Artificial Intelligence in Labor Markets: Impacts, Opportunities, and Challenges

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Abstract. With the rapid development of Artificial Intelligence (AI) technology, its impact on the labor market is increasingly profound. Existing analytical methods exploring the specific impact of AI on the labor market lack quantitative research methods. This paper systematically analyzes the substitution risk and task transformation impacts of AI technology on different occupations (technical, interactive, creative, and repetitive) through a multi-level data collection method combining questionnaire surveys and textual data, and combining natural language processing and propensity score matching (PSM) methods. The research in this paper provides a scientific basis for policy makers and corporate decision makers, as well as an innovative quantitative analysis method and empirical basis for subsequent research.

Keywords: Artificial Intelligence, PSM, Labor Market, AI Impacts.

1 Introduction

The rapid development of artificial intelligence technology is penetrating into many industries with unprecedented depth and breadth, covering manufacturing, service, finance and even more extensive fields. These technologies have not only boosted productivity but also spawned new careers and business models. However, at the same time, the substitution effect of AI technology on traditional jobs has also triggered widespread social discussion and concerns.

In recent years, the impact of artificial intelligence on the labor market has attracted wide attention, and scholars mainly focus on its potential to replace traditional jobs and create new jobs. Frey and Osborne (2017) analyzed the automation possibilities of occupations and pointed out that about 47% of occupations have high automation potential, especially those involving repetitive tasks and well-defined rules [1]. These roles are more likely to be replaced by AI technology due to their low complexity and high predictability. However, in contrast to this, Arntz et al. (2016) proposed from the task level that complex tasks in many occupations, such as interpersonal interaction, judgment and decision making, significantly reduce the overall substitution risk of positions [2].In terms of creating new jobs with AI, Brynjolfsson and McAfee (2014) proposed

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[2].In terms of creating new jobs with AI, Brynjolfsson and McAfee (2014) proposed the "second machine Revolution" theory, suggesting that AI will not only replace some traditional jobs, but also create a large number of new jobs, such as data scientists and machine learning engineers[3]. At the same time, these new occupations pose new challenges to the skill demand, driving the labor market to transition to a high-skill direction. In further research, Acemoglu and Restrepo (2019) point out that the application of AI technologies has brought about a significant skill structure adjustment, which is characterized by a large increase in the demand for unconventional tasks (such as creativity and complex problem solving), and this trend is also supported by Autor (2015)[4][5].In addition, Bessen (2019) delving into the changing demand for skills as AI technologies spread, highlighting how the rise of new skills such as data analytics, programming, and interdisciplinary integration is reshaping the skill structure of the labor market [6][7].

However, the current methods lack quantitative research methods, that is, qualitative analysis is more than quantitative assessment [8]. Therefore, this paper considers quantifying the dynamic impact of AI on occupation and skill demand with the help of relevant methods, which provides accurate data support for formulating coping strategies.

2 Methodology

In order to explore the impact of AI on the labor market, this study combines quantitative and qualitative analysis methods based on questionnaires and open text data, adopts a variety of data processing techniques and models, and deeply explores the multi-dimensional impact of AI technology on the labor market. At the same time, the propensity Score matching (PSM) method was used for causal inference analysis to ensure the scientific and reliability of the research results.

2.1 Data Source

2.1.1 Questionnaire

The questionnaire is designed to systematically assess the impact of AI technologies on structural adjustments in the labor market, changes in skill demand, and worker psychology and behavior. The content of the questionnaire consisted of closed and open questions to allow for both quantitative and qualitative information collection. Closed-form problems cover the following main areas

1) Job change: Respondents were asked multiple choice questions to quantify the impact of AI technology on their job replacement or assistance, such as "What changes do you think AI technology will bring to your job?" (Options: complete replacement, partial replacement, no impact, efficiency improvement, etc.)
2) Skill needs: Survey respondents' mastery of AI-related skills (e.g., data analysis, programming) and training needs.
3) Psychology and Attitude: Quantify worker acceptance of AI technology and its impact on job satisfaction and psychological stress.

Open-ended questions delve deeper into workers' perceptions of AI technology, for example, "What do you perceive as the greatest threats and opportunities posed by AI technology to the labor market?" Through these open responses, a wealth of authentic and nuanced qualitative data is obtained.

To ensure the diversity and representativeness of the sample, we employed both online and offline data collection methods. Online distribution channels included email, social media platforms, and industry forums, which attracted participants from various industries. Offline surveys targeted the manufacturing and service sectors, where AI technology has a substantial impact, yielding more detailed industry-specific data through field visits. Ultimately, we collected 1500 valid questionnaires that encompassed a broad spectrum of demographic and occupational characteristics. The distribution of age, gender and other characteristics of the survey population is shown in Fig. 1.

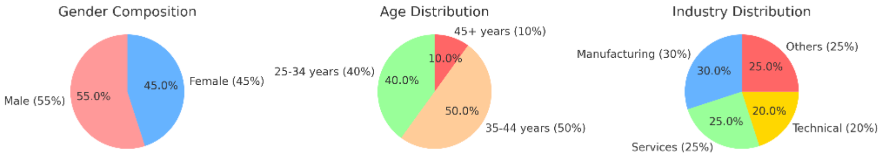

Fig. 1. The demographic characteristics of the respondents and the proportion of the industry structure.

2.1.2 Text Data

Text data were collected from multiple sources, and combined with open responses to questionnaires, discussions on social media, industry literature and expert interviews(Such as OECD and McKinsey report), the research data were supplemented and enriched from multiple dimensions. In order to deeply explore the multi-dimensional impact of artificial intelligence technology on the labor market, this study uses a multi-level data collection method combining questionnaires and text data to obtain high-quality data from different sources, which provides a solid empirical foundation and diverse perspectives for the research.

2.2 Data Analysis

This study systematically reveals the multifaceted impacts of AI technology on the labor market through the comprehensive analysis of questionnaires and open-text data, and conducts causal inference analysis using the propensity score matching (PSM) method to reveal the impacts of AI on different occupations. First, the data from the survey questionnaire were cleaned and normalized to extract structured variables such as gender, age, and industry category from the 1500 valid samples, as well as respondents' quantitative assessments of the risk of substitution, skill needs, and psychological impacts of AI technologies. The open text data were processed through natural language processing (NLP) techniques. Specifically, high-frequency keywords such as “efficiency improvement” and “skill demand” were extracted using the TF-IDF method, and workers' attitudes toward AI technology (positive, negative, and neutral) were quantified and populated into the structured variables through sentiment analysis. The specific technical process is shown in Fig. 2.

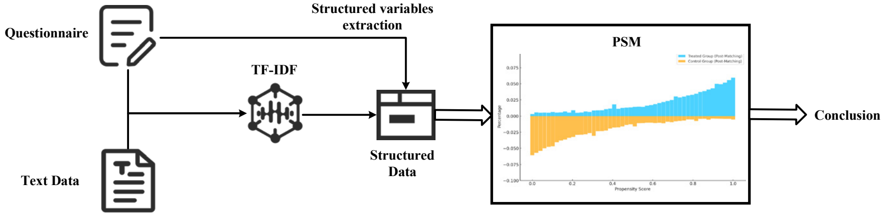

Fig. 2. PSM-based method to analyzing the impact of AI on the Labor Market.

In the propensity score matching (PSM) analysis, the propensity score of each sample is first calculated based on logistic regression by combining the structured variables of the questionnaire and the keywords and sentiment labels extracted from the text data to predict the probability of being assigned to the treatment group (the industry where AI technology is widely used). Then, the nearest-neighbor matching method is used to match the samples of the treatment group with the samples of the control group to ensure the consistency of the distribution of the two groups on key variables.

The combination of questionnaire and open text data balances the comprehensiveness of quantitative and qualitative analyses. The questionnaire data provides structured support for the labor market, while the natural language processing technology can extract deep information from unstructured text. Finally, the propensity score matching (PSM) method is introduced to causally analyze the treatment and control groups, controlling confounders through matching, and accurately quantifying the dynamic impacts of AI technology on job substitution, salary changes, and skill demand.

3 Results

This study relies on high-performance hardware (NVIDIA Tesla V100 GPU) and Python statistical tools (Scikit-learn). By integrating data from questionnaires and open literature, this study employs the propensity score matching (PSM) method to quantitatively analyze the distinct impacts of artificial intelligence (AI) technology on four occupational categories: technical, interactive, creative, and repetitive. Among them, PSM uses logistic regression model and nearest neighbor matching method to calculate the score, and the score will reflect the correlation between the probability of unemployment and the development of AI. The higher the score, the easier the occupation is to be replaced. The research results are shown in Fig. 3 and Fig. 4

The results show that technical occupations have more even propensity scores, indicating that their tasks are susceptible to AI influence rather than complete replacement, e.g., engineers and programmers can utilize AI tools to improve efficiency and accuracy, but basic technical positions (e.g., entry-level IT support) may be at risk of partial replacement. To this end, targeted skills enhancement programs should be developed, focusing on cultivating higher-order programming, data analysis and AI technology application skills, while encouraging enterprises to increase their investment in technology research and development, and providing workers with professional training in the operation of AI tools.

The propensity score of interactive occupations is concentrated in the low-score region, verifying its low risk of substitution, this is due to the fact that AI currently lacks the capability to substitute for humans in providing value through emotional communication. Creative occupations show a concentrated low-scoring regional distribution, which indicates that this occupation type is not easy to be replaced, and the core of creative occupations lies in the generation of novel and unique ideas and solutions, and this innovation process involves situational understanding, aesthetic judgment, and diversified ways of thinking, and AI is currently incapable of fully simulating human creativity. In the field of education, emphasis should be placed on cultivating students' creativity, interdisciplinary synthesis, and emotional and aesthetic judgment. The distribution of propensity scores for repetitive occupations is highly concentrated in the high score region, indicating that their regularized tasks are vulnerable to replacement by AI, such as assembly line workers and data entry clerks gradually being replaced by automation. So it is recommended to improve the support system for occupational transition, transfer workers to high value-added fields through skills training, and establish flexible unemployment protection and re-employment programs to mitigate the impact of technological shocks on low-skilled workers.

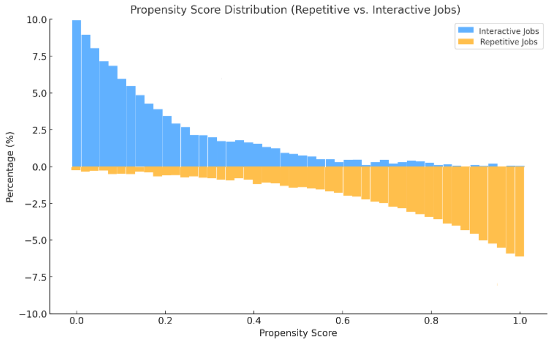

Fig. 3. Distribution of scores for interactive work and repetitive work.

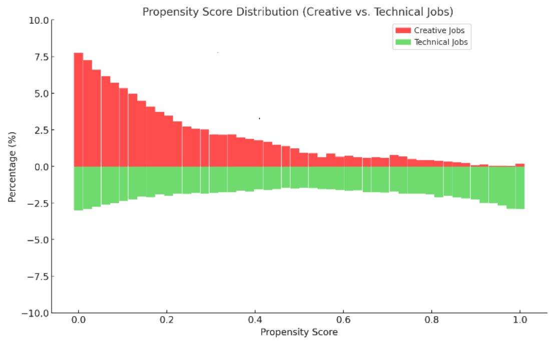

Fig. 4. Distribution of scores for creative work and technical work.

For opportunities, AI technology offers new development possibilities for all types of occupations. Technical occupations are able to expand task complexity and enhance innovation and work efficiency with AI; At the same time, the popularity of AI technologies has driven up the demand for skills such as data analysis, programming, and cross-disciplinary integration, which creates demand for high-skill jobs in the labor market and injects new momentum into economic growth. Future policies should fully integrate these opportunities and challenges to provide strong support for workers' career transition, skills retraining, and the sustainable development of the labor market.

4 Conclusion

This paper systematically analyzes the multidimensional impact of Artificial Intelligence (AI) technologies on the labor market through an innovative research methodology, particularly in terms of the risk of occupational substitution and the dynamics of changes in skill demand. The study employs a combination of questionnaire and text data for multi-level data collection, comprehensively covers both structured and unstructured data, introduces propensity score matching (PSM) and natural language processing methods, and utilizes causal inference techniques to control for confounding variables, thus ensuring the scientific and reliable scientific and reliable findings of the innovative quantitative research. This study will contribute to the development of research in the field of AI and the workforce

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