving the efficiency of some work and reducing some labor inputs, artificial intelligence is also beginning to affect task division and skill requirements within occupations. Compared with previous automation technologies that mainly affected repetitive manual labor,

the current influence of artificial intelligence has extended to cognitive tasks such as information processing, text generation, and data analysis. Currently, artificial intelligence has not caused large-scale job contractions at the macro level. However, from the perspective of specific occupations and laborers, job adjustments, skill updates, and income differentiation have gradually emerged.

3.1. The proportion of internal job tasks replaced has increased, and the pressure for job position adjustments has been transmitted to the workers

The direct impact of artificial intelligence on the labor market is primarily manifested in the reconfiguration of tasks within occupations. Traditional automation has mainly focused on repetitive manual labor and rule-based tasks in production, while generative artificial intelligence has expanded into knowledge-based work domains such as text processing, information retrieval, data analysis, code generation, and content creation. As a result, the scope of artificial intelligence's impact has gradually expanded from traditional manufacturing roles to fields such as finance, law, administration, marketing, and software development.

Existing research has reached a relatively consistent understanding on this point: artificial intelligence does not necessarily lead to the disappearance of entire occupations, but rather first replaces tasks within occupations that can be standardized, digitized, and programmed[27]. The International Labor Organization's 2025 task-level assessment also indicates that the impact of generative artificial intelligence should be judged within the context of the internal task structure of occupations. Most affected jobs still require human participation and are therefore more likely to undergo job transformation than to disappear entirely.

However, existing research has not reached a completely consistent conclusion on whether task substitution will translate into actual employment decline. One type of research emphasizes the role of AI in replacing automated tasks, arguing that when a profession has a high proportion of automatable tasks, the possibility of enterprises reducing the demand for related positions will increase; another type of research finds that enterprises may use AI to increase the productivity of workers and redistribute the replaced tasks to other job contents, thus the substitution of tasks does not necessarily translate into unemployment[28].

Recent data from the US labor market provide more specific evidence. Based on large-scale wage data, it was found that after the widespread adoption of generative AI, early-career workers in AI-high-exposure occupations experienced a relative decrease in employment of approximately 13%, while more experienced workers had relatively stable employment performance. The study also found that the employment decline was mainly concentrated in occupations where AI is more likely to exert an automation effect, rather than occupations that mainly enhance workers' capabilities[29].

This change in developed countries is related to their industrial structure. Economies in Europe and the United States have a higher proportion of knowledge-intensive and digital occupations, and artificial intelligence can directly enter many office and professional service tasks, resulting in relatively high task exposure. The potential impact of generative AI on the high-skilled, urban labor market is expanding [30]. However, the situation is different in developing countries. Economies with a high proportion of agriculture, transportation, retail, and informal employment have a relatively lower overall occupational exposure level. But this does not mean that developing countries are less affected. Insufficient basic digital infrastructure, enterprises' adoption of AI capabilities, workers' digital skills, and workers' adoption of AI capabilities

are all likely to limit the productivity gains brought by AI and create new technological gaps. Research by the International Labor Organization and the World Bank on Latin America found that digital infrastructure and existing inequality may limit the positive impact of generative AI on employment and productivity.

Therefore, the job adjustment brought about by artificial intelligence cannot be simply understood as "the disappearance of occupations". The more obvious change at present is the reconfiguration of internal tasks within occupations, and whether this ultimately leads to a decrease in employment is closely related to occupational structure, how enterprises adopt AI, and workers' experience.

3.2. The scale of new AI-related positions is limited, and the employment compensation effect is constrained

While artificial intelligence replaces some tasks, it also creates new job content and position demands, such as AI system development, data management, model deployment, AI application services, and technical maintenance. This employment compensation effect is an important component in explaining the impact of artificial intelligence on employment[31].

Existing research offers two different judgments on this point. Some studies believe that after technological progress increases productivity, it can expand the supply of products and services, and the decrease in enterprise costs may bring new production activities and employment demands; another group of studies believe that the new positions and the replaced positions have significant differences in skill requirements, so even if the number of new positions increases, it may not directly absorb the original workers.

This issue is more obvious in knowledge-intensive industries in developed countries. AI-related positions usually require higher digital skills, professional knowledge, and technical capabilities, and the entry threshold is higher than that of the standardized task positions being replaced. Therefore, the growth of AI new positions cannot automatically complete the reconfiguration of employment in the labor market. At the same time, some enterprises have begun to reduce demand for basic knowledge-based positions, which may also narrow the channels for young workers to enter professional careers[32]. Employment of early-career workers in AI-related occupations has declined, while experienced workers have not seen the same degree of decline. This phenomenon indicates that the problems brought by artificial intelligence are not only "a decrease in the number of positions", but also changes in the entry channels of occupations[33].

The actual conditions for achieving employment compensation in developing countries are more complex. The range of employment affected by the potential impact of artificial intelligence varies significantly among countries with different income levels. The proportion of occupations directly exposed to automation shock in low-income economies is relatively limited, but the reality is that constraints such as the lack of digital infrastructure, insufficient enterprise technology transformation capabilities, and the shortage of AI-related professional talents will inhibit the cultivation of new job positions and hinder the diffusion of technological dividends to the entire society. Thus, when judging whether the new positions created by artificial intelligence can offset the employment pressure caused by the replacement of traditional tasks, it is not only necessary to focus on the quantity and scale of new positions, but also to further consider multiple real dimensions such as the skill compatibility level between new positions and replaced positions, the spatial distribution pattern, and the entry threshold of positions.

3.3. The pace of skill iteration has accelerated, and workers are facing pressure to switch skills

The impact of artificial intelligence on the labor market is further manifested in changes in skill requirements. Existing studies generally agree that in the AI era, not only do a few algorithm engineers need to update their skills, but also a large number of ordinary workers need to adjust their original job capabilities. However, there is no completely consistent judgment on "which skills have increased and which have decreased".

On one hand, the demand for AI-related professional skills is growing rapidly. Research on the recruitment market shows that positions requiring AI skills usually have a higher wage premium. British recruitment data research also found that the wage premium of AI skills in related positions can reach a relatively high level. On the other hand, the vast majority of workers do not need to become AI researchers. The OECD research indicates that most workers affected by AI do not need to master professional AI skills such as machine learning and natural language processing. In the future, most workers will need digital skills, data analysis and interpretation abilities, and management, problem-solving, creativity, and innovation abilities. This indicates that skill changes are not simply a "low-skilled to high-skilled transfer", but rather an adjustment of the skill combination within the occupation. Some standardized information processing skills have become less important, while the importance of data analysis, AI tool application, judgment, and complex problem-solving abilities has increased.

In developed countries, the main problem is the accelerated pace of skill updates: enterprises can adopt AI tools relatively quickly, but workers' skills often take longer to update. Whether enterprise training and education systems can keep up with technological change is a key factor. The problems in developing countries are more complex. Some workers not only lack AI-related skills, but also lack basic digital infrastructure and training opportunities. Thus, AI may simultaneously create "technical skills gap" and "digital infrastructure gap"[34]. If educational and training resources cannot be expanded simultaneously, the productivity gains brought by AI may mainly concentrate among workers with digital capabilities and in enterprises. Therefore, skill differentiation does not simply manifest as "an increase in AI professionals and a decrease in ordinary workers", but more reflects the differences in workers' ability to utilize AI and the differences in the opportunities for skill update among different groups.

3.4. Uneven distribution of technological dividends, and intensified divergence in employment benefits for the labor force

After artificial intelligence enhances productivity, how the technological gains are distributed among enterprises, capital, and laborers is another important issue in labor market research. Existing studies have paid significant attention to whether AI can widen the wage gap. On one hand, workers with AI-related skills typically have higher wage returns. Recruitment data research has found that AI skills can create a significant wage premium. On the other hand, AI may also boost wages by improving the work efficiency of some ordinary workers. Therefore, technology does not necessarily only benefit highly skilled workers[35].

Recent research in the United States provides an important observation window: employment among 22-25-year-olds in occupations with high exposure to AI has declined significantly, while more experienced workers have relatively stable employment. This indicates that technological gains may be related to accumulated experience, task structure, and the way AI is used by the laborers. Differences between countries are also obvious. High-income countries have more complete digital infrastructure and higher adoption rates of AI in enterprises and workers can more directly access AI tools, but they also face a higher level of occupational exposure. Low-income countries have a lower proportion

of occupations directly replaced by AI, but may not be able to fully obtain the productivity gains brought by AI due to insufficient infrastructure and skills.

Thus, artificial intelligence may create a differentiation pattern that is not exactly the same as traditional technological change: some workers increase their productivity through AI and earn higher returns, while others face employment pressure because their tasks are replaced or they lack opportunities to update their skills[36]. Whether technological gains can lead to broader benefits for the labor force depends on whether enterprises, education systems, and employment policies can be adjusted simultaneously.

4. The adjustment path for the structural changes in the labor market driven by artificial intelligence

The changes in the labor market brought about by artificial intelligence cannot be solely accomplished by individual workers. The previous analysis indicates that artificial intelligence has altered task division within occupations and changed enterprises' requirements for workers' skills. The conditions for different workers to obtain technological benefits vary. Adjusting the labor market requires the participation of workers, enterprises, educational institutions, and the government. It is necessary to reduce unnecessary employment impacts during the application of technology and provide conditions for workers to undergo skill transformation and career mobility. Current research mainly discusses labor market adaptation in the context of artificial intelligence from aspects such as skill updating, enterprise organizational adjustment, education system reform, and employment policy support.

4.1. Strengthening the update of workers' skills and reducing the cost of career transitions

Existing research generally holds that skill updating is an important condition for workers to adapt to AI, but training content cannot simply be equated with AI professional education. Most workers affected by AI do not need to master advanced AI skills such as model development, but need to improve digital skills, data analysis and interpretation abilities, as well as strengthen problem-solving, creativity, and innovation capabilities[37]. Workers are the most directly affected by AI entering the workplace. Facing changes in job tasks, workers need to adjust their skill structure according to the characteristics of their occupations and cannot rely solely on their original work experience to maintain their employment competitiveness. For most ordinary workers, skill updates focus not on mastering the underlying research and development technologies of AI, but on improving abilities such as AI tool usage, information recognition, result judgment, and human-machine collaboration, and on combining AI application capabilities with their original professional skills.

On the one hand, differentiated training content can be established based on the degree of AI impact on different occupations. For knowledge-intensive occupations such as finance, accounting, administration, and marketing, the focus can be on strengthening AI-assisted analysis, text generation, data processing, and result verification capabilities; for positions such as manufacturing, logistics, and customer service, training can be centered around intelligent equipment operation, digital work processes, and human-machine collaboration. The closer the training content is to actual work tasks, the lower the cost for workers to complete the skill transition.

On the other hand, it is necessary to expand opportunities for workers to pursue further education. Internal training within enterprises, training at vocational colleges, and public employment training can complement each other, providing workers with more flexible learning methods. For workers already affected by job adjustments, vocational skills training, employment guidance, and

job recommendations can help them enter similar occupations and avoid losing market value due to single-job skills and long-term withdrawal from the labor market[38].

For young workers, attention should also be paid to career-entry issues in the AI era. If many junior positions are reduced, young people may lack opportunities to gain work experience through entry-level roles. Therefore, in the skill-training process, not only should high-level AI skills be emphasized, but practical work abilities, professional knowledge, and complex problem-solving abilities should also be strengthened, so young workers can complete the transition from learning to employment in an AI-assisted environment.

4.2. Promote enterprises to optimize job allocation and establish a training mechanism that matches technological application

Enterprises directly implement AI applications and adjust jobs. When introducing AI, enterprises should avoid equating technology adoption with personnel reduction. Instead, they should rearrange the division of labor between workers and AI based on specific tasks. For repetitive tasks that AI can handle, technology can improve efficiency, while workers can be redirected to tasks AI cannot fully replace, such as customer service, complex decision-making, quality control, and innovation.

Enterprises also need to promote technological transformation and employee training simultaneously. To retain employees' industry experience and organizational knowledge, enterprises can support internal job transfers. Before introducing AI, enterprises can analyze job tasks, clearly define which tasks will be handled by AI and which by employees, and design training content based on the new job requirements. For positions that are significantly affected, priority should be given to providing re-employment training rather than directly resolving personnel adjustments caused by technological application through layoffs.

Internal enterprises also need to establish a continuous skills update mechanism. For example, different levels of AI training courses can be set based on job changes, and the use of AI tools can be incorporated into employees' career development and performance evaluation systems. Employees who can improve work efficiency through AI should be given corresponding career development opportunities. For employees who need retraining, job matching and training support should be provided. This can not only reduce the cost of rehiring and training employees but also reduce the sudden impact of technological application on workers[39].

In addition, enterprises that pursue productivity improvement through AI should also pay attention to how technological benefits are distributed between the enterprise and workers. After AI improves labor productivity, workers can share some of the technological benefits through wage incentives, job promotions, and investment in training, preventing technological progress from manifesting only as a decrease in labor costs.

4.3. Adjust the educational training methods to narrow the gap between the supply of talents and the demand for positions

The skills changes brought about by artificial intelligence occur not only within enterprises but also pose new requirements for the existing education system. Universities, vocational colleges, and training institutions need to adjust talent-cultivation content in line with labor-market changes, reducing the disconnect between educational content and actual job requirements.

Universities can integrate AI applications into professional education instead of simply setting up standalone AI courses. Different majors can increase corresponding AI application training based on their own employment directions. For example, economic management majors can strengthen data analysis,

intelligent decision-making, and AI-assisted research capabilities; news and communication majors can strengthen generative AI application and information verification capabilities; and law and education majors can carry out practical training centered around AI-assisted business. This way, it can retain the foundation of professional education while improving graduates' adaptability when entering AI-assisted work environments[40].

Vocational education should place more emphasis on practicality. For occupations significantly affected by artificial intelligence and automation, professional courses and training content can be adjusted to meet industrial demands, and vocational skills training can include digital skills, human-machine collaboration, and intelligent equipment application[41]. Vocational education and enterprises can establish a more stable cooperative relationship, allowing students to be exposed to real AI application scenarios during the learning stage and reducing the post-graduation job adaptation costs.

Continuing education also needs to expand its coverage. The skills changes brought about by artificial intelligence will affect not only young people about to enter the labor market, but also many employed workers who need to update their skills[42]. Therefore, educational institutions can collaborate with enterprises, industry associations, and public employment service institutions to provide short-term, modular skills courses, allowing workers to improve their skills in their spare time.

4.4. Improve employment policies and public services to mitigate the employment impact caused by technological transformation

When artificial intelligence leads to job contraction, public employment services need to shift from "helping people find jobs after unemployment" to "providing support for job transitions before changes occur". Job adjustments driven by artificial intelligence follow certain market laws, but differences in educational background, skill level, and training resources among workers mean some groups may struggle to complete career transitions based on their own abilities[43]. Therefore, the government needs to further improve public employment services and incorporate the job changes brought about by artificial intelligence into the adjustment scope of employment policies and vocational training policies.

Firstly, it is possible to strengthen employment monitoring under the influence of artificial intelligence. The government can establish an employment information monitoring mechanism based on changes in industry, occupation, and skill requirements, promptly grasp which occupations are significantly affected by technology and which job demands are increasing, and provide information on career changes and skill requirements through public employment service platforms to workers. This can enable workers to receive signals for career transitions before significant job reductions occur, reducing the possibility of passive unemployment [44].

Secondly, it can expand vocational training support for workers undergoing technological transformation. For workers affected by AI substitution, training subsidies, vocational skills improvement programs, and employment services can reduce the cost of skill transitions. Training policies should not only focus on re-employment after unemployment but also cover workers who remain employed but whose job tasks have significantly changed, allowing early implementation of skill updates.

Thirdly, it can improve cross-regional and cross-industry employment services. New jobs generated by artificial intelligence may differ from traditional jobs in regional distribution, industry demand, and skill requirements. Relying solely on internal employment transitions within the original industry cannot solve

all problems. Public employment services can provide career recommendations, skill certifications, training resources, and job matching services to help workers move from contracting industries to new employment sectors[45].

Finally, it is necessary to improve the social security and employment support mechanisms against the background of technological change. For workers who cannot complete career transitions in the short term, unemployment benefits, employment assistance, and temporary training support can be provided to reduce the living pressure during the transition period. The policy focus is not to prevent enterprises from using artificial intelligence, but to encourage technological innovation while reducing the risks workers bear during the transition.

5. Conclusion

Artificial intelligence is transforming the operating mode of the labor market, but this change cannot be attributed solely to "machines replacing labor". Existing research shows that artificial intelligence first enters specific tasks within occupations and changes the division of labor between workers and technology through task substitution, task enhancement, and the creation of new tasks. Changes in task structure further affect skill requirements, resulting in differences in employment opportunities, skill updates, and technological benefits among different workers.

The paths of change in different economies are not entirely the same. Developed countries have a higher proportion of knowledge-intensive occupations, so the exposure to AI is higher, and the adjustment of tasks within occupations and changes in primary positions are more obvious; developing countries have a relatively lower overall exposure level, but the lack of digital infrastructure, skill supply, and enterprises' technology adoption capabilities may limit technological benefits. The ILO's global assessment shows that about one quarter of workers are in occupations with some level of generative AI exposure, while the highest exposure level accounts for only 3.3% of global employment. This result also indicates that current AI is more likely to drive changes in job content than to directly cause large-scale job disappearance. Therefore, adjusting the labor market in the context of artificial intelligence requires attention to both technology application and updating workers' capabilities. Enterprises need to reconfigure work tasks and increase employee training, the education system needs to shorten the distance between talent cultivation and job requirements, workers need to improve their application of AI tools and career transition capabilities, and the government needs to reduce the cost of technological transformation through public employment services, vocational training, and social security.

Due to constraints of data availability and research scope, there are still several limitations of this research. First, this article mainly analyzes occupations and theoretical mechanisms at the macro level and has not yet conducted empirical tests using enterprise micro-data and individual tracking data. The micro-mechanisms of actual adoption of artificial intelligence technologies, the process of enterprise task reconfiguration, and the differences in individual skill adaptation are not depicted in sufficient detail. Second, because generative artificial intelligence is relatively new, the research in this article still focuses on short-term structural changes and does not continuously track and verify the long-term dynamic effects of artificial intelligence on employment mobility, long-term wage differentiation, and generational changes in occupations. Third, in its cross-national comparative analysis, the article compares heterogeneity only at the macro level, lacks systematic empirical research on micro differences among developing-country enterprises, industries, and workers, and insufficiently explores the boundary conditions of AI employment effects under different institutional environments and digital foundations. Fourth, this article

mainly discusses task reconfiguration, skill differentiation, and changes in the employment structure. It has not quantitatively analyzed the distribution ratios and transmission differences of productivity dividends from AI production across capital, enterprises, and workers, and the endogenous mechanism of income differentiation still needs deeper analysis. Fifth, this article finds that substituting AI for primary positions may compress career entry channels for young workers, but it has not conducted specialized research on employment access difficulties and career growth differences among youth, and there is still room to expand the discussion of group heterogeneity.

Based on this article's research process and the limitations of existing research, combined with current gaps in AI research in the labor market, future research can deepen and expand related studies from five dimensions to address deficiencies in the existing research system. First, distinguish between potential AI exposure and the actual effects of technology implementation. Currently, most academic studies rely on the index of AI exposure at the occupational level to measure the impact of technology on the job market, which can only measure the potential AI risks at the occupational level and cannot accurately depict the actual degree of AI technology adoption by enterprises, the actual application scenarios, and the real impact on the labor market. This creates a measurement deviation: "AI exposure not equal to actual employment impact." Future research needs to construct a hierarchical indicator system, strictly distinguish the three levels of potential occupational exposure, actual technology adoption by enterprises, and the actual employment effect after implementation, accurately separate the expected impact of technology from the actual reconfiguration effect, and improve the accuracy of empirical research.

Second, supplement empirical evidence for long-term causal identification. Generative artificial intelligence is a disruptive technology that has been widely implemented in recent years. Existing studies mostly rely on short-term employment data, questionnaire survey data, and static exposure indices for cross-sectional analysis, making it difficult to identify the long-term, lagging impact of technology iterations on the labor market. The reshaping effects of artificial intelligence on employment scale, wage level, career mobility, and job iteration are continuous, lagging, and dynamic. Short-term data cannot fully capture market adjustment dynamics. Therefore, subsequent research should rely on long-term panel tracking data to clarify the long-term causal mechanism between AI technology iterations and labor market changes.

Third, focus on the differentiated impact on young workers' career entry channels. Existing studies mostly focus on the substitution and optimization effects of artificial intelligence on overall employment structure and job numbers, and pay less attention to structural changes in labor market access. This article finds that artificial intelligence has a significant substitution effect on industry primary basic positions, which are core entry points for young workers to accumulate work experience and enter the career track. AI's squeeze on primary positions not only changes the employment quantity structure but also compresses career growth channels for young people and raises employment barriers. This differentiated predicament of this specific group is a direction that future research needs to focus on in depth.

Fourth, deepen the research on the distribution mechanism of AI technology dividends. Artificial intelligence optimizes production models and enhances labor productivity through task reconfiguration. However, the academic community has not yet clarified the distribution pattern of the technological productivity dividend. The question remains whether the added value generated by technological progress flows more to capital to increase capital returns, empowers workers to achieve wage premium growth, or whether both capital and labor benefit

and grow in a coordinated manner. The influencing factors and distribution logic of these effects still lack systematic empirical support. In the future, it is necessary to explore the "artificial intelligence-production efficiency-wage income" transmission path and clarify the mechanisms by which different entities acquire the technology dividend.

Fifth, improve the micro-empirical evidence base for developing countries. Currently, most empirical studies and theoretical tests on the employment effects of AI are based on developed countries and mature market economies. The corresponding institutional environment, industrial structure, skill supply, and technological application scenarios are more mature, and the research conclusions have strong scenario limitations. In contrast, developing countries have weak digital infrastructure, significant skill stratification among workers, and uneven adoption capabilities of enterprises. The labor market effects of AI in developing countries show clear differentiated characteristics. Future research should rely on micro data from enterprises and micro surveys of workers in developing countries and emerging economies to conduct cross-national heterogeneity comparisons, filling gaps in the scenarios and samples of existing research.

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