

# The Economic Impact of Generative Artificial Intelligence: A Review of Research from the Perspective of Task Content

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## Abstract

The rapid iterative development of generative artificial intelligence technology is fundamentally reshaping production methods and labor forms. Its ability to penetrate non-routine cognitive tasks breaks the impact boundary of traditional automation technologies, and also promotes task content analysis method to become the mainstream research paradigm in this field. This paper systematically sorts out the theoretical evolution and research progress of the economic impact of generative AI from the perspective of task content. From the two dimensions of industrial development and labor market, it integrates the research results of core topics such as enterprise adoption, productivity effect, market structure, labor complementarity and substitution, and changes in employment structure. It focuses on clarifying the sources of divergence and applicable boundaries of different research conclusions. Studies show that existing literature has formed a basic consensus that generative AI exerts impact mainly through the reconstruction of intra-occupational tasks. However, there are still significant divergences in the total employment effect, the implementation degree of productivity gains, and the mechanism of cross-country heterogeneity. The main limitations of current research in this field include the short research time span, lack of evidence from developing economies, and insufficient research on long-term dynamic mechanisms. The contribution of this paper is to restore the seemingly divergent literature conclusions to differences in methodological premises with a unified three-effect coordinate, and put forward corresponding testable designs for each type of research gap. Future research needs to be further deepened around the two core dimensions of industry and labor market, improve localized measurement systems, and expand long-term dynamic analysis.

## Keywords

generative artificial intelligence, task-content analysis method, substitution effect, labor market, cross-country heterogeneity

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## 1. Introduction

### 1.1 Research Background and Problem Statement

The technological breakthrough of Generative Artificial Intelligence (GenAI) centered on large language models is triggering a new round of technological changes. Different from the previous rounds of automation

that mainly replaced routine manual and routine cognitive tasks, generative AI has the capabilities of text generation, logical reasoning and multimodal content creation, which can directly intervene in unconventional cognitive work scenarios and break the classic judgment that high-skilled positions are not impacted by automation [1,2]. The leap of this technical feature reduces the explanatory power of the classic skill-biased technological progress framework. Academia needs to go deep into the task content level to accurately capture the real mechanism and heterogeneous performance of technological shocks.

Despite the rapid accumulation of research, the existing literature still has a pervasive gap: the economic impact of generative AI has not been fully solved in the two aspects of causal identification at the task granularity and external validity in cross-national contexts. The former makes the estimation of the total employment effect fluctuate between technical feasibility and economic feasibility, and the latter makes the conclusions based on developed economies difficult to extrapolate directly. The literature review of this paper is organized around these two gaps, and corresponding testable research directions are proposed in the sixth part.

At the level of industrial practice, the adoption process of generative AI by enterprises continues to accelerate, and technology diffusion has extended from the technology industry to finance, manufacturing, service and other fields [3]. At the same time, the differentiation of the global labor market has gradually appeared, and the gap in digital capabilities continues to widen. However, academia has not formed a unified conclusion on whether generative AI presents a substitution effect or a complementary effect on labor. Some studies draw pessimistic conclusions about the large-scale employment substitution based on the calculation of occupational exposure. Other studies find significant productivity empowerment effects based on micro experiments and administrative data. The core source of divergence lies in the differences in research granularity and the insufficient decomposition of mechanisms at the task level [1,4].

## **1.2 Scope and Structural Organization of the Review**

Taking the Task-based Approach as the core clue, this paper systematically sorts out the theoretical and empirical literature on the economic impact of generative AI. The full text is divided into six parts. The second part reviews the theoretical evolution of task-biased technological progress, sorts out the core measurement methods of occupational exposure and skill structure in the generative AI era, and builds the analytical foundation of the full text. Starting from the dimension of industrial development, the third part analyzes the impact and research progress of generative AI in three aspects: enterprise adoption, productivity empowerment and market structure. Focusing on the labor market, the fourth part sorts out the relevant research conclusions on task reconstruction, skill changes and employment structure evolution from the dual mechanisms of complementary effect and substitution effect. The fifth part discusses the heterogeneous impacts of economies at different development levels, and clarifies the cross-national applicability deviation of traditional exposure indicators. The sixth part summarizes the overall limitations of existing studies, and prospects the future research directions around the two core dimensions of industry and labor market.

The literature basis of this paper covers three categories. The first is the classic theoretical literature on task-biased technological progress, which forms the theoretical cornerstone of the analysis. The second is the cutting-edge research on the economic impact of generative AI, including micro-scenario analysis, administrative data research and cross-national comparative research. The third is special reports issued by authoritative institutions such as the World Bank and the International Labour Organization, which provide macro evidence at the global level.

Compared with the existing review literature, this paper has two marginal contributions. First, this paper unifies the scattered evidence in the two fields of industry and labor under the three-effect coordinate of substitution, productivity and new task creation. It makes the literature divergences on issues such as total employment volume and wage distribution be reduced to differences in methodological premises rather than conflicts of empirical facts. Second, in terms of gap analysis, this paper does not only list the limitations, but also gives corresponding testable research directions for each type of gap. Among them, the adjudication design of “intra-task performance and inter-job wage simultaneous observation” can be directly implemented.

## 2. Theoretical Foundations and Measurement Methods

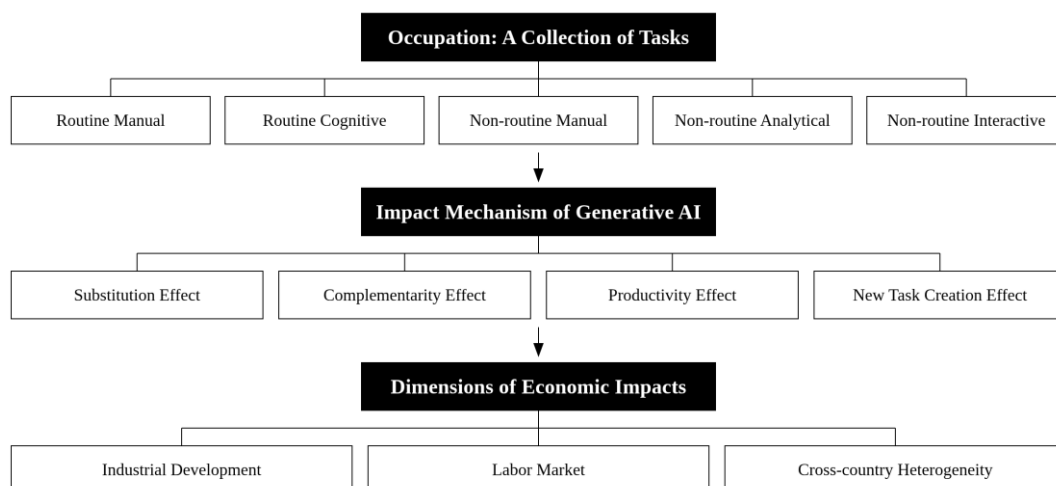
### 2.1 The Theoretical Framework of Task-Biased Technological Progress

The core logic of the task-based approach is to regard occupations as a set of tasks. The impact of technological progress on labor depends on the technical feasibility and economic feasibility of specific tasks, rather than the overall attribute characteristics of occupations. This analytical framework was first systematically proposed by Autor et al. [5]. It divides job tasks into five categories: routine manual, routine cognitive, non-routine manual, non-routine analytical, and non-routine interactive. It points out that the progress of computer technology at the end of the 20th century mainly replaced routine tasks, forming a U-shaped structure of employment polarization. Autor [6] further pointed out that automation rarely completely replaces a certain occupation. Instead, it reshapes the task composition within the occupation and enables workers to switch to complementary tasks with comparative advantages. This judgment constitutes the direct theoretical source of the task reconstruction concept.

On this basis, Acemoglu and Restrepo [7] constructed a more generalized task model, decomposing the impact of technological progress into three types: substitution effect, productivity effect and new task creation effect. Their subsequent research further demonstrated that the dynamic balance between task automation and new task creation plays a decisive role in long-term employment and wage growth [8], and pointed out that the final impact of technological progress on employment depends on the relative strength of the three types of effects. This theoretical framework provides a benchmark paradigm for analyzing the economic impact of generative AI. However, the traditional task classification does not cover the penetration ability of generative AI in non-routine cognitive tasks, so it is necessary to update task boundaries and measurement methods [1].

In summary, the task-based approach provides a unified analytical coordinate for the economic impact of generative AI. Following the decomposition of Acemoglu and Restrepo [7], any impact can be ultimately decomposed into task-level substitution effect, productivity effect and new task creation effect. Among them, the productivity effect is specifically manifested as human-machine complementarity in the labor market. Therefore, this paper adopts the term “productivity effect” in the industrial dimension and “complementary effect” in the labor market dimension, and the two refer to the same mechanism. Given the insufficient empirical accumulation of the new task creation effect, this paper takes substitution effect and productivity effect as the main evidence body, and incorporates the creation effect as a dynamic balance item into the discussion. The third and fourth parts of this paper expand along this coordinate. The third part focuses on the implementation forms of the three effects in enterprise adoption, productivity and market structure from the industrial dimension. The fourth part focuses on the specific manifestations of the three effects in job tasks, skill requirements and wage distribution from the labor market dimension. The two types of evidence jointly answer the same question: at the task granularity, what exactly does generative AI substitute, complement and create, and how do these task-level shocks transmit to the economic outcomes of enterprises and labor markets through task reconstruction. The overall analytical framework is shown in Figure 1.

Figure 1: Generative from the perspective of task content AI Economic Impact Analysis Framework



## 2.2 Generative AI Measurement System for Occupational Exposure Levels

After the emergence of generative AI, academia has constructed multiple sets of occupational exposure indicators based on different task databases and capability evaluation methods, which can be mainly divided into two categories.

The first category is the top-down measurement based on occupational task databases. Relying on the O\*NET occupational task database and combining the capability boundary evaluation of large language models, Eloundou et al. [2] measured the GPT technology exposure level of more than 900 occupations in the United States. They found that at least 10% of tasks in about 80% of American labor positions are affected by generative AI, and the proportion of affected tasks in about 19% of positions exceeds 50%. Based on O\*NET data as well, Felten et al. [9] constructed exposure indicators from the dimension of language capability requirements and obtained similar distribution characteristics. Yu et al. [3] extended this method to the enterprise level and constructed AI adoption intensity indicators based on corporate annual report texts.

The second category is the bottom-up measurement based on expert evaluation or work scenarios. The International Labour Organization [4] calibrated exposure indicators across countries combining the occupational task characteristics of different economies. It is found that the direct application of American O\*NET data will significantly overestimate the actual exposure level of developing economies. German scholars built a measurement system more suitable for the European labor market relying on the local BERUFENET occupational database [10].

Existing measurement methods have two major limitations. First, most indicators are based on occupational task data of developed economies and lack cross-national applicability. Second, static exposure only reflects technical feasibility, ignoring practical factors such as economic costs, organizational adaptation and regulatory constraints, so it often overestimates the actual impact intensity [1,11].

## 2.3 Measurement of Vocational Skills from a Task-Based Perspective

Corresponding to task measurement, academia usually divides occupational skills into three levels to match the skill bias of AI shocks. The first is manual skills, which refer to skills relying on physical operation and on-site execution. The second is general digital skills, which include basic computer operation and data processing skills. The third is cutting-edge technical skills, which are intelligent technology-related skills such as AI development, model application and human-machine collaboration [10].

Genz et al. [10] constructed the Occupational Technical Skill Share (OTSS) indicator based on Germany's BERUFENET database. It adopts text recognition methods to quantify the proportion structure of the three types of skills in each occupation, providing a standardized measurement tool for analyzing changes in skill structure. The advantage of this indicator is that it can dynamically capture changes in occupational connotation instead of relying on static occupational classification.

## 3. Generative AI Impact on Industrial Development

### 3.1 Enterprise AI the Diffusion Characteristics of Adoption and Industry Heterogeneity

From the perspective of the industrial implementation forms of substitution effect and complementary effect, the industrial penetration of generative AI is not evenly distributed, but presents obvious gradient characteristics. Its diffusion speed and depth depend on industrial digital foundation, task attributes and enterprise scale.

At the enterprise level, scale and technical foundation are the core factors determining the adoption depth. Based on the SEC 10-K annual report texts, Yu et al. [3] constructed a five-level AI adoption rating system. Taking S&P 500 enterprises as research samples, the study finds that 11% of enterprises have realized the in-depth embedding of AI in core business processes and 10% have reached the production-level application level by 2025. The overall in-depth adoption rate has increased more than three times compared with 2022, but the growth is highly concentrated in leading enterprises. The technology industry contributes about two-thirds of in-depth integration cases and serves as the core carrier for AI implementation. This finding is consistent with

the classic rule of enterprise digital transformation, that technology adoption has significant scale preference and path dependence characteristics.

At the industrial level, the integration path shows clear gradient differentiation [3,12]. In knowledge-intensive industries such as information transmission and finance, AI can be deeply embedded in core business processes, such as financial risk control modeling, code generation and content creation, which can be directly transformed into productivity improvement and product innovation, forming the core scenario for AI value release. In service industries including wholesale and retail, medical care and education, AI applications are concentrated in auxiliary links such as customer service and operation optimization, with cost reduction and efficiency improvement as the main empowerment path and a medium adoption speed. In physical industries such as manufacturing and agriculture, current AI applications are mostly limited to partial links such as R&D, design and supply chain scheduling. The penetration rate of the entire industrial chain is relatively low, and the cycle of technological empowerment is longer.

### **3.2 Productivity-Enabling Mechanisms and Corporate Profitability Responses J Type Curve Hypothesis**

From the micro mechanism of productivity effect, existing studies indicate that generative AI promotes industrial efficiency upgrading mainly through three paths. First, it replaces repetitive information processing tasks and reduces the input cost of routine cognitive labor. Second, it accelerates cross-domain knowledge integration and shortens the cycle of innovative research and development. Third, it assists complex decision-making processes and improves the accuracy of management and operation [1,4]. The joint effect of the three mechanisms ultimately reflects the potential improvement of total factor productivity.

Digital transformation studies have found a J-shaped pattern in which corporate profits decline first and then rise. Whether the adoption of generative AI replicates this dynamic currently only has indirect evidence. Mechanically, in the initial stage of technology introduction, enterprises need to bear high fixed costs such as computing power procurement, system docking, personnel training and organizational process adjustment. Meanwhile, AI applications have not penetrated core business links, and the release of efficiency gains is limited, so profit margins may face short-term pressure. As applications expand from pilot tests to in-depth embedding in the whole process and supporting organizational adjustments are gradually completed, productivity gains may appear on a large scale. The cross-sectional evidence of S&P 500 enterprises studied by Yu et al. [3] is consistent with the above inference. Enterprises in the AI exploration and pilot stage show no significant improvement in profit margins, while enterprises with in-depth integration of AI in all businesses have significantly higher profit levels. However, this evidence comes from horizontal comparisons among enterprises and cannot verify the time path of the rising-then-falling profit margin of a single enterprise. The J-shaped curve remains an untested hypothesis in the context of generative AI.

However, at the macro level, the actual implementation degree of industry-wide productivity gains is still controversial. Some industrial studies show that efficiency improvement in knowledge-intensive industries has initially appeared, and per capita output has increased significantly in fields such as software development, legal services and content creation. Nevertheless, industry-wide productivity data has not shown an obvious inflection point, indicating the existence of the AI productivity paradox. The reasons for this phenomenon include that most enterprises are still in the technology exploration stage with AI applications failing to cover core processes, supporting adjustments such as organizational reform and skill training lag behind, and the existing statistical system cannot fully measure product quality improvement and category innovation brought by AI [11].

In summary, enterprise-level evidence shows that the productivity effect is not automatically generated. Its realization relies on organizational complementary inputs, its benefits are tilted toward leading enterprises and cause productivity differentiation, and relevant measurement results diverge due to different indicator calibers. This means that the transformation of task-level productivity effects into corporate performance is moderated by two variables: scale and organizational conditions.

### **3.3 Evolution of Market Structure and Changes in the Competitive Landscape**

The impact of generative AI on the competitive pattern is essentially the result of the transmission of task-level substitution effects and new task creation effects to the market level. The substitution effect greatly

reduces the execution cost of routine tasks, but the benefits are mainly captured by leading enterprises with in-depth integration capabilities. The new task creation effect gives rise to new markets such as basic model research and development and computing power supply. The high fixed cost and low marginal cost characteristics of these markets are naturally conducive to scale leaders. The combined effect of the two types of effects promotes the differentiation of digital capabilities within the industry and the market concentration trend on the supply side.

First is the productivity differentiation within the industry. Leading enterprises achieve in-depth AI integration and value capture by virtue of their advantages in computing power, data and talents. Limited by costs and technical capabilities, small and medium-sized enterprises mostly only carry out shallow tool invocation, and it is difficult to form systematic efficiency improvements [3,12]. The essence of this differentiation is the embodiment of the scale economic characteristics of generative AI. The research and development of basic models and the construction of computing power infrastructure have extremely high fixed costs and extremely low marginal use costs, enabling scale advantages to be quickly converted into technical advantages and forming a cumulative cycle in which benefits converge to superior enterprises. The pre-resource barriers for technology adoption aggravate productivity differentiation in the industry. Only enterprises with a certain digital foundation can fully release AI potential.

Second is the market concentration risk on the supply side. Capital investment in the field of AI infrastructure is highly concentrated. Leading technology enterprises occupy most of the AI-related capital expenditures and dominate the basic model and computing power supply market. Most small and medium-sized enterprises rely on third-party API services to obtain AI capabilities, with weak technical autonomy and limited bargaining power [3,12]. Leading enterprises can continuously improve model performance by virtue of data scale advantages, thereby gathering more users and data, forming a positive cycle to consolidate competitive barriers. The opacity of algorithms and the closure of technical ecosystems may lead to covert unfair competition behaviors such as algorithmic collusion and differentiated pricing. In addition, the substantial decline in content generation costs may cause excess low-quality supply, intensify industrial homogeneous competition, and further weaken the incentives for market entities to carry out original innovation.

#### **4. Generative AI the Mechanism of Impact on the Labor Market**

The impact of generative AI on the economic system will eventually be transmitted to the labor market, changing the task content, skill requirements and employment structure of labor. Compared with the macro impacts at the industrial level, changes in the labor market are more directly related to individual welfare and income distribution, and are also the research field where the task content analysis method is most intensively applied at present. Based on the task content analysis framework, this part systematically sorts out the complementary effect and substitution effect of generative AI on the labor market from the two dimensions of task reconstruction and inter-post demand changes, and integrates two types of evidence of micro-scenario research and macro-data research.

##### **4.1 Complementary Effects: Productivity Gains and Skill Upgrading in Human–Machine Collaboration**

###### **4.1.1 Efficiency Gains and Capability Convergence at the Micro-Task Level**

From the intra-task evidence of complementary effects, micro-scenario research is the core means to identify the efficiency effect of human-machine collaboration. Randomized controlled experiments on professional writing tasks show that the use of generative AI tools can reduce workers' task time consumption by an average of 37% and improve output quality by 0.45 standard deviations [13]. This efficiency improvement mainly stems from the time compression in the first draft writing stage. Workers are able to reallocate more time to creative conception, content polishing and quality control, which fundamentally changes the intra-job task structure. Subsequent studies in fields such as translation, programming and data analysis have also reported similar efficiency gains [1]. Field experiments in call center scenarios show that generative AI assistance can increase the productivity of new employees by 34% and significantly improve overall call efficiency [14].

From the perspective of heterogeneous evidence, the productivity improvement effect of generative AI presents significant ability convergence characteristics. Workers with low initial abilities obtain a significantly higher marginal efficiency improvement from AI than workers with high initial abilities. The mechanism is that low-ability workers have a large initial efficiency gap in routine cognitive tasks, and generative AI directly fills their ability shortcomings in basic execution links. In contrast, high-ability workers already maintain a high efficiency level in routine tasks, and the role of AI is mainly reflected in time consumption compression with relatively limited marginal improvement in output quality. This effect leads to the convergence of productivity gaps among workers in routine cognitive tasks.

It is worth noting that micro-level efficiency gains are most significant in standardized and structured single tasks. When tasks involve complex situational judgment and multi-stakeholder coordination, the complementary effect of AI will decrease significantly.

#### **4.1.2 Wage Effects and Employment Characteristics at the Macroeconomic Level**

Whether the micro-level efficiency gains can be transmitted to the overall labor market needs to be verified by macro research based on administrative data. Research based on Finland's full-population administrative data shows that after the launch of ChatGPT, the average wages of occupations with high AI exposure increased by about 2% compared with the control group, while no significant changes occurred in employment scale. This result indicates that in Finland's formal labor market, the productivity improvements brought by generative AI are mostly converted into wage premiums for workers rather than reductions in job numbers [15].

This conclusion has clear sample boundaries. Finland features a high digital foundation, strong labor market protection system and high-skilled labor structure, and its conclusions cannot be directly extended globally. In economies with different institutional environments, industrial structures and digital development levels, the distribution methods of productivity gains may differ significantly.

#### **4.1.3 The Digital Transformation of Occupational Skill Structures**

Generative AI not only changes labor productivity, but also continuously reshapes the skill demand structure of occupations and promotes the overall upgrading of the skill structure toward digitalization and intelligence.

Based on the OTSS indicator of Germany, the research of Genz et al. [10] shows that from 2012 to 2023, the proportion of manual skills in the German labor market decreased by 4.8 percentage points, while the proportion of cutting-edge intelligent technology-related skills increased by 6.7 percentage points, presenting an overall upgrading trend of occupational skills. From the perspective of influence paths among different groups, the impact of generative AI on workers' capabilities features two-way expansion. Low-skilled workers can rely on AI assistance to complete cognitive tasks that previously exceeded their capabilities, expanding their occupational competence to higher levels. High-skilled workers can use AI to free up time occupied by routine tasks, allocate more human capital to complex decision-making and cross-domain innovation, and further raise the ceiling of professional capabilities.

The German labor market also presents a U-shaped structure of employment growth. Employment growth is concentrated in jobs with low and high cutting-edge skill intensity, while the employment growth of jobs with medium cutting-edge skill intensity tends to stagnate. This pattern directly corresponds to the dual effects of AI. Jobs with low cutting-edge skills mainly focus on interpersonal interaction, manual operation and on-site services, which face low substitution risks from generative AI and maintain stable employment demand. Jobs with high cutting-edge skills continuously generate new demand along with the expansion of the AI industry. In contrast, jobs with medium cutting-edge skills are mostly responsible for routine digital processing and standardized information processing, which are the core substitution targets of generative AI, resulting in obvious squeezed employment growth [10].

### **4.2 The Substitution Effect: Task Restructuring and Changes in the Employment Structure**

#### **4.2.1 The Boundary of Task Substitution's Effectiveness**

From the functional boundary of the substitution effect, existing evidence suggests that the substitution of labor by generative AI first occurs at the subtask level within posts, rather than directly eliminating complete

posts. The higher the proportion of routine cognitive tasks within a post, the more significant the reconstruction range of its task combination [1,4].

In terms of the boundary of task substitution, the substitution scope is concentrated in standardized and procedural routine cognitive tasks, such as information sorting and induction, first draft writing, basic translation and data entry. Tasks involving value judgment, in-depth interpersonal interaction, complex situation handling and unstructured problem solving cannot be completely replaced by AI in the short term [2,9]. Existing evidence supports that the core impact of AI on posts is mainly task reconstruction rather than overall post disappearance. Most posts will experience adjustment and upgrading of task content instead of being directly eliminated.

#### **4.2.2 Reconstructing Job Roles and Upgrading Skill Requirements**

With the continuous advancement of task substitution, a large number of positions dominated by routine cognitive work are undergoing systematic changes in their inherent attributes. Analysis conducted by the International Labour Organization and the OECD based on recruitment data from multiple countries shows that the recruitment criteria for positions such as administrative clerks, customer service staff and basic software developers have produced structural changes: the proportion of enterprises' demand for standardized execution skills keeps declining, while higher requirements are put forward for capabilities including result verification, demand decomposition, quality control and disposal of complex scenarios. Synchronously, the focus of the skill set required by positions has shifted from simple execution capability to high-order cognitive capability, human-machine collaboration capability and problem-handling capability.

This change indicates that even if the total number of positions does not decrease significantly, workers still have to bear the transformation pressure brought by skill iteration. Practitioners who cannot keep up with the new task structure will suffer wage reduction or even unemployment; workers who master human-machine collaboration capabilities can obtain higher salary returns.

#### **4.2.3 The Dynamic Evolution of Employment Volume and Structure**

From the long-term balance of substitution effect and new task creation effect, the academic community has not reached a unified conclusion on the impact of generative AI on total employment, and there are two core judgments.

Studies based on static exposure measurement tend to hold relatively pessimistic judgments. Based on the technical substitutability of occupational tasks, such studies estimate the scale of employment facing substitution risks. Some studies have concluded that about a quarter of global jobs face high substitution risks [2]. However, the limitation of such methods is that they only consider technical feasibility and ignore dynamic factors such as demand expansion caused by price decline, new job creation and organizational adjustment, so they usually overestimate the long-term employment impact [1,11].

Studies incorporating dynamic mechanisms hold relatively neutral judgments. Based on the task model framework, such studies point out that in addition to the substitution effect, there are productivity effect and new task creation effect. The reduction of production costs brought by AI will promote the expansion of product demand and further increase labor demand. At the same time, AI technology itself will create new occupations and tasks, such as AI trainers, prompt engineers and AI ethicists. In the long run, the change direction of total employment depends on the relative strength of the three types of effects. The core impact is not the reduction of total employment, but the accelerated restructuring of employment structure [1,7].

It is worth emphasizing that the divergence between pessimistic and neutral judgments on total employment does not stem from empirical facts, but from methodological premises. The static exposure method only calculates technical feasibility, while the dynamic task model incorporates both price effect and new task creation. In other words, pessimistic conclusions are essentially the projection of static methodology, rather than independent empirical findings. This identification provides a direct basis for the research gaps in the sixth part.

The consensus of existing evidence is that the substitution of generative AI has a distinct task bias, rather than a simple skill level bias. Different from traditional automation which mainly replaces medium and low-skilled jobs, generative AI impacts routine cognitive tasks in medium and high-skilled occupations, exposing medium and high-skilled groups to technological shocks. This feature challenges the interpretation framework

of traditional skill-biased technological progress, deviates from the existing expectation that automation shocks are concentrated in low-skilled jobs, and explains why occupational-level exposure measurement is prone to misleading results. Even high-skilled occupations show differentiated substitution intensity due to different proportions of internal routine tasks [2,4].

Furthermore, the deep-seated methodological divergence is the divergence in task mechanism modeling. Exposure studies only model the substitution effect in mechanism, while dynamic task models incorporate both price transmission of productivity effect and new task creation. The debate on convergence and polarization in the field of wage distribution can also be reduced to the same problem: which dominates in equilibrium, the ability convergence mechanism within tasks or the skill scarcity mechanism between tasks. The value of the task content perspective lies in providing a unified judgment framework for such divergences. As long as the performance distribution within tasks and the wage structure between tasks are observed in the same dataset, the opposite predictive directions of the two mechanisms can be empirically separated. This judgment has not been completed, forming the most critical current research gap.

### 4.3 The Evolution of Wage Distribution and the Skill Premium

The impact of generative AI on wage distribution is a cutting-edge research topic at present. The role of task automation in raising wage inequality has been verified in previous technological changes [16], but there are directional divergences in the existing evidence. Noy and Zhang [13], who conducted randomized controlled experiments on occupational writing, found that generative AI significantly reduces the output gap of low-skilled workers, supporting the path of ability convergence and narrowed gaps. In contrast, Eloundou et al. [2] and Felten et al. [9], based on occupational exposure, emphasize the scarcity of high-order cognition and cutting-edge technical skills, pointing to the path of expanding skill premium.

The two types of seemingly conflicting conclusions differ only in measurement objects. The former measures the individual performance distribution within tasks, while the latter measures the skill price between jobs, and the two are not directly comparable in terms of task granularity. Future research needs to observe both intra-task performance and inter-job wages at the same data level to judge the relative weight of the two paths.

According to the existing evidence, the short-term effects show differentiated characteristics: the wage level of routine cognitive tasks faces downward pressure, while workers with AI application capabilities and complex judgment capabilities obtain wage premium. The long-term impact depends on the adjustment speed of the education and training system. If the skill supply can quickly adapt to the new demand structure, the degree of wage inequality may not expand significantly; otherwise, the differentiation may be intensified [1,4]. The comparison of data types, methods, conclusions and applicable boundaries of major core literatures is shown in Table 1.

*Table 1: Generative AI Comparison of Core Literature on Economic Impacts*

| Literature         | Data Types and Methods                                           | Key Conclusions                                                                                                  | Applicable Scope                                          |
|--------------------|------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------|
| Eloundou etal [2]  | O*NET Professional Data and Language Model Capability Assessment | Approximately 80% of jobs have at least 10% of their tasks affected by generative AI.                            | Static exposure, overestimation of long-term substitution |
| Felten etal [9]    | O*NET Data and Language Proficiency Dimension                    | Obtain a similar occupational exposure distribution.                                                             | Based on U.S. occupational data                           |
| Yu etal [3]        | SEC10-KAnnual report text                                        | Deep adoption is concentrated among leading enterprises.                                                         | Covers only the S&P.500                                   |
| Genz etal [10]     | Germany BERUFENET Database and OTSS Indicator                    | Digital Upgrading of the Vocational Skills Structure                                                             | Only compatible with the European market.                 |
| Kauhanen etal [15] | Administrative data for the entire population of Finland         | The wage premium for high-exposure occupations is approximately 2%, the employment scale has remained unchanged. | Finland's unique institutional environment                |
| Noy and Zhang [13] | Randomized Controlled Trial of Professional Writing              | Task duration has decreased, and output quality has improved.                                                    | Single standardized task scenario                         |

## 5. Generative AI Cross-country Heterogeneity in Economic Impacts

The realization weights of the aforementioned three effects are not consistent globally. The substitution effect depends on the task structure, the productivity effect depends on organizational and computing power input, and the new task creation effect depends on R&D and talent endowments. The systematic differences between developing economies and developed economies in the three conditions determine the cross-country heterogeneity of the economic impacts of generative AI. This section conducts a comparison following this logic.

### 5.1 The Asymmetric Nature of Transnational Influence

The economic impacts of generative AI show significant asymmetry in economies with different development levels [17]. Developing economies may face a pattern in which the substitution effect takes the lead and the empowerment dividend lags behind [11,12].

The formation of this pattern has a clear mechanism chain. From the substitution perspective, routine cognitive posts vulnerable to AI substitution such as civil service and basic customer service have low requirements for digital infrastructure, and technical substitution can be realized only with basic internet access. Most practitioners of such posts in developing economies already have basic network access conditions, so the substitution effect of generative AI can be quickly transmitted to this group, and the employment impact appears first.

From the empowerment perspective, most efficiency-enhancing posts that can rely on AI to improve productivity are medium and high-skilled knowledge-intensive posts, which have significantly higher requirements for high-speed and stable networks, affordable computing power services, human capital with digital skills, and industrial digital supporting facilities. Developing economies just have obvious shortcomings in these high-level digital capabilities, which prevents the full implementation of AI productivity dividends.

According to the calculation of international financial institutions, about 26% of global jobs are exposed to the potential substitution risk of generative AI, with a total of 66.9 million jobs [12]. Given the overestimation tendency of the static exposure method pointed out in the fourth part, this figure should be regarded as a technical upper bound rather than a realistic prediction. What is more worthy of attention is the structural distribution: cognitive and routine white-collar posts account for the highest proportion, and the impact is concentrated in middle-income groups.

### 5.2 Cross-National Applicability BIAS in Occupational Exposure Measurement

An important finding of existing studies is that the traditional exposure indicators constructed based on occupational data of developed economies will systematically overestimate the actual substitution risks in developing economies [4,12].

The core reason is that the same occupations have significantly different task contents in economies with different income levels. The same occupational posts in developing economies usually include more manual operation, on-site service and interpersonal interaction tasks, and the proportion of unconventional analytical tasks is lower than that in developed economies, while the latter is the core action object of generative AI. The data from the 2026 World Development Report show that only 4.5% of posts in low- and middle-income countries face high automation risks, which is significantly lower than the 14.2% in high-income countries [11].

This finding has important policy implications. Developing economies should not directly copy the AI impact assessment and response policies of developed economies, but formulate differentiated strategies based on local occupational task structures.

### 5.3 The Evolution of the Concept of the Global Digital Divide

Generative AI is driving the connotation upgrading of the global digital divide, shifting from the traditional access gap to the gap in technical application capabilities. The traditional digital divide is mainly reflected in the access difference of the internet and digital devices, while the capability gap in the AI era is reflected in multiple dimensions such as computing power supply, digital skills, industrial digital foundation and institutional environment. The existence of the capability gap makes the benefits of technological progress

concentrate in developed economies and dominant enterprises, and developing economies may face the risks of deepened technological dependence and hindered industrial upgrading [11,12].

## 6. Research Limitations and Future Prospects

A preliminary judgment can be formed by synthesizing the full-text evidence. At the task level, the complementary effect is the most fully realized with the most consistent evidence. The substitution effect is concentrated on routine cognitive tasks with clear boundaries, but its magnitude is overestimated by static methods. The new task creation effect is observable, but its scale is still restricted by factor endowments and institutional conditions. The final determination of the relative weights of the three effects awaits the establishment of long-cycle data and a unified measurement framework. The following section sorts out the existing limitations from four dimensions respectively.

### 6.1 Main Limitations of Existing Research

First, the research time span is biased towards the short term, and the research accumulation on long-term dynamic impacts is insufficient. The large-scale commercial application of generative AI has lasted for a short time. Most existing literature focuses on the short-term performance of technological shocks, and has not formed sufficient research conclusions on the long-term equilibrium effect after the full diffusion of technology, the scale and structure of new job creation, and the in-depth changes of industrial forms.

Second, research regions are concentrated in developed economies, while research on developing economies is relatively weak. Most existing core studies are based on occupational and labor market data of developed countries such as the United States and Germany, and there are few systematic studies on developing economies, which restricts the global universality of research conclusions.

Third, the analysis of heterogeneity in influence mechanisms is insufficient, and the functional differences in different scenarios have not been fully clarified. Existing studies pay more attention to the heterogeneity at the industry and skill levels, but have not formed a systematic research framework for how factors such as enterprise organizational models, labor market systems and industry regulatory environments regulate the economic impacts of AI.

Fourth, research on non-economic dimensional impacts is relatively deficient. Existing literature mainly focuses on economic indicators such as productivity, employment and wages, while research on dimensions such as work quality, labor intensity and job matching quality under the impact of generative AI is still in the initial stage.

Based on the above analysis, the existing research gaps can be summarized into four types of propositions corresponding to the above four limitations one by one, as shown in Table 2.

*Table 2: Gaps in Existing Research and Corresponding Prospects*

| Gap Proposition                                                                                                | Cause                                                                                                                   | Corresponding Outlook                                                                                                                                                                         |
|----------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| The long-term direction of the employment-aggregate effect remains uncertain (corresponding to Limitation 1).  | The static exposure method ignores dynamic mechanisms; long-term panel data are missing.                                | Construct a task-granularity panel to identify the dynamic transition between substitution and creation.                                                                                      |
| The cross-country applicability of exposure indicators is insufficient (corresponding to Limitation 2).        | Based on occupational data from advanced economies; economic feasibility constraints were not incorporated.             | Relying on locally sourced occupational data for calibration, cost and institutional adjustment factors are incorporated.                                                                     |
| The mechanisms for institutional and organizational regulation remain unclear (corresponding to Limitation 3). | The heterogeneity analysis is confined to the industry and skill levels, without incorporating institutional variables. | Construct a cross-country comparable institutional adjustment model to examine the moderating effects of labor market protection and industry regulation on the weights of the three effects. |
| Research on non-economic dimensions is lacking (corresponding to Limitation Four).                             | Focusing on productivity and employment while neglecting job quality and workers' welfare.                              | Constructing a Task-Content Evaluation Framework That Balances Efficiency and Welfare                                                                                                         |

## 6.2 Prospects for Future Research Directions

In terms of industrial development, future research can be advanced from two aspects. First, aiming at the unclear applicable boundary of the J-curve of corporate profitability, enterprise panel data covering the entire stages of technology introduction, pilot implementation and in-depth integration can be constructed. Combined with SEC 10-K text adoption ratings and financial indicators, the emergence time of profit margin inflection points and their industry heterogeneity can be tested. Second, in view of the unknown long-term consequences of the market concentration trend, AI infrastructure investment, API dependence and market share data can be linked to identify the formation mechanism of digital differentiation and its impact on the innovation incentives of small and medium-sized enterprises.

In terms of the labor market, future research can be carried out along four paths. First, targeting the long-term uncertainty of the total employment effect, a labor market panel covering the technology diffusion cycle can be constructed, and the occupational task database can be connected with administrative wage records to identify the dynamic transformation of substitution effect and creation effect at the task granularity level. Second, in view of the insufficient cross-country applicability of exposure indicators, based on local occupational task data of developing economies such as India NCO and China Occupational Classification Dictionary, the generative AI exposure can be recalibrated at the task granularity level, and economic feasibility correction items such as computing power cost and institutional constraints can be introduced.

Third, in view of the unclear mechanism of skill demand changes and human capital adaptation, the vertical changes of skill requirements in job recruitment texts can be tracked to identify the specific direction of skill upgrading and provide a basis for the adjustment of the education and training system. Fourth, aiming at the limitation of unclear institutional and organizational regulation mechanisms, a cross-country comparable institutional regulation model can be constructed to test the regulation effect of variables such as labor market protection system and industry supervision environment on the relative weight of the three effects.

In view of the insufficient attention paid to non-economic dimensions in existing studies, indicators such as work quality, labor intensity, task autonomy and job matching quality can be incorporated into the task content analysis framework in the future, construct an evaluation system that balances efficiency and worker welfare, and investigate the impact of generative AI on human-machine collaboration experience and workers' subjective welfare.

On this basis, further expanded research can be carried out from the policy perspective to analyze the regulatory effect of industrial policies, labor market policies, education policies and other policies on the economic impact of AI, so as to improve the practical reference value of the research.

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