Research on Employee Skill Remodeling and Career Development Path of Enterprises in the Era of Artificial Intelligence

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Abstract. The rapid evolution of artificial intelligence (AI) technology has had a multidimensional and dynamic impact on the global labor market, replacing low and middle-skill jobs through automation, as well as giving rise to emerging occupations and exacerbating structural shifts in skill demand. This study focuses on the interaction between employee skill reshaping and career development paths in enterprises in the era of AI and systematically reveals the disruptive impact of technological advancements on job competencies through literature analysis, empirical research, and industry case studies. It is found that AI technology promotes the transformation of skill demand from Programmed Operation to Data-Driven and Composite Data-Driven, and human-computer collaboration has become the core path of ability upgrading; the career development path presents the trend of vertical promotion complexity and horizontal flow innovation, and the personalized design needs to balance the algorithmic efficiency and occupational autonomy; there is a bi-directional interactive relationship between skill remodeling and career path, and the skill upgrading promotes the career transformation, while the career goal inversely guides the career development path. There is a two-way interaction between skill remodeling and career paths, with skill upgrading promoting career transformation and career goals reversing the direction of skill investment. The study further points out that in the future, it is necessary to deepen the analysis of micro-mechanisms, incorporate ethical considerations, and explore the path of collaboration between government and enterprises, to address the challenges of algorithmic bias and skill mismatch.

Keywords: Artificial Intelligence, Skill Reshaping, Career Paths, Human-Machine Collaboration, Employment Polarization.

1 Introduction

In recent years, the impact of the rapid development of AI technology on the global labor market has been characterized by multidimensional dynamics. From the perspective of technological empowerment, AI significantly improves efficiency by optimizing the production process, for example, Shaanxi Fusi Automobile Company increased its production efficiency by 40% after the introduction of an automatic assembly line, and

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at the same time gave rise to emerging occupations such as data analysis and intelligent system operation and maintenance [1]. As far as the technology substitution effect is concerned, every 1% increase in robot penetration in the manufacturing industry leads to a 0.18% drop in labor demand, with low-skilled jobs being particularly hard hit [2]. This employment polarization phenomenon, as a structural feature of the labor market in the age of artificial intelligence, has shown a generalization trend, specifically manifested in the accelerated loss of middle-skill jobs, and the dichotomy phenomenon of the coexistence of the surge in demand for high-skill jobs and the survival of low-skill job stock.

The pervasive use of AI technologies in the manufacturing sector has had a dual impact on economies, with automation-driven task substitution significantly reducing employment in conventional occupations, while skill-biased technological change (SBTC) has amplified the wage premium for high-skilled workers through productivity-enhancing effects [3,4].

There are three major gaps in the existing research, one of which is the lack of research on the mechanism of skill remodeling, and related scholars have pointed out that traditional skill depreciation and AI skill premium coexist, but the dynamic process of skill conversion has not yet been clarified [5]. Secondly, there is a lack of in-depth analysis of the impact of heterogeneity, and relevant scholars have found that the employment promotion effect of AI on high digitalization occupations reaches 1.8 times but inhibits low digitalization occupations [6]. Third, the mechanism of the long-term "U-shaped" effect is yet to be solved. Relevant scholars have found that the AI investment of enterprises and the income of employees have a tendency to decrease and then increase, but the cross-industry transmission path still needs to be verified [7]. This study aims to reveal the bidirectional driving mechanism of skill upgrading and career transformation, which makes up for the unidirectional limitation of traditional research. It fills the research gap of the impact of industry heterogeneity through the analysis of the differentiated paths of manufacturing and service industries; and elucidates the compensatory effect of short-term inhibition and long-term promotion of AI technology based on the U-Shaped Effect mechanism. The study innovatively integrates the two-way mechanism, industry comparison and long-term dynamic perspective, and systematically responds to the three core gaps of the skill remodeling process, the impact of heterogeneity and the long-term effect of technology.

2 AI Technology Evolution and Changing Enterprise Skill Needs

2.1 Dynamic Adjustment of Enterprise Job Skills Inventory

AI has a substitution effect on middle-skill jobs, which has become a consensus in the academic community. The theory of skill polarization proposed by relevant scholars shows that computer technology is very easy to replace middle-skill jobs, but it is difficult to outlaw high-skill jobs and low-skill jobs, thus causing the demise of traditional middle-skill jobs [8]. The impact of AI on middle-skill jobs is essentially a redefinition of the division of labor by technology. However, if the creation rate of new occupations lags behind the disappearance of old jobs, it may lead to a short-term intensification of structural unemployment.

Through relevant scholars' empirical analysis of the manufacturing industry, it can be seen that the demand for skills diverges from single operational capabilities toward strong skills, such as cross-domain knowledge, systematic problem solving, etc., and weak skills, such as the execution of process-oriented, etc. [9]. Relevant scholars found that machine learning technology through the capital-skill complementary role, prompts enterprises to increase the demand for data analysis and R & D operations and other positions, this skill-binding situation shows that the demand for competence in the period of artificial intelligence is not only a purely linear replacement, but also the intermingling of traditional skills and digital skills [10].

2.2 Human-Machine Synergy and Composite Capability Upgrade

Human-computer collaboration is regarded as a key path to upgrade enterprise capabilities in the AI era, and after the popularization of AI technology in all aspects, human-computer collaboration will become a practice, which requires employees to master technical operation and cross-discipline collaboration, and their capability structure should be developed from a single-skill to the direction of "technology + operation + updating" composite, and the framework of Human-Computer Complementarity) has been proposed by related scholars. Scholars have proposed a framework of Human-Computer Complementarity, which highlights the need for humans to strengthen their complex competencies in things that AIs are not proficient in [11]. Related scholars have concluded that employees must have composite abilities such as human-computer interaction design, and equipment fault determination, and traditional skills must be integrated with the ability to use digital tools [9]. Therefore, the cultivation of compound capabilities requires breaking down traditional departmental barriers and promoting cross-border integration of knowledge.

The deeper point of conflict at the moment exists where technological tools are not in harmony with organizational culture, and IBM's Watson system used for human resource decision-making exposes an ethical gap in the regulation of algorithmic bias [12]. Therefore, human-computer collaboration should not remain at the level of tool use only but needs to reconfigure the organizational culture.

3 Mechanisms for Reskilling Employees in Enterprises

3.1 Comparative Study of Traditional Skills and Skill Needs in the Age of AI

The skill demand in the AI era has the characteristics of deprogramming and strong socialization, and it has changed from experience-oriented to data and innovation-oriented, and both technical hard power and communication soft power are critical, and the skills in the past focused on repeated operations, but in the AI era, the skills have to cover systematic thinking and the use of intelligent tools [9]. Relevant scholars say that traditional production relies on experience precipitation, but in the AI era, data should be used to stimulate decision-making. The focus of skills changes from physical labor to intellectually intensive activities [11]. Scholars recognize, by contrast, that skills that once relied on empirical intuition, such as manual work, will rely on data analysis, programming skills, and critical thinking in the AI era [12]. The AI era is still flawed, and workers with low education may fall into the Skill Trap, where old skills are devalued but the barriers to training for new skills are too high [3,13].

The essence of the skills trap is the contradiction between technological progress and social equity, and the lagging nature of the skills transition exposes the deeper problem of the education system being out of step with industrial demand. That's why companies can offer modular digital courses for low-skilled employees and provide career navigation services at the same time. In addition, governments can increase investment in vocational education and incorporate AI-based courses into the public education system.

3.2 Characteristics of Employee Skill Needs of Enterprises in Different Industries

The technical characteristics of the industry coupled with the codability of the tasks play a role in the demand for skills, resulting in a situation where the manufacturing industry favors hard skills and the service industry values soft skills. Scholars mentioned that most of the skills necessary for manufacturing are focused on equipment operation and guarding and process improvement, while the tertiary sector focuses on data analysis and system planning [10].

Technology-intensive service industries require employees to be aware of algorithm design and have the ability to make ethical judgments [14]. Scholars have argued that the high-tech industry relies too much on machine learning technology, and the skills needed in this industry are skewed towards the algorithm development end of the spectrum, whereas the traditional manufacturing industry puts more emphasis on the operation and guarding situations of robots [11].

There are still different views at this stage, and studies by relevant scholars show that the demand for specialized skills in manufacturing continues to escalate, while small and medium-sized service enterprises may have difficulty in keeping up with the trend of skill enhancement due to resource constraints, which in turn leads to a widening of the gap in the industry [15].

4 Mechanisms for Reskilling Employees in Enterprises

4.1 Evolution of Vertical Promotion Paths

Artificial intelligence technology drives the transformation of career development paths from traditional linear models to dynamic multidimensional structures. Existing research on vertical promotion mechanism reveals its inherent contradictions, tournament theory suggests that ranking-based promotion can incentivize competition, but related scholars have found that the fast promotion path of traditional vertical path may exacerbate the ability screening bias- Employees with high learning ability form an accumulated advantage in human capital after early promotion, while late promoters face the Catching-Up Trap, which leads to the career path solidification [16].

AI technology has further amplified the complexity of vertical promotion, and scholars have used the specific human capital model to point out that AI-driven job differentiation requires a shift in promotion criteria from general-purpose competencies to "technical + managerial" composite skill sets. For example, in the manufacturing industry, promotion to management positions requires both experience in equipment operation and data analysis skills [17].

Enterprises need to break the logic of promotion based only on technical theory and introduce a dynamic ability assessment system. The "skill point system" can be adapted to quantify non-technical indicators such as project results and cross-departmental collaboration, so as to provide a diversified channel of proof of competence for those who are promoted at a later stage.

4.2 Innovations in Horizontal Mobility Mechanisms

Lateral mobility enhances the probability of promotion through composite human capital, but its utility is constrained by the organizational context. Scholars have pointed out that when companies rely excessively on qualification systems, this of lateral mobility Structuring Traps can lead to cross-functional talent mobility instead of exacerbating the problem of skill fragmentation. For example, after a mechanical engineer moves to a supply chain management position, his or her technical expertise is gradually devalued due to the lack of continuous application opportunities [18]. The cultural adaptation costs that accompany lateral mobility in some companies may offset its benefits.

The value of horizontal mobility lies in the construction of a "T-shaped talent" pool, that is, a deep knowledge base and technical expertise in a particular field of specialization, as well as cross-field generic skills. Cross-functional mobility not only optimizes the allocation of talent but also fosters organizational innovation.

4.3 Individualized Developmental Pathway Designs

AI technology provides new tools for personalized pathway design, and related scholars using the talent analysis framework show that AI course recommendation systems can make training matches 35% better, but the unobservability of employees' implicit career motivations leads to a 20% risk of mismatch [19].
Algorithm-driven paths may trigger subjectivity erosion. Relevant scholars believe that when the algorithm crosses the boundary to manipulate the domain that should be dominated by human beings, it will shake the human-oriented institutional framework, weaken the autonomous judgment ability of human beings, and make the individual passive in the assumption of risk responsibility [20].

The essence of personalized paths is to respect the individual's career sovereignty, and algorithmic tools should serve the development of people, not replace them in making choices. Therefore, enterprises should retain roles such as artificial career counselors, tap the potential needs of employees through in-depth interviews, and incorporate subjective career visions into the AI recommendation model, so as to realize collaborative decision-making between humans and machines.

5 Relationship between Employee Skill Reskilling and Career Development Paths in Enterprises

5.1 The Impact of Skill Reskilling on Career Pathways

From the perspective of the impact of skill reshaping on pathways, AI has exacerbated the structural mismatch between skill supply and demand. This process forces career paths to shift from a single channel to a mesh structure, and the vertical-horizontal multi-path model of related scholars points out that micro-certificates increase the rate of obtaining qualifications for the promotion of employees with non-traditional educational backgrounds, but the compatibility of internal and external certification standards of enterprises needs to be solved [21]. The structural mismatch of skills supply and demand is not only a product of technology iteration, but also a reflection of the deep-seated contradiction between the traditional education system and the rapidly changing industrial demand. The cycle of skills updating has been shortened from ten years in the past to two years or even less, while the design of career paths is still stuck in the old paradigm of "lifelong career". This contradiction is forcing employees to move flexibly between functions or fields, rather than following a traditional single career path that progresses incrementally.

5.2 Career Pathways Lead to Skill Reskilling

The guiding effect of career paths on skill remodeling is reflected in the two-way mechanism of institutional drive and behavioral feedback. The strategic matching theory of related scholars reveals that a clear career ladder can guide employees to invest in the organization's strategic priority skills, for example, through the dual-track path of "technical expert-project manager" in new energy vehicle enterprises, the rate of skills transition to battery management system development has increased [22]. However, overly structured paths may inhibit exploratory learning, and the design of such a standardized promotion system may stifle the compounding potential of employees, although it may improve efficiency in the short term.

6 Conclusion

By constructing a three-dimensional analysis framework of "technology evolution-skill reshaping-career path" and adopting a combination of cross-industry case comparisons and theoretical modeling, this study systematically analyzes the mutual mechanism of skill iteration and career development in the era of artificial intelligence. The study finds that the skill demand presents human-machine synergy and dynamic iterative characteristics, and the traditional unidirectional causal paradigm has been broken through, revealing that there is a bi-directional driving relationship between skill enhancement and career development, where skill upgrading promotes career transformation, and at the same time, the career goal guides the learning of skills in the reverse direction. In addition, the case study of manufacturing skill certification system and service industry human-machine collaboration confirms the reconfiguration effect of digital intelligence tools on career paths.

There is still room for deepening the micro-mechanisms, ethical considerations and cross-level synergistic analysis in this paper. First, the specific pathways of skill remodeling affecting career development are not sufficiently explained. Second, this paper does not fully incorporate the issues of ethics and fairness. In addition, this paper mainly focuses on the internal mechanism of the organization and lacks an integrated analysis of the government-enterprise and industry collaboration at the macro level, which limits the systemic nature of the research findings.

In view of the above limitations, the future research of this paper can be expanded into three aspects. First, deepen the refinement of micro-mechanism research. Second, ethical boundaries should be expanded to establish an evaluation model of algorithmic transparency and career mobility trust. Finally, innovative hybrid research methods are needed to provide systematic solutions for career governance in the smart era.

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