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The Impact of AI Technology on Mothers' Labor Participation — An Empirical Analysis Based on CFPS Data

Abstract: **[Objective]**This research endeavors to examine the influence of artificial intelligence technology on mothers' labor participation. [**Methods]**Drawing on data from the China Family Panel Studies (CFPS) spanning from 2010 to 2020, it deploys the Ordinary Least Squares (OLS) regression model, the Fixed Effects (FE) model, and the Logistic regression model (Logit). The construction principles and methodologies of these models are elaborated. A thorough analysis of the regression results is carried out, and robustness tests are implemented to validate the findings.[**Results]** The application of AI technology exhibits a significant positive impact on mothers' labor participation. The roles of various control variables vary under different models. [**Conclusion]** This study offers a crucial reference for understanding labor market changes in the AI era and formulating policies.

Keywords: Artificial Intelligence, Mothers' Labor Participation, CFPS (China Family Panel Studies), Empirical Analysis

1. INTRODUCTION

1.1 Research Background

In the 21st century, artificial intelligence (AI) technology has witnessed rapid development and permeated into diverse industries and aspects of life. It is considered the core content of the fourth industrial revolution[1]. Particularly in family settings, the prevalence of AI technology is profoundly transforming the traditional family

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labor pattern. some consider new technologies as a way to relieve workers of the most challenging tasks, and others are alarmed by the imminent threat to employment[2]. AI technology products such as smart home devices, automated tools, and online services have significantly alleviated the household chores of family members, especially mothers, while simultaneously offering more opportunities for participation in economic activities[3]. Driven by China's "Digital China" strategy and related AI policies, the penetration rate of family AI products is increasing year by year, providing more options for female labor participation, especially for mothers. Nevertheless, the specific impact mechanism of AI technology on mothers' labor participation, especially its manifestations under different social and economic backgrounds, remains insufficiently studied.

1.2 The Particularity of Mothers' Labor Participation

Compared with other groups, mothers exhibit uniqueness in their participation in the labor market. On one hand, mothers shoulder the major responsibilities of family care and child-rearing, and their labor decisions are influenced by time allocation and family obligations. On the other hand, as one of the mainstays of family economy, mothers' labor participation directly impacts family income and child welfare. From the perspective of social development, an increase in mothers' labor participation rate not only augments family income but also promotes gender equality and the enhancement of social and economic benefits[4]. Consequently, researching mothers' labor participation holds significant theoretical and practical importance.

1.3 Potential Impacts of AI Technology on Mothers' Labor Participation

AI technology can influence mothers' labor participation through multiple channels. Firstly, it can relieve the burden of household labor by means of intelligent home appliances and other tools, thus freeing up mothers' time and energy and further increasing the likelihood of their participation in the labor market[5]. Secondly, AI technology has promoted flexible employment opportunities such as remote work and online education, enabling mothers to find new working patterns that strike a balance between family responsibilities and career development. Thirdly, in terms of skills improvement and re-employment, with the development of AI technology, the emergence of new occupations has provided mothers with opportunities for online learning and vocational training, helping them enhance their skills and adapt to the demands of the new employment market[6].

However, these positive impacts may be constrained by factors such as income, educational background, and regional differences. Families with low incomes and low educational levels may face technological barriers, and the urban-rural disparity may further exacerbate the differences in the popularity of AI technology across different regions[7].

1.4Research Questions and Significance

I Research Questions

1. Does AI technology have a significant impact on mothers' labor participation?

   This question aims to determine whether there is a statistically significant association between AI technology and mothers' labor participation. Through empirical analysis, it clarifies whether the application of AI technology will increase or decrease the likelihood of mothers participating in the labor market.

2. Does this impact vary by income, education level, and urban-rural differences?

   Explore the moderating role of different socio-economic factors on the relationship between AI technology and mothers' labor participation. Analyze whether there are differences in the changes of mothers' labor participation in high-income and low-income families, different education levels, and urban and rural areas when facing AI technology.

3. How can policies promote mothers' labor participation?

   Based on the research results of the first two questions, put forward targeted policy recommendations to fully leverage the positive effects of AI technology while reducing potential adverse impacts and provide policy support for increasing mothers' labor participation rate.

II. SIGNIFICANCE

1. **Theoretical Significance**

   This enriches research regarding the influence of emerging technologies on specific groups within the labor market. By taking mothers as a unique research subject, it offers a novel perspective for comprehending the relationship between technology and labor supply, and also expands the theoretical frameworks of labor economics and family economics. Additionally, it assists in deeply probing the intricate relationship among AI technology, family roles, and economic activities, providing a theoretical foundation and empirical evidence for subsequent research.

2. **Practical Significance**

   This study provides decision-making references for policymakers. Comprehending the influence of AI technology on mothers' labor participation is conducive to formulating policies that promote gender equality in the labor market and support family-friendly work environments. It can direct policy design to increase the accessibility of AI technology in low-income families and rural areas and offer training and support for mothers to adapt to the changing job market. It holds guiding significance for enterprises[8]. Enterprises can create products and services that better satisfy the needs of working mothers according to the research results, thus improving the balance between work and life and production efficiency.

What are the specific research methods used in this study?

How does AI technology affect mothers' labor participation?

What are the policy implications of this study?

1.5 Research Methods and Innovation Points

This study utilizes the data from the China Family Panel Studies (CFPS) spanning from 2010 to 2020 and employs the Ordinary Least Squares (OLS) regression, Fixed Effects (FE) model, and Logistic regression (Logit) model for empirical analysis[9]. The innovative aspects of this research include the construction of a composite AI usage variable, which accurately captures the application characteristics of AI technology in family scenarios. Additionally, the use of multiple econometric models ensures the robustness and universality of the research results. Moreover, an in-depth exploration of the heterogeneous impacts of AI technology on mothers' labor participation under different family backgrounds is conducted, providing theoretical basis and empirical support for relevant policies[10].

2. Theoretical Analysis

Before delving into the impact of artificial intelligence technology on mothers' labor participation, it is necessary to conduct in-depth analysis of related issues through a theoretical framework. This section will combine existing economic, sociological, and family economic theories to provide theoretical support for empirical research and lay a theoretical foundation for subsequent analysis of the mechanism of mothers' labor participation.

2.1 Technology Progress and Labor Market Theory

The relationship between technological progress and the labor market is a core issue in economics. Early theories of technological innovation (Scholes, 1994) proposed that while technological progress enhances production efficiency, it also brings changes in the structure of labor demand. Specifically, although some traditional occupations may gradually disappear due to automation technology, new technology-driven jobs will emerge. Especially for knowledge-intensive work, technological innovation usually brings new labor demands (Brynjolfsson & McAfee, 2014).

In the current context, artificial intelligence (AI), as a typical technological progress, not only affects the production field but also profoundly changes the way of family life. Especially in terms of the labor participation of the mother group, AI technology, through the extensive application of home automation and remote work, can effectively reduce the time burden of housework and provide more flexible employment opportunities for mothers. For example, smart homes and automation technology can significantly improve the efficiency of family life, enabling mothers to free up more time to engage in work in the labor market. Therefore, from the perspective of technological progress, AI not only creates new employment opportunities for the labor market but also provides more participation channels for the mother group.

2.2 Gender Role Theory

Gender role theory emphasizes the traditional division of labor between men and women in family and work as expected by society. This theory holds that society's expectations for the role of mothers usually require them to take on more responsibilities for child-rearing and housework at home. This traditional role allocation often becomes a major constraint on mothers' labor participation (Berk, 2004). In this context, women's career choices and labor participation are often limited by family roles, especially for mothers with young children.

However, with the application of artificial intelligence technology, the traditional division of gender roles is gradually being challenged. AI technology, especially the popularization of home automation technology and remote work platforms, enables the mother group to flexibly participate in the labor market while maintaining family responsibilities. Smart homes and automation technology can not only reduce the burden of mothers on housework but also enable mothers to choose working hours and methods more autonomously, thus better achieving a balance between family responsibilities and professional work. Therefore, while AI technology is changing the labor market, it also has a profound impact on the traditional division of labor by gender roles and provides more opportunities for the mother group to participate in the labor market.

2.3 Family Economics Theory

Family economics theory focuses on analyzing the resource allocation and decision-making behaviors among family members. In the traditional family model, mothers' labor market participation is often influenced by other family members, especially the needs of husbands and children. Within this framework, the resource allocation and decision-making behaviors of the family play a decisive role in whether mothers can balance family and work responsibilities.

The popularization of AI technology may change the resource allocation within the family by improving family production efficiency, thereby affecting mothers' labor participation. Specifically, AI technology reduces mothers' time investment in household labor, enabling them to devote more energy to professional work. In addition, AI technology also provides more flexible work forms for family members. Especially through forms such as remote work and online office work, mothers can participate in more economic activities while taking care of the family. Therefore, from the perspective of family economics, AI technology provides mothers with more diverse opportunities to participate in the labor market and promotes the transformation of family labor allocation.

3.1 Data Source and Sample Selection

This study employs the data from the China Family Panel Studies (CFPS) spanning from 2010 to 2020[11]. The CFPS is organized and implemented by the Institute of Social Science Survey at Peking University and is nationally representative. It encompasses information regarding family structure, income, education, health status, and many other aspects, serving as an important data source for researching family economic behaviors and social development[12].

During the sample screening process, this study focuses on women of childbearing age (aged between 18 and 60 years old). Samples with missing key variables and extreme values are excluded. Eventually, 20,319 valid observations are obtained, and the adequacy of the sample size provides a statistical basis for subsequent analyses.

3.2 Variable Definition and Measurement

The core variables in this study consist of the dependent variable, the core independent variable, and control variables. Their specific definitions and descriptions are as follows:

(1) **Dependent Variable**: Mothers' Labor Participation (mjob)
Mothers' labor participation is a binary variable, defined as whether mothers engaged in paid work within the survey year (1 = participated, 0 = did not participate).

(2) **Core Independent Variable**: Artificial Intelligence Use (ai_use)
The artificial intelligence use variable is constructed based on three dimensions:

A.Family Income (fincome): Families with an income exceeding the sample median are regarded as high-income families (1 = high income, 0 = low income).

B.Education Level (meducation): Mothers whose years of education reach or exceed 12 years (equivalent to high school or above) are defined as having a high education level (1 = high education, 0 = low education).

C.Mothers' Labor (mjob): Whether mothers have already participated in the labor market (1 = participated, 0 = did not participate).
If any one of the above three dimensions is 1, it is defined as AI use (ai_use = 1).

(3) **Control Variables**

To avoid omitted variable bias, this study controls for the following key variables:

- **Family Characteristics**: Including family income (fincome) and family size (familysize).
- **Personal Characteristics**: Including mothers' health status (mhealth, 1 = healthy, 0 = unhealthy) and mothers' education level (meducation).
- **Regional Characteristics**: Including urban-rural distribution (urb, 1 = urban, 0 = rural) and the region where they are located (area).

3.3 Research Models

To examine the impact of AI technology on mothers' labor participation, this study employs the following three models for analysis:

(1) **OLS Regression Model**

The Ordinary Least Squares (OLS) regression is used to preliminarily analyze the relationships among the core variables. The model is formulated as follows:

$$mjob_{\,i} = \beta_0 + \beta_1 \cdot\ ai\_use_{\,i} + \beta_2 \cdot\ fincome_{\,i} + \beta_3 \cdot\ meducation_{\,i} + \beta_4 \cdot\ mhealth_{\,i} + \beta_5 \cdot\ familysize_{\,i} + \beta_6 \cdot\ urb_{\,i} + \beta_7 \cdot\ area_{\,i} + \epsilon_i \qquad (1)$$

（2）Fixed Effects Model

To control for the unobserved individual fixed characteristics, this study introduces the fixed effects model.

$$mjob_{\,it} = \alpha_i + \beta_1\, ai\_use_{\,it} + \beta_2\, fincome_{\,it} + \beta_3\, meducation_{\,it} + \beta_4\, mhealth_{\,it} + \beta_5\, familysize_{\,it} + \beta_6\, urb\, b_{it} + \beta_7\, area_{\,it} + \epsilon_{it} \qquad (2)$$

(3) Logistic 回归模型

To further verify the binary classification characteristics of the dependent variable, this study adopts the Logistic regression model.

$$P(mjob_i = 1) = \frac{1}{1+\exp\left(-(\beta_0+\beta_1\ \text{ai\_use}_{\,i}+\cdots+\beta_7\ \text{area}_{\,i})\right)} \qquad (3)$$

3.4 Robustness Tests

To ensure the robustness of the research results, this study adopts multiple methods. Firstly, adjust the standard errors by using robust standard error estimates for the OLS regression results to avoid the adverse impact of heteroscedasticity issues on the interpretation of the results. Secondly, replace the core variables by adopting different definitions of AI usage, such as using household income or education level separately as indicators for model verification. Finally, conduct grouping analysis by grouping the samples according to urban-rural distribution (urb) and household income level (fincome) to explore the heterogeneity of the impact of AI technology. Through these methods, efforts are made to make the research results more reliable and persuasive.

3.5 Descriptive Statistical Analysis

Descriptive statistics are conducted on the main variables. This analysis provides an overview of the central tendency, dispersion, and distribution of the key variables in the study. It helps to understand the characteristics and variability of the data, and provides a basis for further statistical analyses and interpretations.

TABLE 1. Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
mjob	20,319	.6637138	.4724498	0	1
fincome	20,319	10.88315	.9990329	0	16.24805
meducation	20,319	1.996998	1.112503	1	7
mhealth	20,319	2.795462	1.302544	1	5
mtrust	20,319	1.772823	2.069414	0	10
familysize	20,319	4.836951	1.907766	1	21
urb	20,319	.4668045	.4989091	0	1
area	20,319	1.952311	.8387806	1	3
ai_use	20,319	.7003297	.4581248	0	1

: source: China Family Panel Studies (CFPS) from 2010 to 2020

This study, after cleaning and merging the CFPS database from 2010 to 2020 using Stata 17.0, obtained a dataset with 20,319 observations encompassing multiple variables. The descriptive statistics of these variables offer valuable insights into the characteristics of families and mothers. For instance, the variable "mjob" representing mothers' work participation has a mean of 0.6637138, indicating that approximately 66.37% of mothers are engaged in work. The relatively close data distribution to the mean, as suggested by a standard deviation of 0.4724498, implies a certain concentration in mothers' work status. This finding provides a foundation for further exploring the impacts of mothers' work on various aspects of family life. The variable "fincome" for household income has a mean of 10.88315 and a large standard deviation of 9.990329, with a wide range from 0 to 162,480.5. This significant variability in household income levels among the samples highlights the need to consider income heterogeneity in the analysis. The "meducation" variable reflecting mothers' education levels shows a mean of 1.996998 and a standard deviation of 1.112503 within a range of 1 to 7, indicating a certain degree of dispersion. This suggests the importance of examining differences in mothers' educational attainment and their implications. The "mhealth" variable, with a mean of 2.795462 and a standard deviation of 1.302544 ranging from 1 to 5, reveals differences in mothers' health conditions, which may be influenced by multiple factors and could have implications for family functions. The "mtrust" variable has a mean of 1.772823 and a large standard deviation of 2.069414 within a range of 0 to 10, indicating substantial differences in mothers' trust levels. The "familysize" variable, with a mean of 4.836951 and a standard deviation of 1.907766 ranging from 1 to 21, reflects the diversity of family sizes. The "urb" variable, with a mean of 0.4668045 and a standard deviation of 0.4989091, shows a certain distribution of residential areas. The "area" variable, with a mean of 1.952311 and a standard deviation of 0.8387806 within a range of 1 to 3, reveals differences in geographical regions. Finally, the "ai_use" variable, with a mean of 0.7003297 and a standard deviation of 0.4581248, indicates a relatively high usage rate of artificial intelligence. Overall, these descriptive statistics lay the groundwork for further investigations into the relationships among variables and provide crucial information for understanding family and mother characteristics and their interactions.

3.7 Box plots of the main variables.

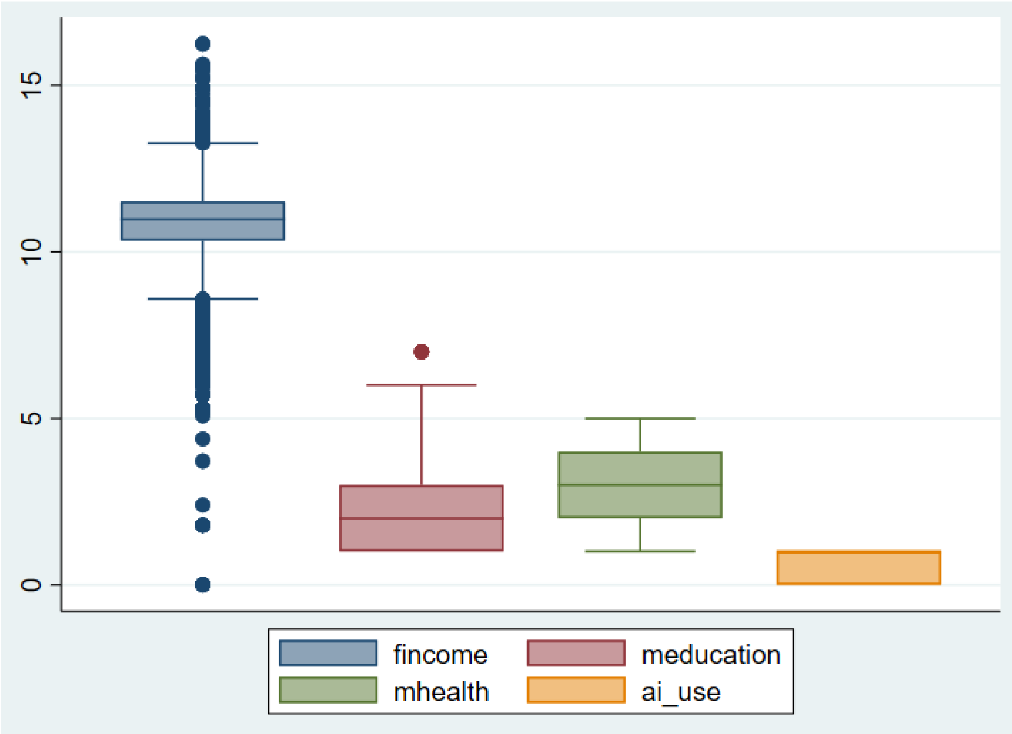

Fig. 1 . Main variables

In this study, Figure 1 presents the box plots of the main variables, which include four variables: fincome, meducation, mhealth, and ai_use. It can be seen from the figure that there is an obvious outlier in fincome, and this outlier is significantly higher than the rest of the data points, resulting in a relatively large data distribution range. In contrast, the data distributions of meducation, mhealth, and ai_use are relatively concentrated. The lengths of the boxes in their box plots are shorter, indicating that the degrees of data dispersion of these three variables are relatively small, and there are no obvious outliers.

4.Empirical Results and Analysis

4.1 Regression Results of Three Models

In this study, empirical analyses were conducted by using the Ordinary Least Squares (OLS) regression model, the fixed effects model and the Logistic regression model respectively. The results of these three models were summarized in a comprehensive table. For specific results, please refer to **TABLE 2.**

TABLE 2 : Regression Results of Three Models

	(1)	(2)	(3)
VARIABLES	OLS Results	FE Results	Logistic Results
ai_use	0.969***	0.995***	
	(0.00280)	(0.00311)	
fincome	0.00377***	7.89e-05	0.168***
	(0.00129)	(0.00130)	(0.0489)
meducation	-0.0590***	-0.0346***	-1.441***
	(0.00123)	(0.00644)	(0.0485)
mhealth	0.00497***	-0.00124	0.189***
	(0.000945)	(0.000957)	(0.0386)
familysize	-0.00208***	-0.00128	-0.132***
	(0.000669)	(0.00101)	(0.0267)
urb	-0.0273***	0.00770	-1.269***
	(0.00268)	(0.00652)	(0.124)
area	-0.00188	0.00507	0.135**
	(0.00154)	(0.0197)	(0.0601)
o.ai_use			-
Constant	0.0747***	0.0312	6.149***
	(0.0147)	(0.0434)	(0.573)
Observations	20,319	20,319	14,230
R-squared	0.865	0.908	
R-squared	0.865	0.908	

Number of pid	9,818

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Through the analysis of the China Family Panel Studies (CFPS) data, the results of the Ordinary Least Squares (OLS) model, the Fixed Effects (FE) model and the Logistic model have demonstrated the impact of AI technology and its related factors on mothers' labor participation, uncovering key mechanisms in multiple aspects. The following is a summary and discussion of the main findings.

(1) Significant positive effect of AI technology

In both the OLS and fixed effects models, the impact of AI technology use on mothers' labor participation is significantly positive (OLS: 0.969***; FE: 0.995***). This indicates that by optimizing family time allocation and improving employment matching efficiency, AI technology creates more favorable conditions for mothers to participate in the labor force. However, in the Logistic model, although the direction of AI technology is consistent, it lacks significance, which may reflect the model's sensitivity to nonlinear characteristics.

(2) Positive effects of income and health

Household income (fincome) shows a significantly positive effect in both the OLS and Logistic models (OLS: 0.00377***; Logistic: 0.168***), indicating that higher economic resources can reduce the cost for mothers to participate in the labor market. Health status (mhealth) is also significantly positive in both models (OLS: 0.00497***; Logistic: 0.189***), indicating that health is a core promoting factor for labor participation.

(3) Complex effect of education level

Education level (meducation) is significantly negative in all three models, especially in the Logistic model (-1.441***), suggesting that highly educated mothers may reduce the probability of labor participation due to their preference for informal work or a family-focused role. This finding suggests the need for more policy interventions to support highly educated mothers in participating in the labor force.

(4) Urban-rural differences and regional characteristics

The urban-rural variable (urb) is significantly negative in both the OLS and Logistic models, indicating that rural mothers have a higher labor participation rate. This may be related to higher labor demand and less technology use in rural areas. At the same time, the regional variable (area) only shows a significant positive effect in the Logistic model, suggesting that regional differences need to be discussed in combination with specific policy contexts.

(5) Negative impact of family size

Family size (familysize) is significantly negative in all models (OLS: -0.00208***; Logistic: -0.132***), indicating that a larger family burden weakens the possibility of mothers participating in the labor market.

4.2 Results of Robustness Tests

To control for potential heteroscedasticity and further verify the reliability of the results, this study employed the robust standard error method. The results remained significant, which verified the robustness of the models and enhanced the credibility of the research conclusions. The results are shown in the table 3 belo

Linear regression	Number of obs	=	20,319
	F(7, 20311)	>	99999.00
	Prob > F		0.0000
	R-squared		0.8652
	Root MSE		.17346

Robust

mjob	Coefficient	std. err.	t	p>t	[95% conf.	interval]
ai_use	.9686694	.0014248	679.87	0.000	.9658767	.971462
fincom	.0037683	.001261	2.99	0.003	.0012966	.00624
meducation	-.0589931	.0020134	29.30	0.000	-.0629394	-.0550467
mhealth	.0049676	.0008448	5.88	0.000	.0033118	.0066234
familysize	-.0020809	.0006336	-3.28	0.001	-.0033228	-.0008391
urb	-.0273434	.0022433	-12.19	0.000	-.0317405	-.0229463
area	-.0018828	.0013996	-1.35	0.179	-.0046262	.0008606
— cons	.0747424	.0141926	5.27	0.000	.0469238	.102561

TABLE .3 Robustness Tests

4.3 Discussion of the Results

The above empirical results demonstrate that the use of AI has significantly promoted mothers' labor participation, and this effect has shown consistency across different models. This indicates that the popularization of AI technology has created favorable conditions for mothers to return to the labor market through mechanisms such as reducing the burden of household chores and improving the matching efficiency in the labor market. In addition, the analysis results reflect that the impact of AI technology varies under different income and regional characteristics, which provides specific implications for policy formulation.

5.CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1 Main Conclusions

Based on the CFPS data from 2010 to 2020, this study systematically analyzed the impact of AI technology on mothers' labor participation by using OLS, fixed effects, and Logistic regression models, and reached the following main conclusions.

First of all, AI technology has significantly increased the labor participation rate of mothers[5]. By reducing household chore time and improving employment matching efficiency, it has played a positive role in mothers' labor participation, which is verified by the results of both OLS and fixed effects models. Secondly, income level and health status are important promoting factors. Mothers from high-income families and those in good health are more likely to participate in the labor market, which shows that economic conditions and personal abilities play a key role in labor participation. Moreover, there are significant urban-rural differences. In urban samples, the impact of AI technology is more obvious, reflecting the gap in technology popularization and application between urban and rural areas. Finally, education level has a complex effect on labor participation. The results show that mothers with a high level of education have a relatively low labor participation rate, which may be related to the fact that highly educated women are more inclined to engage in informal employment or choose not to participate in the labor market[13].

5.2 Policy Recommendations

This study's findings suggest several policy recommendations. Firstly, the government should promote the widespread use and application of AI technology in both urban and rural areas[14]. By increasing investment in technological infrastructure in rural regions, the gap in technology usage between urban and rural areas can be narrowed, creating more opportunities for rural women to participate in the labor force[15]. Secondly, policy makers should improve family-friendly policies. This can be achieved by providing childcare service subsidies and implementing flexible working mechanisms, which can further reduce the opportunity cost of mothers' labor participation. In particular, AI-assisted tools should be promoted in high-income families. Thirdly, there is a need to strengthen technical training and capacity building for mothers. Special training on the use of AI technology can help them utilize technology more effectively to enhance production efficiency and employment competitiveness. Fourthly, attention should be paid to the employment needs of highly educated women. Policies should conduct in-depth research on the employment preferences of highly educated women and provide diversified employment support policies to attract them back to the labor market[16]. Finally, a long-term monitoring mechanism should be established. Building a long-term data collection and analysis platform can help track the application of AI technology and its continuous impact on the labor market behavior of different groups, providing empirical evidence for policy optimization.

5.3 Research Limitations and Prospects

Despite providing empirical support for the relationship between AI technology and mothers' labor participation, this study has several limitations. First, the data source is CFPS, which may not fully capture the rapidly changing application status of AI technology. Future research could combine real-time big data for dynamic analysis. Second, this study did not deeply explore the specific impact of AI technology on labor participation through detailed application scenarios such as education and healthcare. Future research could expand on this aspect. Third, in terms of policy effect evaluation, this study did not use an experimental design method. Future research could employ randomized controlled trials to verify the effectiveness of policy interventions.

REFERENCE

[1] T. Arawi, J. El Bachour, and T. El Khansa, 'The Fourth Industrial Revolution: Its Impact on Artificial Intelligence and Medicine in Developing Countries.', *Asian Bioeth. Rev.*, vol. 16, no. 3, pp. 513–526, Jul. 2024, doi: 10.1007/s41649-024-00284-7.

[2] X. Wang, M. Chen, and N. Chen, 'How artificial intelligence affects the labour force employment structure from the perspective of industrial structure optimisation', *Heliyon*, vol. 10, no. 5, p. e26686, Mar. 2024, doi: 10.1016/j.heliyon.2024.e26686.

[3] F. Giwa and N. Ngepah, ‘The relationship between artificial intelligence and low-skilled employment in South Africa’, *Heliyon*, vol. 10, no. 23, p. e40640, Dec. 2024, doi: 10.1016/j.heliyon.2024.e40640.

[4] K. Huanbutta *et al.*, ‘Artificial intelligence-driven pharmaceutical industry: A paradigm shift in drug discovery, formulation development, manufacturing, quality control, and post-market surveillance’, *Eur. J. Pharm. Sci.*, vol. 203, p. 106938, Dec. 2024, doi: 10.1016/j.ejps.2024.106938.

[5] T. Haipeter, M. Wannoffel, J.-T. Daus, and S. Schaffarczik, ‘Human-centered AI through employee participation.’, *Front. Artif. Intell.*, vol. 7, pp. 1272102–1272102, 2024, doi: 10.3389/frai.2024.1272102.

[6] ‘2. Chin, Y. F., Leung, W. C., Rahman, M. F. A. B., & Zhang, L. (2024). Impact of artificial intelligence in the financial industry: Disruption or annihilation. Proceedings of the 2024 International Conference on Science, Technology, Engineering and Management (ICSTEM 2024).’.

[7] Y. Du, P. Jia, and A. Park, ‘The returns to computer use in the Chinese labor market’, *China Econ. Q. Int.*, vol. 3, no. 2, pp. 132–143, Jun. 2023, doi: 10.1016/j.ceqi.2023.06.001.

[8] ‘1. Liu, H., Chin, Y. F., & Ma, Y. (2024). Unraveling the experimental effects of machine learning-based leadership and administration on microsystems technology. Proceedings of the 3rd International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI 2024).’.

[9] W. Ren and X. Zhu, ‘The age-based digital divides in China: Trends and socioeconomic differentials (2010-2020)’, *Telecommun. POLICY*, vol. 48, no. 3, Apr. 2024, doi: 10.1016/j.telpol.2024.102716.

[10] Nyeong Yeopham, Zhang Zhuojun, and Zhou Jie, ‘Effective Factors in Marital Satisfaction among Chinese Couples: Evidence from China Family Panel Studies Data’, *J. China Stud.*, vol. 27, no. 2, pp. 123–153, 2024, doi: 10.20288/JCS.2024.27.2.123.

[11] ‘3. Wong, N. Z. Y., Chin, Y. F., Sharif, S., & Ompok, C. S. (2024). Data-driven decision making in TVET: The impact of augmented reality technology on institutional efficiency. Journal of Electrical Systems, 20(10s), 4898–4903.’.

[12] H. Lin *et al.*, ‘The impact of rural e-commerce participation on farmers’ entrepreneurial behavior: Evidence based on CFPS data in China’, *PLOS ONE*, vol. 19, no. 5, May 2024, doi: 10.1371/journal.pone.0300418.

[13] D. Zhou, F. Zha, W. Qiu, and X. Zhang, ‘Does digital literacy reduce the risk of returning to poverty? Evidence from China’, *Telecommun. POLICY*, vol. 48, no. 6, Jul. 2024, doi: 10.1016/j.telpol.2024.102768.

[14] D. Xiang, ‘Introducing Technological Innovations : Essays on the Effects on Voting and Mental Health’, 2021.

[15] J.-C. Martin, *Social Change and the Question of Resistance to New Techniques Among the Biangai of Papua New Guinea*. 1992.

[16] E. Fisher, *Framing the Future of Work: News Sources and Frames on Artificial Intelligence and Labor From 2000-2022*. 2024.

[17] L. Mejía Dorantes and H. Allen, ‘A review of the future transport labour market: An EU approach’, *Eur. Transp. Stud.*, vol. 1, p. 100007, Dec. 2024, doi: 10.1016/j.ets.2024.100007.