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Digital Transformation, Gender Discrimination, and Female Employment

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Abstract: With the demographic dividend disappearing, the key to achieving high-quality development in China is to promote full employment of the workforce. Women are a significant group in the job market, but they frequently face greater pressure and higher employment thresholds. Ensuring high-quality employment for women will be one of the most important tasks in the future. Based on the China Family Panel Studies data, this paper uses two-way fixed effects models, causal stepwise regression analysis, and structural equation models to study the impact of digital transformation of households on female employment and how it works. The empirical results show that digital transformation of households significantly promotes female employment. For low-security employment and high-security employment, the promotion effect of digital transformation is significant. Further mechanism analysis shows that digital transformation of households mainly increases women's human capital, improves their search for information, and stimulates improvements in social skills, thus effectively eliminating employment-related gender discrimination and ultimately promoting women's employment. This paper can provide a significant reference for alleviating female employment pressure, promoting full employment, and achieving high-quality development in the context of digital transformation.

Keywords: digital transformation; female employment; gender discrimination; two-way fixed effects model; SEM

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1. Introduction

In 2022, there will be 320 million women employed in China, accounting for 43.2 per cent of all employed persons in society. At present, China is facing the dual pressures of ageing and low fertility, with insufficient new sources of labor. Therefore, it is extremely important to realize high-quality employment on the basis of the existing total labor force. Women are one of the key focus groups, and promoting their high-quality employment can alleviate the pressure of the aforementioned labor shortage. However, for a long time, women have been subject to serious employment discrimination and employment pressure. In 2023, the overall income of women in the workplace was 12.6% lower than that of men, and an income gap between men and women clearly existed. Globally, about 2.4 billion women of working age do not have equal access to economic opportunities. Meanwhile, the wave of digital transformation is unstoppable. In 2022, the total digital economy of the five countries of the United States, China, Germany, Japan, and South Korea was USD 31 trillion, accounting for about 58% of the total GDP. Digital transformation is conducive to optimizing employment structures, improving the quality of employment, and ultimately achieving high-quality development of China's economy.

Compared with men, women's employment choices tend to be more influenced by the micro aspects of the family. In particular, the care of infants and young children may make women choose flexible employment or even make them return to their families. Additionally, one of the advantages of digital transformation is that it can break time and space constraints, promote the interconnection of information, and increase the flexibility of labor. Therefore, digital transformation can help women balance their relationships with work and family. However, with the development of digitalization, artificial intelligence technology will reduce the demand for jobs in low-skilled sectors in a short period of time and raise the employment threshold for women [1,2]. Relevant data show that the labor participation rate of Chinese women has decreased from 73% in 1990 to 63.73% in 2023. Therefore, it is of great practical significance that we explore the impacts and mechanisms of household digital transformation on female employment from the micro perspective.

This paper will empirically test the impact of household digital transformation on female employment based on the 2014 and 2020 China Family Panel Studies (CFPS) data, trying to reveal the mechanism of the role of household digital transformation in employment and its extent. At the same time, it will analyze the role of digital transformation in improving human capital, leveraging social skill advantages, solving the problem of information asymmetry, and eliminating gender discrimination in employment, so as to provide theoretical support and policy recommendations for further determining the economic effect and effect of digital transformation in promoting gender equality. This paper can provide micro-level reference for analyzing the promoting effect of digital transformation on female employment. The innovations of this paper are as follows. (1) Based on micro data, this paper explores the impact of digital transformation on women's employment by taking households as a unit, providing empirical evidence for analyzing the effect of digital transformation on employment. (2) This paper utilizes statistical methods such as causal stepwise regression and structural equations to explore in depth the relationship between the four mechanism variables and explores two paths through which household digital transformation influences female employment. (3) This paper categorizes women's employment into low-security employment and high-security employment, and then conducts regressions to analyze the impact of household digital transformation on women's employment security.

2. Theoretical Analysis and Literature Review

2.1. The Impact of Digital Transformation on Female Employment

Liu [3] explored the impact of the digital economy on employment from multiple perspectives. The digital economy expands the scale of the job market, brings employment dividends, optimizes the job market environment, and promotes the upgrading of industrial structure. Using five years of data from the CGSS database and utilizing the double difference method and the PSM-DID model, Qi et al. [4] found that digital life can promote individual employment. As feminist Sadie Plante wrote in Zeros and Ones: Digital Women and the New Techno-culture, with the development of new manufacturing and information processing industries, the importance of muscle power is gradually decreasing, and the importance of intelligence, interpersonal and communication skills is gradually increasing. The more advanced the machine, the more working women there will be [5]. Digital transformation provides a large number of fresh jobs.

Zhang et al. [6] suggested that women's employment choices are actually a trade-off between work, family and leisure. Chen et al. [7] explored the impact of elderly care on the supply of women in the labor market and found that intensive caregiving produces a "threshold effect" that reduces labor force participation and that caregiving tasks reduce weekly working hours. Zou et al. [8] used CFPS four-period data, using the instrumental variables method, and found that early childhood caregiving reduces women's labor force participation and working hours, and intergenerational caregiving significantly increases the labor force participation rate and working hours of young and middle-aged married women. The time available for women to work is fragmented by childcare, among other things. Family constraints cause many women to forego full-time work, The "motherhood penalty" prevents women from working opportunities and makes it hard to achieve high-quality employment [9]. However, this also increases women's incentives to engage in remote work. Herr et al. [10] pointed out that in the process of urbanization and informatization, the demand for flexible work opportunities and flexible forms of employment is greater for female employed persons, as important subjects who take on the productive activities of caring for the family and society. At the same time, the digital transformation of households has reduced the time women spend on leisure. These new jobs break the time and space constraints on employment imposed by traditional jobs, meaning women are able to participate in social labor more flexibly and better balance work and family. Feldman et al. [11] explored how the use of the Internet in the context of digitization changed employment based on an information-seeking perspective, and found that the quality of job searches was significantly better for individuals using the Internet than those using regular paper media. Cyber-feminists believe that gender becomes less important in cyberspace, and a person's sense of independence is instead more important. In the digital era, various obstacles that constrain women's development, such as religious traditions and childbirth, have been broken [12]. Therefore, Hypothesis 1 is proposed in this section.

Hypothesis 1 (H1). *Digital transformation can promote female employment.*

2.2. Micro-Mechanism of Digital Transformation Affecting Female Employment

The concept of human capital can be traced back to Plato's Republic. Human capital, also known as nonmaterial capital, is a kind of capital manifested in the employed person, for example, their knowledge, skills, health, and so on. Human capital is formed through investment in human resources, which primarily involves expenditure on education, healthcare, domestic labor, mobility, and immigration. Schultz's [13] human capital theory clearly shows that in the contemporary era, human capital is the most important factor in promoting the growth of the national economy. Mincer [14] suggests that human capital can be significantly enhanced by increasing the number of years of education, work experience, and improving skill levels, which in turn increases labor productivity and promotes employment.

On the one hand, digital transformation promotes the upgrading of industrial structure, adjusts the employment structure of labor force, and increases the demand for highly skilled personnel. This means higher requirements of female laborers. In order to adapt to the new requirements of work, female employed people learn and charge in their leisure time through the Internet to improve their human capital. On the other hand, digital transformation has broadened the channels through which laborers can acquire various skills and knowledge through the Internet. Ding et al. [15] used data from the 2018 CFPS to empirically test whether the use of the Internet has broadened the information channels of the employed. Thus, digital transformation can increase the level of women's human capital, and this section proposes Hypothesis 2.

Hypothesis 2 (H2). *Digital transformation promotes female employment by improving the level of female human capital.*

According to the DMP model (Diamond–Mortensen–Pissarides model), it can be seen that women's decision making about jobs is based on the comparison of reservation wage and market wage [16]. During the search process, if the market wage is greater than or equal to the reservation wage, the job seeker will accept the job and enter the job market. Conversely, the job seeker may reject the job and continue searching for a job. If the job search does not yield additional benefits while continuing to search for a job, the job seeker will stop searching and decide to be employed or not. When the information in the job market is asymmetric, the marginal cost and benefits of the information search determine the number of searches made [17]. The key to the employment choice is then the reservation wage and the ease of the search. If the reservation wage of job seekers is high, the market wage at which they choose employment also needs to be high, which means higher requirements for the salary of the job. If the search cost is high, job seekers search less frequently and the probability of finding the ideal job will decrease.

The entry of job seekers into the job market involves both firms and employees. On the one hand, digital transformation can provide enterprise managers with more convenient and lower-cost methods of searching for information. Zhai et al. [18], based on the data of Chinese A-share listed companies from 2007 to 2020, found that digital transformation is conducive to reducing the cost of information searches of enterprises, which is conducive to reducing the degree of information asymmetry and thus reducing the probability of making irrational decisions. On the other hand, the Internet can improve the degree of female job seekers' understanding of the information of the entire job market, avoiding the selection of excessively unreasonable reservation wages. At the same time, it can reduce the information search cost of female job seekers and improve their job search efficiency. The fundamental feature of digitalization is the interconnection of information. This can reduce the level of information asymmetry in the job market, raise the income level of female workers, and promote high-quality employment. Mao et al. [19] suggest that the use of the Internet can improve matching efficiency and thus promote female non-self-employment. Holman [20] studied the quality of employment in Europe from the perspective of employment type and found that the use of the Internet helps to reduce the degree of information asymmetry in the labor market, meaning employees can obtain job information in a timely and efficient manner, which leads to an increase in employment opportunities and helps to improve the quality of employment. Krueger [21] found that there is a significant wage premium utility in using the Internet, and workers who use the Internet can obtain a wage premium of 10–15%. Digitalization considerably improves the efficiency of matching between individuals and occupations. Therefore, this section proposes Hypothesis 3, as follows.

Hypothesis 3 (H3). *Digital transformation promotes female employment by reducing the cost of information search and alleviating the degree of information asymmetry.*

Compared to men, women have an inherent advantage in social skills, which is mainly reflected in the following three aspects. First, women are more expressive, speak more subtly in communication, and are better at observing social details. Second, women have more advantages in terms of personality: modesty and gentleness are examples of this. Third, women have better advantages in behavior; their daily activities are based on cooperation, and they are more observant.

Against the background of digitalization, Ding [22] et al. argued that the total amount of employment in society as a whole is increasing with the advancement of technology. Digital transformation promotes employment restructuring. Welch [23] proposed the "muscle–brain" theory, which argues that labor is composed of both physical and mental elements, and that automation raises the demand for mental work and helps women gain a comparative advantage in the labor market. Some occupations are easy to replace, such as machine operation, logistics, and transportation, which are male-dominated industries tend to be programmable. Additionally, female-dominated industries, such as education and healthcare, are hard to substitute, demanding frequent interpersonal communication. Therefore, the physical strengths of male jobholders are gradually eroded, while women's social skills complement this digital transformation [24–26]. In the context of digitalization, the total amount of employment across society has relatively increased, and many occupations have become smarter. As a result, women's advantages in soft skills are more obvious. In the face of an increasingly changing society, as long as women take the initiative to learn, their development will have unlimited potential. Based on biased technological change theory, with the popularization of computers in routine work, more women participate in unconventional tasks with higher wages. Therefore, Hypothesis 4 is proposed in this section.

Hypothesis 4 (H4). *Digital transformation promotes female employment by leveraging the advantage of their social skills.*

Zhong et al. [27] examined the impact of employment-related gender discrimination on the labor market by constructing a dynamic stochastic general equilibrium model and found that the elimination of employment gender discrimination can provide a favorable employment environment for female employment. According to World Bank data, China's female labor force participation rate is higher than the global average, but it has been declining in recent decades, and the rate of decline has been higher in recent years than in the past. Using the CHIP database, Li et al. [28] examined the size and composition of the gender income gap in different survey periods, and found that the wage gap between men and women has been widening, with gender discrimination being the main influencing factor. Luo et al. [29] conducted Oaxaca–Blinder decomposition of the gender wage function, including industrial factors, and found that for a long time, there has been more serious employment gender discrimination in most industries, women's employment is under great pressure, and it is difficult to realize equal pay for men and women for the same work. The reason for this is the severe gender discrimination in the labor job market, which makes it difficult to guarantee equal pay for equal work for both men and women. So, can digital transformation eliminate gender discrimination in the job market? The basic feature of digitalization is the interconnection of information. Digital transformation facilitates access to real labor productivity information rather than forecasts based on the average productivity of that employment group in the labor market. Phelps [30] suggests that there is in fact a discrepancy between an individual's true and expected productivity, and that this discrepancy leads to market discrimination by the employed. This subsection then proposes the following Hypothesis 5.

Hypothesis 5 (H5). *Digital transformation promotes female employment by alleviating gender discrimination in the labor market.*

Next, the relationship among the four mediating variables is analyzed. First, in a digital context, female workers enhance their human capital level through learning to the adapt to requirements of the job market. Through field research, Liu et al. [31] suggest that the lack of subsequent accumulation of human capital is the main cause of women's disadvantaged position in the job market. Therefore, improving the level of women's own human capital can alleviate gender discrimination in employment. The number of women in well-paid positions has increased, promoting high-quality employment for women. Second, digitalization promotes interconnection of information, and enterprises select employees based on actual needs of the post. Meanwhile, Zhang et al. [6] proposed that individuals receiving new information through the Internet are impacted by information from various platforms, which will have an effect on their gender preference and help to alleviate the phenomenon of gender discrimination. Third, women's social skills advantages are fully utilized in the context of digitalization. Using three years of CLDS data, Li [32] found that digitization brings about a premium on women's social skills and a devaluation of men's physical skills, thereby mitigating employment gender discrimination in the labor market. To sum up, the phenomenon of gender discrimination in the employment market will eventually be eliminated by raising the level of women's human capital, alleviating the degree of information asymmetry, and stimulating the advantages of women's social skills. According to the analysis above, the alleviation of gender discrimination in the job market can promote female employment. Therefore, Hypothesis 6 is proposed.

Hypothesis 6 (H6). *Digital transformation ultimately promotes women's employment by increasing the level of human capital, alleviating information asymmetry, and stimulating social skill advantages, which in turn alleviates gender discrimination in employment.*

H1 and H6 represent six hypotheses, respectively, and the relationships among the hypotheses in this paper are shown in Figure 1 below.

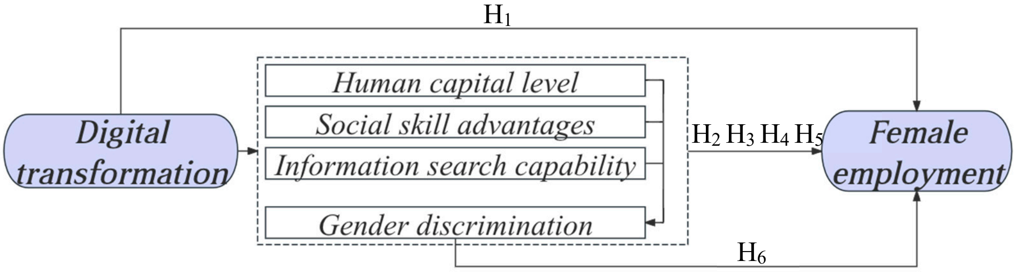

Figure 1. The mechanism of the impact of digital transformation on female employment.

3. Data Sources and Variable Explanations

3.1. Data Sources

The data used in this paper mainly refer to two levels: the household micro level and the provincial level. The micro-level data of families were obtained from the data of the CFPS in 2014 and 2020[1]. The 65,677 individual-level data were matched one by one to the households to which they belonged, and finally, 12,526 sample data were obtained at the household level. The selection of the database is primarily based on the following two main points. First, CFPS data contain variables related to the digital transformation of households, including personal, family and work information, which is highly consistent with the content to be studied in this paper. Second, CFPS data include both personal and household databases; the survey covers 25 provinces, cities, and autonomous regions[2]; and the survey samples both rural and urban areas as a whole. At the provincial level, the data principally come from the 2014 and 2020 China Statistical Yearbooks.

3.2. Variable Explanations

3.2.1. Dependent Variable

The dependent variable in this paper is female employment, which is examined in terms of whether women are employed and their employment security. The employment status of women is divided into employed and non-employed, among which not working includes those who have dropped out of the job market and those in a state of unemployment. Employment security status is categorized into low-security employment and high-security employment. According to the latest standard of the National Bureau of Statistics, the working age is defined as 16–59 years old[3]. The definitional variables are the proportion of female householders in employment, and the proportion of female householders in low- and high-security employment. The variable "whether or not they have signed a labor contract with their workplace" was chosen as the measurement criterion, and the signing of a contract was defined as high-security employment (and vice versa). Within the database, it was not possible to determine the contract signing status of some samples, so these samples were excluded from the calculation of the proportion of women in households with low- and high-security employment.

3.2.2. Independent Variable

The core independent variable of this paper is digital transformation; we therefore attempt to construct an index from the micro perspective. Based on CFPS data, factor analysis is used to construct the digital transformation index at the household level. Specific factors include whether there are mobile devices and a computer for accessing the Internet, whether people engage in online shopping, and the importance of the Internet for work, life, and business activities. The numerical variables are standardized. The index of digital transformation of households is a continuous variable with a value range of [0, 1]. The larger the value, the higher the degree of digital transformation of households.

3.2.3. Mediating Variable

The mediating variables of this paper are human capital, information search, social skills, and gender discrimination. Human capital is measured by two indicators, namely, frequency of using the Internet for learning and importance of the Internet for learning. The frequency of using the Internet for learning was assigned a value, the importance of the Internet for learning was standardized, and mean value of the two indicators was calculated as value of this indicator. The level of information seeking was measured by variable importance of the Internet as a channel for information. The advantage of social skills is measured by two indicators, namely, frequency of socialization and importance of the Internet for socialization, which are compiled into the same factor human capital. Gender discrimination in employment is measured by the variable of household perceptions of the division of labor between men and women. This variable is defined as the respondent's agreement with the notion that men are career-oriented and women are family-oriented. The responses were scored based on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). The higher the score, the higher the agreement with the concept. When standardized, a larger value indicates a deeper degree of gender discrimination in employment.

3.2.4. Control Variable

This paper draws on the study by Yin et al. [33] and selects a range of factors that may influence the level of female employment and security, mainly at the female, household, and regional levels. The control variables at the female level include the educational level and marital status of female workers. Control variables at the household level include the proportion of elderly people and minors, indebtedness, and property status. The control variable at the regional level is the average wage in the province in which the household is located. Samples with missing dependent variables, independent variables, and control variables are excluded, as well as samples with no working-age women in the two periods and a yearly income below 0. The specific meanings of the final variables are shown in Table 1. The means and standard deviations are shown in in the Appendix A.

Table 1. Variables mentioned in this study.

Variable Type	Variable Name	Variable Symbol
dependent variable	employment ratio flexible employment ratio inflexible employment ratio	Emp Lo_Emp Hi_Emp
independent variable	digital transformation of households index	Digi
mediating variable	human capital information search social skills gender discrimination	Hum_Cap Inf_Seek Soc_Ski Gen_Dis
female level control variable	education level	Edu_lev
	marital status	Mar_Sta
family level control variable	the proportion of elderly people the proportion of minors household debt family has a house	Pro_Eld Pro_Min Hou_Deb Fam_Hou
regional level control variable	average wage	Ave_wag

3.3. *Model Design*

3.3.1. Baseline Regression Model

This section constructs a two-way fixed effects model between digital transformation of households and women's employment to empirically test the impact of digital transformation of households on women's employment. The specific model is as follows.

$$Emp_{it} = \alpha + \beta Digi_{it} + \gamma Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

where Emp_{it} represents the employment proportion of working-age females of family i in year t $Digi_{it}$ represents the digital transformation index of family i in year t, β is used to measure the impact of digital transformation of households on female employment; $Controls_{it}$ represents the control variable; μ_i is the family fixed effect; φ_t is the time fixed effect; ε_{it} is the error term.

3.3.2. Mediating Effect Model

The four channels through which digital transformation of households affects female employment are human capital, information search, social skills, and gender discrimination. In order to further explore their specific mechanisms of influence, this section refers to the causal stepwise regression of Wen et al. [34] to test the mediating effect.

$$Emp_{it} = a_0 + a_1 Digi_{it} + \beta Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{2}$$

$$Inter_{it} = b_0 + b_1 Digi_{it} + \beta Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{3}$$

$$Emp_{it} = c_0 + Inter_{it} + a_1 Digi_{it} + \beta Controls_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{4}$$

In addition to the above mediating influence effect path, there is another influence path. That is, the digital transformation of households affects the first three mediating variables, and the first three mediating variables negatively affect gender discrimination, thus promoting female employment in the family. The specific model is as follows.

$$Sexism_{it} = d_0 + d_1 Hum\_Cap_{it} + d_2 Inf\_Seek_{it} + d_3 Soc\_Ski_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{5}$$

where Gen_Dis_{it} represents the degree of female employment discrimination in year t of family i, and Hum_Cap_{it}, Inf_Seek_{it} and Soc_Ski_{it} represent the level of human capital, the capability to search for information, and the advantage of social skills in year t of family i respectively.

3.4. Analysis of Endogeneity

In this paper, we use two-way fixed effects model in the empirical study to analyze the impact of household digital transformation on female employment. There may be endogeneity problems caused by omitted variables and reverse causality in the research process. That is, households with a higher proportion of female employment have a higher degree of digital transformation. A high proportion of female employment may be a cause rather than a consequence of the digital transformation of households. The influences on female employment are more complex and are affected by many other factors in addition to the control variables already selected in this paper. To overcome the endogeneity problem, this section constructs two instrumental variables to re-estimate the model. First, referring to Zhang et al. [35], topographic relief is used as an instrumental variable. On the one hand, geography affects the digital infrastructure in the area where the household is located, thus satisfying the correlation. On the other hand, topographic relief does not have a direct effect on female employment in the household, satisfying the condition of exogeneity. Second, the interaction term of topographic relief and the amount of Internet broadband access logged by one period in each region are used as the instrumental variables for digital transformation in the current period. Similarly, the instrumental variable satisfies the conditions of correlation and exogeneity.

4. Empirical Analysis

4.1. Baseline Regression

Based on the CFPS data in 2014 and 2020, this section uses the two-way fixed effects model to conduct baseline regression. In the process of regression, control variables at the female, household and regional level were gradually added, and the specific test results are shown in Table 2.

Table 2. Baseline regression results.

Variable	(1)	(2)	(3)	(4)
Digi	0.126 *** (0.034)	0.112 *** (0.027)	0.098 *** (0.027)	0.100 *** (0.019)
Mar_Sta		0.768 *** (0.012)	0.750 *** (0.012)	0.750 *** (0.012)
Edu_lev		0.307 *** (0.026)	0.302 *** (0.026)	0.301 *** (0.025)
Pro_Eld			−0.692 *** (0.019)	−0.169 *** (0.019)
Pro_Min			−0.111 *** (0.031)	−0.113 *** (0.031)
Hou_deb			0.000 (0.001)	0.001 (0.001)
Fam_Hou			−0.028 * (0.015)	−0.027 * (0.015)
Ave_wag				0.137 (0.082)
Control variable	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
R^2	0.019	0.662	0.676	0.677
N	12,526	12,526	12,526	12,526

Note: Heteroscedasticity robust standard deviations are in parentheses. * $p < 0.1$, *** $p < 0.01$.

As shown in Table 2, household digitalization significantly improves female employment. From an economic perspective, the impact coefficient of digital transformation of households on women's employment is 0.1. That is, for every 1-unit increase in digital transformation, the proportion of women's employment increases by 0.1 units, and this promotion is significant at the nominal level of 1%. Hypothesis 1, that digital transformation of households has a significant promotional effect on female employment, is valid. Analyzing from the perspective of control variables, the proportion of working females who are married and the level of education have a significant facilitating effect on female employment. The proportions of the elderly and minors and having a house have a significant negative effect on female employment.

4.2. The Impact of Digital Transformation on Women's Employment Security

In order to more comprehensively analyze the impact of digital transformation on women's employment security, this subsection divides women's employment into low-security employment and high-security employment, calculates the proportion of women's low-security employment and the proportion of high-security employment in each household, and then constructs the model separately. The model estimation results are shown in Table 3. As shown in Table 3, the promoting effect of household digital transformation on female employment is significant in both low-security employment and high-security employment. In terms of statistical significance, the coefficient of household digital transformation and female high-security employment is 0.395, which is significant at the 1% nominal level. That is, for every 1-unit increase in digital transformation, the proportion of female high-security employment in households will increase by 0.395 units. Digital transformation makes female employment more secure.

Table 3. The impact of digital transformation on women's low-security and high-security employment.

Variable	Lo_emp	Hi_emp
Digi	0.062 *** (0.023)	0.451 *** (0.030)
Mar_Sta	0.091 *** (0.010)	0.176 *** (0.014)

Table 3. *Cont.*

Variable	Lo_emp	Hi_emp
Edu_lev	0.040 * (0.021)	0.101 *** (0.029)
Pro_Eld	−0.015 (0.016)	0.010 (0.021)
Pro_Min	−0.061 ** (0.026)	−0.044 (0.035)
Hou_deb	0.000 (0.001)	0.002 ** (0.001)
Fam_Hou	−0.027 ** (0.013)	0.003 (0.017)
Ave_wag	0.153 ** (0.070)	−0.044 (0.093)
Control variable	Yes	Yes
Fixed effect	Yes	Yes
R^2	0.171	0.171
N	12,526	12,526

Note: Heteroscedasticity robust standard deviations are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Endogeneity Tests

There may be effects of omitted variables and reverse causality on the empirical analysis, so this paper uses the instrumental variable method to carry out the endogeneity test. Columns (1) and (2) of Table 4 report the main estimation results using topographic relief and topographic relief × number of broadband Internet access as instrumental variables, respectively. The F-value of the first stage using both instrumental variables is greater than 10, and the instrumental variables satisfy the correlation requirement and are not weak instrumental variables. Endogeneity testing was conducted on the model and the p-value was less than 0.05, thus proving the necessity of the endogeneity test. The empirical results show that the promoting effect of digital transformation of households on female employment is still significant; the estimated coefficient is significant at the nominal level of 5%, and the coefficient variation is within a reasonable range. The conclusions of this paper are still significant after using instrumental variables to further deal with endogeneity issues.

Table 4. Endogeneity tests results.

	(1)	(2)
Digi	0.333 ** (0.138)	0.557 ** (0.228)
R^2	0.616	0.547
N	12,526	12,526
Instrumental variable	Topographic relief	Topographic relief × number of broadband Internet users
Control variable	Yes	Yes
Weak instrumental variable F-value	36.172	27.843
Endogenous p-value	0.049	0.022

Note: Heteroscedasticity robust standard deviations are in parentheses. ** $p < 0.05$.

4.4. Robustness Tests

Considering that women's employment-related decision making will be affected by many complex factors, we conducted a robustness test to verify the robustness of the conclusions.

4.4.1. Changing the Criterion of Labor Age

In the baseline regression analysis, this paper adopts the standard of labor age stipulated by the National Bureau of Statistics. In order to eliminate sample differences and estimation errors caused by different labor age standards, the labor age standard used in most of the literature (16–70 years old) is adopted in the robustness section. The estimation results show that digital transformation can still significantly promote women's employment after replacing the labor age standard. The conclusions of this paper hold robustly.

4.4.2. Changing the Measure of Digital Transformation of Households

In the baseline regression analysis, the factor analysis method is used to construct the index of digital transformation of households, and the maximum likelihood method is used to extract the factors. The compilation of the index is affected by many factors, which may bring estimation errors due to the difference in factor extraction methods. Therefore, in the robustness test section, the factors are extracted based on the principal component analysis of factor analysis. After reconstructing the index for constructing the model, the estimation results show that the digital transformation of households can still significantly promote female employment. The conclusions of this paper are generally robust.

4.4.3. Excluding the Sample of Households in Municipalities Directly under the Central Government

In China, municipalities directly under the Central Government play an important role in politics, economy, transportation and other aspects and tend to have a larger residential population. There are currently four such municipalities, Beijing, Tianjin, Shanghai and Chongqing. The estimation results show that the digital transformation of households can still significantly promote female employment. The conclusion of this paper is relatively robust. The results of the robustness tests are shown in Table 5.

Table 5. Robustness tests results.

Variable	(1)	(2)	(3)
Digi	0.099 *** (0.020)	0.054 *** (0.017)	0.115 *** (0.013)
Mar_Sta	0.750 *** (0.012)	0.701 *** (0.009)	0.731 *** (0.006)
Edu_lev	0.301 *** (0.025)	0.277 *** (0.018)	0.292 *** (0.012)
Pro_Eld	−0.169 *** (0.019)	−0.012 (0.011)	−0.154 *** (0.009)
Pro_Min	−0.115 *** (0.031)	−0.112 *** (0.023)	−0.132 *** (0.015)
Hou_deb	0.000 (0.001)	0.000 (0.001)	−0.000 (0.000)
Fam_Hou	−0.027 * (0.015)	−0.016 (0.012)	−0.019 (0.006)
Ave_wag	0.133 (0.083)	0.104 * (0.060)	0.075 *** (0.016)
Control variable	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
R^2	0.676	0.616	0.638
N	12,526	16,209	11,435

Note: Heteroscedasticity robust standard deviations are in parentheses. * $p < 0.1$, *** $p < 0.01$.

5. Further Analysis

5.1. Regression Equation Tests

This section uses the causal stepwise regression method to test the mediating effects of human capital, information search, social skills and gender discrimination. Columns (1) to (4) of Table 6 analyze the relationship between digital transformation of households and each of the four mechanism variables. It can be seen from Table 6 that the digital transformation of households significantly affects human capital, information search, social skills and gender discrimination at the nominal level of 1%. The digital transformation of households promotes the accumulation of women's human capital, improves their information search level, strengthens their social skills, and suppresses gender discrimination.

Table 6. Mediation model regression tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Fem_emp				**Gen_dis**
Digi	0.448 *** (0.024)	0.157 *** (0.030)	0.142 *** (0.027)	−0.402 *** (0.024)	0.083 *** (0.021)	0.096 *** (0.027)	0.092 *** (0.019)	0.081 *** (0.027)	——
Hum_cap					0.038 ** (0.017)				−0.169 *** (0.008)
Inf_seek						0.025 * (0.014)			−0.118 *** (0.007)
Soc_ski							0.055 *** (0.015)		−0.274 *** (0.009)
Gen_dis								−0.046 *** (0.017)	——
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.360	0.425	0.622	0.187	0.677	0.677	0.678	0.678	0.222
N	12,526	12,526	12,526	12,526	12,526	12,526	12,526	12,526	12,526

Note: Heteroscedasticity robust standard deviations are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The relationship among digital transformation of households, each mechanism variable, and women's employment is shown in Table 6. From Columns (5) to (8) of Table 6, it can be seen that the coefficient of the promoting effect of the digital transformation of households on female employment is smaller than 0.1 in the baseline regression, so there is a partial mediating effect. The coefficients of human capital, information search, and social skills with female employment are all significantly positive. This shows that the digital transformation of households can promote female employment by increasing human capital, enhancing the level of information search and leveraging the advantage of social skills. Female workers can learn through the Internet to enhance their employment skills. At the same time, female jobholders can search for needed information more easily, which in turn facilitates employment. In the digital age, women's social skills are infinitely amplified. The new era needs diversified talents, and women's own advantages can promote their employment. The coefficient of gender discrimination is significantly negative. With the digital transformation, the traditional ideological bias of "male dominates outside and female dominates inside" has been broken. Gender discrimination in employment has been alleviated, and more and more women choose to go out for employment. Thus, Hypotheses 2 to 5 are verified.

The relationship between the four mechanism variables is shown in column (9) of Table 6. As shown in column (9) of Table 6, the enhancement of women's human capital, information-seeking ability, and social skills all contribute to a reduction in gender discrimination in employment. Taken together, the above analysis shows that the digital transformation of the household is conducive to the enhancement of women's human capital, information-seeking ability, and social skills, which in turn mitigates gender discrimination in the job market and ultimately promotes women's employment. Therefore, Hypothesis 6 is verified.

To make the mechanism test more stable, this section conducts a Sobel–Goodman test and bootstrap test. The Sobel–Goodman test results are shown in Table 7. As shown in Table 7, the p-values of the tests for the four mediating variables are less than 0.05, except for the indirect effect of information search. The bootstrap test results are shown in Table 8. It can be seen from Table 8 that the p-values of each effect test of the four mediating variables are less than 0.05. Therefore, the conclusions of the two testing methods are basically the same as those of Table 6. The indirect and direct effects of human capital, social skills, and gender discrimination are significant, and the direct effect of information search is significant.

Table 7. Sobel–Goodman test results.

	Type	Coefficient	Std. Error	z	*p*-Value
Hum_cap	Indirect effect	0.0143 ***	0.0038	3.7626	0.0002
	Direct effect	0.0881 ***	0.0088	10.0112	0.0000
Inf_seek	Indirect effect	0.0023	0.0019	1.1664	0.2434
	Direct effect	0.1001 ***	0.0082	12.2434	0.0000
Soc_ski	Indirect effect	0.0061 **	0.0026	2.3141	0.0000
	Direct effect	0.0962 ***	0.0837	11.5011	0.0000
Gen_dis	Indirect effect	0.0224 ***	0.0031	7.3343	2.2×10^{-13}
	Direct effect	0.0799 ***	0.0085	9.4303	0.0000

Note: Heteroscedasticity robust standard deviations are in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Table 8. Bootstrap test results.

	Coefficient	Std. Error	z	*p*-Value	95% Confidence Interval	
Hum_cap	0.032 ***	0.007	4.800	0.000	0.019	0.045
Inf_seek	0.006 ***	0.003	2.090	0.037	0.000	0.012
Soc_ski	0.014 ***	0.004	3.430	0.001	0.006	0.022
Gen_dis	0.018 ***	0.003	7.040	0.000	0.013	0.023

Note: Heteroscedasticity robust standard deviations are in parentheses. *** $p < 0.01$.

5.2. Structural Equation Model Tests

In order to more accurately test the impact of the digital transformation of households on women's employment, this section further adopts the multiple mediation effects model based on structural equation modeling (SEM) to verify the mediating effects of the four mediating variables. After several corrections, the standardized path coefficients of the final SEM are shown in Table 9. The standardized path coefficients of the specific structural equation model are plotted in Appendix B.

Table 9. Normalized path coefficients for SEM.

Hypothesis	Path	Standardized Path Coefficient Estimates
H_1	Digi→Emp	0.037 ***
H_2–H_5	Digi→Hum_Cap	0.533 ***
	Hum_Cap→Emp	0.004 *
	Digi→Inf_Seek	0.396 ***
	Inf_Seek →Emp	0.002 *
	Digi→ Soc_Ski	0.514 ***
	Soc_Ski →Emp	0.016 *
	Digi→Gen_Dis	−0.384 ***
	Gen_Dis→Emp	−0.005 *
H_6	Digi→Hum_Cap	0.559 ***
	Hum_Cap→Gen_Dis	−0.180 ***
	Gen_Dis→Emp	−0.015 *
	Digi→Inf_Seek	0.409 ***
	Inf_Seek→Gen_Dis	−0.129 ***
	Gen_Dis→Emp	−0.015 *
	Digi→Soc_Ski	0.554 ***
	Soc_Ski→Gen_Dis	−0.254 ***
	Gen_Dis→Emp	−0.015 *

Note: Heteroscedasticity robust standard deviations are in parentheses. * $p < 0.1$, *** $p < 0.01$.

The path coefficient of the effect of digital transformation on female employment is significantly positive at the 1% nominal level, indicating that digital transformation of the household can promote female employment, thus proving Hypothesis 1.

The path coefficients of digital transformation and human capital, information channels, and social advantages are all significantly positive at the 1% nominal level, indicating that digital transformation can effectively increase human capital, broaden employment information channels, and take advantage of social skills. The path coefficients of human capital, information channels, social advantages, and female employment are significantly positive at the 10% nominal level, indicating that increasing human capital, broadening employment information channels, and taking advantage of social skills can promote female employment. Therefore, household digital transformation promotes female employment by increasing female human capital, broadening employment information channels, and taking advantage of social skills. Thus, Hypotheses 2 to 4 are verified. The path coefficient of digital transformation and gender discrimination is significantly negative at the 1% nominal level, indicating that digital transformation can alleviate gender discrimination. The path coefficient of gender discrimination and female employment is significantly negative at the 1% nominal level, indicating that eliminating gender discrimination can effectively promote female employment. Therefore, digital transformation promotes female employment by eliminating gender discrimination in employment. Therefore, Hypothesis 5 is tested.

The path coefficients of digital transformation and human capital, information search, and social skills are significantly positive at the nominal level of 1%. The path coefficients of human capital, information search, social skills and gender discrimination are all significantly negative at the 10% nominal level. The path coefficients of gender discrimination and female employment are significantly negative at the 1% nominal level. The above findings suggest that digital transformation can eliminate gender discrimination and ultimately promote female employment by increasing the level of human capital, improving the ability to search for information, and giving full play to the advantages of social skills. Hypothesis 6 is therefore proven.

6. Heterogeneity Analysis

The results of the baseline regression and robustness test verify that the digital transformation of households has a significant promoting effect on female employment. Despite the inclusion of female-, household-, and regional-level control variables in the analysis process, the responses to the questionnaire are still not completely homogeneous. The employment-promoting effect of the digital transformation of households shows significant variability across groups. Based on this, this section analyzes heterogeneity in terms of geographic location, job market, and household.

6.1. Geographic Location Heterogeneity

The employment-promoting effects of the digital transformation of households may differ between towns and villages with different economic status. Households are categorized into towns and villages based on the place in which they registered for the survey. After controlling for relevant variables, group regression is conducted according to urban and rural areas, and the results are shown in Table 10. The regression results show that the digital transformation of both urban and rural households has a significant effect on female employment. In terms of economic significance, for urban households, the coefficient of digital transformation on female employment is 0.288, which is significant at the 1% nominal level. That is, for every 1-unit increase in the digital transformation index for urban households, the proportion of female employment will increase by 0.288 units. Similarly, for every 1-unit increase in the digital transformation index for rural households, the proportion of female employment will increase by 0.037 units, with the coefficient significant at the 1% nominal level. The heterogeneity test reveals that the employment effect of digital transformation is greater for urban households with higher levels of economic development. Compared to the countryside, towns have better supporting infrastructure and are able to provide more employment opportunities. In the countryside, many male laborers choose to go out to work, leaving their wives at home to take care of the family. At the same time, rural areas provide fewer jobs, and the employment effect of digital transformation is not as strong as in urban areas.

Table 10. A heterogeneous analysis of the impact of the digital transformation of the family on female employment.

	Cities and Towns		**Average Wage**		**Elderly**	
	Cities and Towns	**Rural**	**High Average Wage**	**Low Average Wage**	**Elderly**	**Without Elderly**
Emp	0.288 ***	0.037 ***	0.057 ***	0.675 ***	0.193 ***	0.057 ***
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	6431	6040	6149	6377	2993	9533
R^2	0.137	0.108	0.617	0.693	0.517	0.640
p-value	0.000		0.000		0.064	

Note: Heteroscedasticity robust standard deviations are in parentheses. *** $p < 0.01$.

6.2. Job Market Heterogeneity

The macro job market environment also affects female employment. This subsection empirically examines the impact of household digital transformation on women's employment in different job markets based on the average wages of employed persons in urban units in each province. After controlling for relevant variables, the results are shown in Table 10. The regression results show that the promotion effect of digital transformation on female employment is significant for households in both high-average-wage provinces and low-average-wage provinces. In terms of economic significance, for households in high-per-capita-wage provinces, the coefficient of digital transformation on female employment is 0.057, which is significant at the 1% nominal level. That is, for every 1-unit increase in the digital transformation index for households in high-per-capita-wage provinces, the proportion of female employment will increase by 0.057 units. Similarly, for every 1-unit increase in the digital transformation index of households in low-per-capita-wage provinces, the proportion of female employment will increase by 0.675 units, with the coefficient significant at the 1% nominal level. A test for heterogeneity reveals that for low-per-capita-wage provinces, the employment-promoting effect of households' digital transformation is more significant. In low-per-capita-wage provinces, people are motivated to work and expect high job upward mobility, and digital transformation brings diverse employment options, thus promoting female employment.

6.3. Family Heterogeneity

Elderly support is an important responsibility that women regularly face. This subsection conducts group regression based on whether there are elderly people in the family, and the results are shown in Table 10. The regression results show that in terms of economic significance, for households that support the elderly, the coefficient of digital transformation on female employment is 0.193, which is significant at the 1% nominal level. That is, for households that need to support the elderly, the proportion of female employment will increase by 0.193 units for every 1-unit increase in the digital transformation index. Similarly, for households that do not need to support the elderly, the proportion of female employment will increase by 0.057 units for every 1-unit increase in the digital transformation index, with the coefficient significant at the 1% nominal level. A heterogeneity test reveals that the employment-boosting effect of digital transformation will be greater for households that need to support the elderly. Supporting the elderly requires significant material costs and greater financial pressure on the household. Digital transformation provides more diversified employment options, and the digitalization of households helps women balance family and work, increasing the proportion of female employment.

7. Conclusions and Recommendations

7.1. Conclusions

Digital transformation is bound to become the central aspect of modern social development. Based on the micro perspective, this paper uses the data of the CFPS in 2014 and 2020 to test the impact of digital transformation of households on female employment (and its mechanisms). The empirical results reveal the complex and significant interrelationships between the digital transformation of households, human capital, information search, social skills, gender discrimination, and female employment, providing empirical evidence for the realization of employment for female groups. The main conclusions of this study are as follows.

(1) Our empirical results emphasize the crucial role of digital transformation of households in promoting female employment. In the economic sense, the coefficient of the impact of the digital transformation of households on women's employment is 0.1, which is significant at the nominal level of 1%. This indicates that for every 1-unit increase in the index of the digital transformation of households, the proportion of female employment will increase by 0.1 units. Therefore, the digital transformation of households significantly promotes female employment. This is in line with the findings of Yin et al. [32], that digital transformation significantly increases the probability of employment for women in the household. The facilitating effect of the digital transformation on the high level of contracted security is more pronounced, i.e., the digital transformation of the household is more conducive to securing women's employment. After a series of robustness tests in this paper, the conclusion that digital transformation of households promotes female employment is still valid.

(2) Human capital, information search, social skills, and gender discrimination are key to the complex link between digital transformation of households and women's employment. According to the results of SEM, the standardized direct effect of the digital transformation of households on female employment is 0.072, the standardized indirect effect is 0.031, and the standardized effect is 0.103; all three effects are significant at the nominal level of 1%. Further, the specific mechanisms of these effects are examined, indicating that the digital transformation of households mainly reduces gender discrimination in employment through the accumulation of female human capital, the improvement of searches for information, and the enhancement of social skills, which ultimately promote female employment. Women enhance their human capital through learning and give full play to their advantages in social skills. Women's own employment quality is improved, which alleviates gender discrimination in the job market and ultimately promotes women's employment.

(3) There is heterogeneity in the employment effects of the digital transformation of households. The analysis reveals that the digital transformation contributes more significantly to female employment in urban, low-per-capita-wage provinces and households with elderly dependents than in rural, high-per-capita-wage provinces and households without elderly dependents.

7.2. Recommendations

In summary, in order to further utilize the employment dividend effect of digital transformation, this paper gives the following suggestions.

(1) We should further integrate digital technologies within employment.

We should increase the implementation of digital technology among female groups. Governments at all levels should actively adapt to the wave of digital transformation and add corresponding digital technology training and learning in employment counseling for women, so as to encourage women to master the digital technology required in their work. Regarding external conditions, the construction of regional digital infrastructure should be improved to facilitate the further enhancement of the digital transformation of households. This will help give full play to the employment effect of the digital transformation of households in rural regions.

(2) We should establish a professional employment information service platform.

In order to help women obtain employment information in an efficient and low-cost manner, the government can take the lead in establishing a professional service platform. The recruiting information on the enterprise side should be effectively integrated to ensure the effectiveness of the information on the service platform. At the same time, this will help improve women's ability to search for information, safeguard women's rights and interests when looking for jobs, and promote women's active employment.

(3) We should accelerate the establishment of a sound labor security system.

We should establish a labor security system in the era of the digital economy to improve the level of women's employment security. In the era of the digital economy, the original labor security system is no longer applicable. The government should effectively supervise the implementation of relevant policies and regulations to protect the labor rights and interests of women in employment. Enterprises should establish differentiated algorithm rules and systems to actively protect women's labor rights and interests.

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Appendix A

Table A1. Statistical description of relevant variables.

Variable Symbol	Variable Measurement	Mean	SD
Emp	Number of employed women in households/Total number	0.43	0.32
Lo_Emp	Number of female low-security employment in households/total number	0.04	0.16
Hi_Emp	Number of female high-security employment in households/total number	0.10	0.24
Digi	Build index	0.22	0.26
Hum_Cap	Build index	0.22	0.27
Inf_Seek	The importance of the Internet as an information channel	0.42	0.33
Soc_Ski	Build index	0.30	0.33
Gen_Dis	Opinions on the division of labor between men and women	0.69	0.25
Edu_lev	The proportion of working women with an education level of high school or above	0.04	0.16
Mar_Sta	The proportion of married working women	0.37	0.33
Pro_Eld	Number of elderly people in the family/total number	0.11	0.21
Pro_Min	Number of minors in the family/total number	0.04	0.13
Hou_Deb	The amount of total household debt, calculated by adding 1 to the logarithm	1.98	4.13
Fam_Hou	Family has a house = 1, no house = 0	0.88	0.32
Ave_wag	The average salary of employed personnel in urban units of provinces, calculated by adding 1 to the logarithm	0.88	0.32

Appendix B

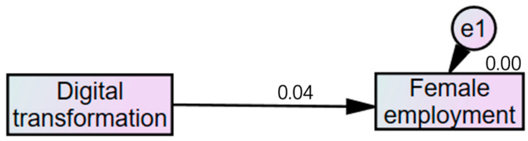

Figure A1. H1 test path diagram.

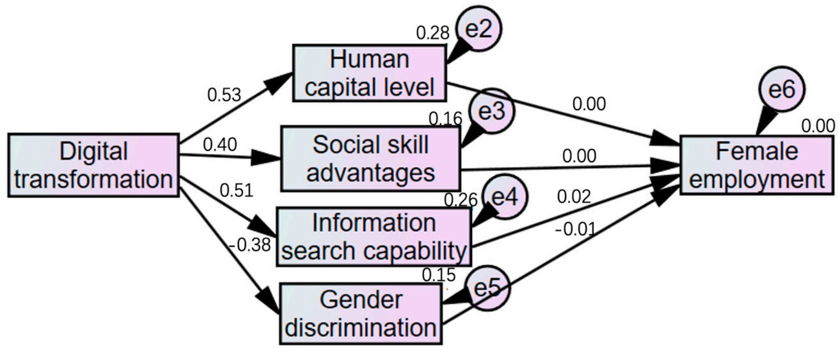

Figure A2. H2–H5 test path diagram.

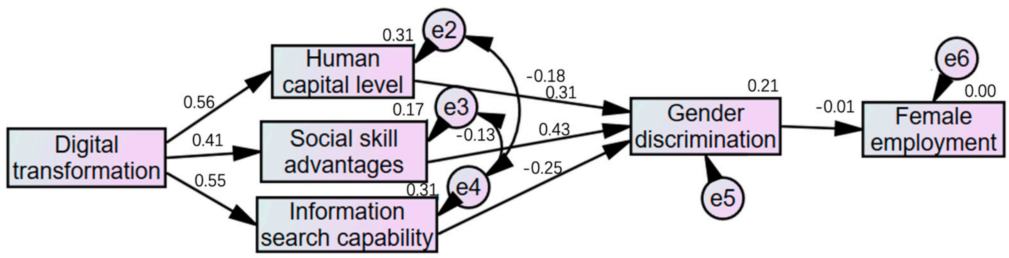

Figure A3. H6 test path diagram.

Notes

[1] In the CFPS database, gender discrimination is only involved in 2014 and 2020, so the data of these two years are used.

[2] The CFPS database covers 25 provinces and municipalities in China except HK, Macao, Taiwan, Xinjiang, Qinghai, Inner Mongolia, Ningxia and Hainan, and the surveyed population accounts for about 95% of the total population in China (excluding HK, Macao and Taiwan).

[3] Since 2013, the National Bureau of Statistics has classified the working-age population according to the age range from 16 to 59.

References

1. Yuan, N. On the Current Employment Structure and Its Adjustment in China. *J. Tech. Econ. Manag.* **2012**, *1*, 108–112.
2. Acemoglu, D.; Restrepo, P. The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [CrossRef]
3. Liu, Y. Research on the impact of digital economy on employment and countermeasures. *Bus. Econ.* **2023**, *12*, 20–22.
4. Qi, Y.D.; Chu, X. The Employment Effect of Digital Life: The Internal Mechanism and Micro Evidence. *Financ. Trade Econ.* **2021**, *42*, 98–114.
5. Plant, S. *Zeros and Ones: Digital Women and the New Technoculture*; Bantam Doubleday Dell Publishing Group: New York, NY, USA, 1997.
6. Zhang, W.D.; Bu, S.Q.; Peng, X.H. Internet Technology, Information Advantage and Off-farm Employment of Rural Labor —Micro Evidence from the 2017 Chinese General Social Survey. *Financ. Econ.* **2021**, *1*, 118–132.
7. Chen, L.; Fan, H.L.; Zhao, N.; Chu, L.L. The Impact of Informal Care on Employment for Women in China. *Econ. Res. J.* **2016**, *51*, 176–189.
8. Zou, H.; Peng, Z.C.; Luan, B.J. Intergenerational Care and Women's Labor Supply: An Analysis of the Paradox of Comprehensive Second Child and Delayed Retirement from the Perspective of Care. *Econ. Perspect.* **2018**, *7*, 37–52.
9. Yang, J.H. Women's high—Quality full employment: Current situation, problems and countermeasures. *J. Shandong Women's Univ.* **2023**, *1*, 12–14.

10. Herr, J.L.; Wolfram, C.D. work environment and optout rates at motherhood across high-education career paths. *Ind. Labor Relat. Rev.* **2012**, *65*, 928–950. [CrossRef]
11. Feldman, D.C.; Klaas, B.S. Internet Job Hunting: A Field Study of Applicant Experiences with On-line Recruiting. *Hum. Resour. Manag.* **2002**, *41*, 175–192. [CrossRef]
12. Haraway, D.J. *Simians, Cyborgs, and Women: The Reinvention of Nature*; Routledge Press: New York, NY, USA, 2013.
13. Schultz, T.W. Investment in Human Capital. *Am. Econ. Rev.* **1961**, *51*, 1–17.
14. Mincer, J.A. *Schooling, Experience, and Earning*; National Bureau of Economic Research: New York, NY, USA, 1974.
15. Ding, S.L.; Liu, C.H. Research on the Internet Use on Employment Quality in the Era of Digital Economy—From the Perspective of Social Network. *Res. Econ. Manag.* **2022**, *7*, 97–114.
16. Mortensen, D.; Pissaries, C.A. New Developments in Models of Search in the Labor Market. *Handb. Labor Econ.* **1999**, *10*, 509–525.
17. Stigler, G.J. Information in the labor market. *J. Political Econ.* **1962**, *79*, 94–105. [CrossRef]
18. Zhai, H.Y.; Liu, Y.S. Can Digital Transformation Improve Corporate Bargaining Power?—Based on the Perspective of Information Search and Customer Conversion Costs. *J. Zhongnan Univ. Econ. Law* **2023**, *6*, 29–41.
19. Mao, Y.F.; Zeng, X.Q. Whether internet use promotes female employment—An empirical analysis based on CGSS data. *Econ. Perspect.* **2017**, *6*, 21–31.
20. Holman, D. Job types and job quality in Europe. *Hum. Relat.* **2013**, *66*, 475–502. [CrossRef]
21. Krueger, A.B. How computers have changed the wage structure: Evidence from microdata. *Q. J. Econ.* **1993**, *108*, 33–60. [CrossRef]
22. Ding, R.C.; Yang, J.C. The impact of technological progress on labor employment in China. *Stat. Decis.* **2002**, *12*, 36–37.
23. Welch, F. Growth in women's relative wages and in inequality among men: One phenomenon or two? *Am. Econ. Rev.* **2000**, *90*, 444–449. [CrossRef]
24. Sorgner, A.; Bode, E.; Krieger-Boden, C. *The Effects of Digitalization on Gender Equality in the G20 Economies*; Kiel Institute for the World Economy: Kiel, Germany, 2017.
25. Frey, C.B.; Osborne, M.A. The future of employment: How susceptible are jobs to computerization? *Technol. Forecast. Soc. Change* **2017**, *114*, 254–280. [CrossRef]
26. Weinberger, C.J. The increasing complementarity between cognitive and social skills. *Rev. Econ. Stat.* **2014**, *96*, 849–861. [CrossRef]
27. Zhong, Y.T.; Chen, L.F. Why Eliminating Gender Discrimination in Employment is So Important? *J. Huazhong Univ. Sci. Technol. (Soc. Sci. Ed.)* **2023**, *37*, 43–54.
28. Li, C.L.; Li, S. Market Competition or Gender Discrimination—Explanation of the Widening Trend of Gender Differences in Income and its Causes. *Sociol. Stud.* **2008**, *2*, 94–117.
29. Luo, C.L.; Teng, Y.C.; Li, L.Y. Industry structure, gender discrimination and gender wage gap. *J. Manag. World* **2019**, *8*, 58–68.
30. Phelps, E.S. The Statistical theory of racism and sexism. *Am. Econ. Rev.* **1972**, *62*, 659–661.
31. Liu, X.R.; Ma, Z.L. Research on the impact of human capital on female college students' employment discrimination—Based on Becker's human capital theory. *Mod. Econ. Inf.* **2013**, *3*, 299–300+313.
32. Li, J.Q. Digital Revolution, Non-routine Skill Premium and Female Employment. *J. Financ. Econ.* **2022**, *48*, 48–62.
33. Yin, Z.C.; Song, Q.Y.; Wu, Y.; Peng, C.Y. Financial literacy, entrepreneurial decision making and entrepreneurial motivation. *J. Manag. World* **2015**, *1*, 87–98.
34. Wen, Z.L.; Ye, B.J. Mediating effect analysis: Method and model development. *Adv. Psychol. Sci.* **2019**, *5*, 731–745.
35. Zhang, J.; Fu, K. Can the construction of information network infrastructure drive the improvement of urban innovation level—Quasi natural experiment based on "broadband China" strategic pilot. *Ind. Econ. Res.* **2021**, *5*, 128–141.